Capturing and modelling complex decision-making in the context of travel, time use and social interactions

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by

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Intellectual property and publications

The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

The work in Chapter 2 of this thesis has appeared in publication as follows:

Calastri, C., Hess, S., Daly, A., Maness, M., Kowald, M. and Axhausen, K. (2017). *Modelling contact mode and frequency of interactions with social network members using the multiple discrete-continuous extreme value model.* Transportation Research Part C: Emerging Technologies, 76, 16-34.

I developed the main idea for this work, under the guidance of Stephane Hess. I performed the data analysis, the modelling work and wrote the manuscript. Stephane Hess and Andrew Daly provided recommendations on the modelling and comments on the results. The manuscript was improved by comments from all the co-authors.

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I developed the main idea for this work, under the guidance of Stephane Hess and Charisma Choudhury. I performed the data analysis, the modelling work and wrote the manuscript. Stephane Hess and Andrew Daly provided recommendations on the modelling and comments on the results. Juan Antonio Carrasco provided support with interpreting and using the dataset. The manuscript was improved by comments from all the co-authors.

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I developed the main idea for this work, under the guidance of Stephane Hess. I performed the data analysis, the modelling work and wrote the manuscript. Stephane Hess and Andrew Daly provided recommendations on the modelling and comments on the results. Juan Antonio Carrasco provided support with interpreting and using the dataset. The manuscript was improved by comments from all the co-authors.

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I developed the ideas for this work on the basis of the ERC proposal by Stephane Hess. I designed the survey, contributed to its deployment and wrote the manuscript. Romain Crastes dit Sourd coordinated the data collection activities. The manuscript was improved by comments from all the co-authors.

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Abstract

The field of choice modelling is evolving rapidly, with ever more complex representations of heterogeneity and a growing interest in discrete-continuous models instead of just discrete choice. Rapid developments are also taking place in terms of new data sources, with a growing revival of revealed preference data instead of stated preference, notably in terms of ubiquitous data and longitudinal surveys. Against this backdrop of developments in choice modelling, there is also a growing recognition of the role of the social environment on behaviour, through the effect of close and far social network members, with social interactions increasingly relying on digital communication. This thesis makes contributions in all of these areas, and differently from previous research, which has often focussed on just one, attempts to jointly explore multiple dimensions. Relying exclusively on revealed preference data, the work provides important insights into how social networks evolve over time, how people within a network interact with each other, and how there are links between a person's social network and his/her activity scheduling. The empirical results provide valuable insights for researchers not just in transport, but also in other fields. The behaviour modelled in this thesis is complex, with heterogeneity in different dimensions, in terms of preferences as well as behavioural processes, at the person level as well as at the individual choice level. At the same time, many of the choices are not mutually exclusive and have a continuous dimension too. The work makes a number of modelling advances, in terms of facilitating the recovery of heterogeneity and in putting forward solutions that allow for a computationally tractable representation of correlation and complementarity in discrete continuous choice, both in estimation and forecasting. Ever more complex representations of behaviour rely on rich data. This thesis highlights the benefits of detailed real world datasets in this context, and provides important insights into the limitations of existing data sources. The thesis closes by introducing a rich unified data collection that can be used for choice modelling applications in different fields.

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Chapter 1

Introduction

1 Background

Human life involves making a variety of choices every day. Some of these are perceived as important, maybe because they have strong financial implications or their consequences will be perceived over time, such as choosing an education or getting married. Others are so habitual they are barely thought of as decisions, such as which route to drive to work or which drink to buy at the local cafeteria. All these decisions have an impact on the provision of services, goods and infrastructure. Discrete choice modelling has been used as a mathematical tool to model and predict choices[1] for over forty years. While complex model structures have existed for several decades, recent advances in computing capacity have led to their more widespread use and in turn motivated new development, with a growing focus on representing complex decision processes and external influences on choices.

The application of such complex model structures requires adequate data, which is often challenging to collect. For example, an increasing number of studies look at activity scheduling (e.g. involving the allocation of multiple resources and the involvement of multiple agents), and accurate data is difficult to collect. Another example is represented by models studying the different environmental and social influences on decisions. While more sophisticated models to account for these factors have been developed, their measurement in a survey is a substantial challenge, and proxies to represent these influences are often used. Data limitations are often dealt with within model structures, either by making specific (often simplifying) assumptions or through the error structure. Neither approach may be satisfactory, as will be discussed in this thesis.

Human behaviour itself is changing, with continuously evolving activity,

[1] for a history of random utility maximisation (RUM) models that led to the emergence of choice models, see McFadden (2000)

travel and communication patterns, which involve choices that are increasingly captured by smart devices. The ability to exploit new and comprehensive data sources and face the challenges associated with them is an important issue in this field.

While much progress has been made in both the development of new model structures and the exploitation of different data sources for their application, there is scope for further work, as it is always the case. In this thesis, a number of important gaps in some of the areas of development that have characterised the field of choice modelling in the last two decades will be addressed and new contributions both on the theoretical and on the applied side will be proposed.

This Introduction provides some context for the different contributions before describing of the specific gaps in detail. Subsequently, the aims of the thesis are presented and an outline of the different contributions made by the thesis is given. We focus on three specific subareas, namely the treatment of context effects, the modelling of discrete and continuous decisions, and the improvement of data collection approaches.

Most applications of choice modelling assume that rational agents maximise individual utility functions, which depend on their socio-demographic characteristics and on attributes of the choice alternatives. In reality, individuals are embedded in complex environments, which shape the way they perceive the world around them, and consequently how they make choices. For example, let us consider the decision of choosing how to spend a free time on a Saturday afternoon. A naive approach will define all the possible activities as the choice set and consider the attributes of these activities and the socio-demographics of the decision maker as determinants of the choice. In reality, only some activities will be available to an individual, maybe because he/she lives in a specific geographic area, and many applications will deal with this, at least to some extent. However, availability and consideration may also vary across choices for the same person. For example, the individual may not consider performing some of the activities if the weather conditions are not favourable for it. In addition, the individual might be performing the activity with friends or family members, whose presence might relate with the choice or duration of the activity. Finally, if the person has performed an activity the previous day or even that very morning, he/she might want to avoid performing it again and rather do something different. It is clear that while this example refers to time use, these elements apply to many other choices. Moreover, this example is not meant to present an exhaustive summary of all the aspects potentially influencing choice, but it highlights those that will be discussed this thesis.

The first theme mentioned in this example is that of the inclusion of availability and consideration sets in choice models. Information about availability is generally easy to capture in travel behaviour surveys. In revealed preference surveys, respondents are asked about what travel modes are available to them. This is more complex in applications related (for example) to purchase behaviour. Even when an alternative is available, it might not be considered because of search costs (Stigler, 1961), personally imposed thresholds and inertia. As the analyst can generally only observe the final choice, attempts have been made at capturing the consideration process. Two main approaches have been used in the literature, the so-called two-stage exogenous models and the single-stage endogenous models. The two-stage exogenous models, based on the seminal work of Manski (1977), entail a separate treatment of the consideration and the choice part of the model (Ben-Akiva and Boccara, 1995; Cantillo and de Dios Ortúzar, 2005; Gaundry and Dagenais, 1979; Shocker et al., 1991; Swait, 2001), while the single-stage endogenous models (differently from the two-stage ones) accommodate the consideration set in the indirect utility (Cascetta and Papola, 2001; Martínez et al., 2009) and allow for fuzzy consideration sets, i.e. accommodate intermediate levels of consideration for each alternative.

The definition of the choice set or the decision itself could also be somehow related to an individual's social environment. The existing literature has provided valuable insights into how social network effects can be integrated into choice models. Several contributions focused on social influence effects (Brock and Durlauf, 2001), where the number of individuals in the reference group making a certain choice (Dugundji and Gulyás, 2008; Fukuda and Morichi, 2007) or the past actions of proximate contacts (Páez and Scott, 2007) have an impact on decisions. While social influence is the most intuitive effect of social networks on choices, it is worth noting that further insights about decision-making can be gained by understanding how social networks themselves operate. For example, while some attention has been devoted to looking at changes in car ownership over time (Prillwitz et al., 2006) and it has been recognised that there is an impact of social networks on the decision to own a car (Belgiawan et al., 2014), the process through which social networks form and change over time, which involve discrete decisions and outcomes, has not been widely studied in choice modelling. Some efforts has gone into studying social interaction frequency (Sharmeen et al., 2014) and network dynamics (Arentze et al., 2012, 2013; Sharmeen et al., 2015) but using cross-sectional or retrospective data, while studies using panel data are very rare and the analyses are at an exploratory level (Sharmeen et al., 2016).

Another aspect that was mentioned in our example above was correlation across decisions over time. This was particularly relevant in the case of time use, and not only in the case of leisure activities. If a person does his/her large shopping on Saturday, he/she will probably not do it on Sunday as well. In the case of time use (but not only), the choice is characterised by the fact that, associated with the discrete choice, there is a continuous choice. For example, an activity is chosen together with the time that will be spent performing it. As in real life these choices are made jointly, it is appropriate to model them with an appropriate framework that recognises this behavioural process. The state-of-the-art model for modelling discrete continuous choices is now the Multiple Discrete-Continuous Extreme Value (MDCEV) model (Bhat, 2008). This model is a generalisation of a multinomial logit model (MNL) for multiple discrete continuous choice contexts and has a simple closed-form probability which is practical even with a large number of alternatives. The models have been applied in different contexts. Most applications have been in the field of travel behaviour, for example to the choice of vehicle type and mileage (Bhat and Sen, 2006), to vacation-related decisions (Pinjari and Sivaraman, 2013) and to the type or timing and duration of activities (Kapur and Bhat, 2007; Paleti et al., 2011; Spissu et al., 2009). The MDCEV model has also been used in applications other than transport. For example, Lu et al. (2016) have applied it to the case of multi-buy alcohol promotions. Woo et al. (2014) used the model to understand how the use of traditional media (e.g. television, radio, newspaper) had been affected by new ones, such as in-home and mobile internet.

The richness of behaviour described above is in line with general observations about real world behaviour. However, for choice modelling, we need to capture such complexities in data suitable for modelling purposes. A major gap has opened in the field of choice modelling in recent years. Notwithstanding some exceptions (for example the work of Chandra Bhat and Joan Walker), many recent methodological advances, in particular the study of heterogeneity, have focussed on stated preference (SP) data and stated choice (SC) data in particular. Despite their appeal, it is not clear that very behaviourally rich (and especially longitudinal) effects can be captured with SP data. In recent years, an increasing number of scholars have recognised the value of using RP data, notwithstanding the many difficulties associated with it, such as frequent high collinearity and limited variation among attributes (Brownstone et al., 2000). Moreover, it is often more difficult to identify the choice set in the presence of RP data, and the attributes of the unchosen alternatives are not always known. On the other side, these data reflect real-life conditions and should be used if one aims at capturing and modelling the complexity of real-life behaviour. The domain of RP data is rapidly growing to include the so-called "ubiquitous" data sources, collected via mobile phones, smart cards, CCTV. These new sources constitute an invaluable resource in that they record repeated choices. Investigating ways to access them, handle them and model them is an important challenge in the field of choice modelling.

2 Research gaps

As mentioned in the previous section, much has been achieved in the field of choice modelling. This thesis seeks to fill some existing gaps in the literature, both methodologically and empirically. These will be highlighted in this section and subsequently addressed in the thesis.

Most of the advances in the field of choice modelling were developed in the field of travel behaviour research (with some notable exceptions in marketing), and adoption in other areas, such as environmental economics and health, has been slow at times. The reason for this is possibly related to the differences in the disciplines, with the knowledge not always being immediately transferrable across applications, but there are some areas that are indeed common to all these fields, namely:

- interest in the role of social networks (both physical and virtual) in decision making;
- a growing awareness that many choices are characterised by a continuous dimension associated with the discrete one;
- the study of complex patterns of heterogeneity, both across individuals, and across choices for the same individual; and
- the emergence of more detailed RP data, especially automatically collected data.

The gaps listed below revolve around these areas, and while most of the application areas in this thesis are in the field of travel behaviour, the advances themselves are useful for different fields of application.

GAP 1

Researchers in choice modelling are gradually beginning to study the role of social networks in choice modelling. However, this work is in its infancy, and gaps exist in different dimensions, pertaining to the formation and evolution of social networks, the way in which different members of a social network interact, and the relationship between a person's social network and his/her choices. Social interactions have mainly been modelled using multi-level and regression models, while social influence has received more attention in choice modelling, although existing work often includes social network variables in the utility assuming these have a causal effect on choices, while this might not necessarily be the case.

One potential area where there is scope for the application of choice modelling across different fields is the study of the processes of social network formation and evolution over time. Apart from a limited number of attempts looking at network formation (Arentze et al., 2013) and evolution (Sharmeen et al., 2016) (but without modeling the maintenance of social contacts over time), choice models have not been used to study these processes. Not only could choice models help gain a better understanding of social network dynamics, but scholars from different applied fields who are proficient in choice modelling could be encouraged to incorporate the effects of social networks in their models and possibly jointly model network evolution with other long term decisions.

GAP 2

The MDCEV model is the state-of-the-art tool for modelling multiple discrete-continuous choices. While accommodating important aspects of this choice process, many complexities of real-life behaviour cannot be represented in this modelling framework. This is analogous to the limitations of the Multinomial Logit (MNL) model which motivated the development of models allowing for more flexible substitution patterns such as Nested Logit. As detailed in Section 1, several extensions of the model have been produced by Chandra Bhat and his co-authors. Nevertheless, some of these advanced tools have been applied in a very limited number of cases, and often by the same scholars who have developed them. Further testing of these methods with different datasets and contributions that could potentially improve their applicability are therefore needed. A very important issue that needs addressing is suggesting ways to account for correlations across discrete-continuous choices so as to be able to observe substitution patterns across them. In the discrete-continuous time use literature some studies have accommodated interactions between different days (Bhat and Misra, 1999; Yamamoto and Kitamura, 1999). One of the extensions of MDCEV accommodates substitutions and complementarities across goods (Bhat et al., 2015) but it is very complex and has not been applied (except from the empirical application presented together with the model formulation). The importance of this point is striking in time use applications, as there are many surveys collecting multi-day datasets that allow to observe regularities and habitual behaviour. Applicable modelling solutions and viable forecasting approaches for the MDCEV framework are needed.

GAP 3

It is probably safe to say that the representation of random taste heterogeneity has been the topic that has received the most attention in the field of choice modelling in the past two decades. Scholars have mainly focused on the heterogeneity across individual people (i.e. “inter-personal”), but an steady number of studies have argued that there can also be variation across the choices made by a single individual (i.e. "intra-personal" heterogeneity), with both theoretical (Becker et al., 2017; Hess and Train, 2011) and applied (Dekker et al., 2016; Hess and Giergiczny, 2015; Hess and Rose, 2009)contributions. This work has often found that the amount of intra-personal heterogeneity is small compared to the inter-personal heterogeneity, and the estimation of models allowing for both is substantially harder. A reason for the small effects could be that most of these studies relied on stated choice data where the choice tasks were too close to each other, either in terms of time or type of choice. A different picture could emerge with richer or more longitudinal data, especially revealed preference data related to choices made by the same person but involving different characteristics or spanning over a longer time period. For example, with very habitual behaviour, such as driving to work every day during a week, intra-personal variation is likely very limited. But if this behaviour is at more distant points in time, e.g. months or years apart or in different circumstances the level of heterogeneity at the individual level might be higher as there is more scope for unobserved factors varying across the choices (e.g. travelling with different people or for different reasons). RP data could be a crucial asset in unveiling patterns of inter and intra-personal heterogeneity, and more work is needed to address this issue.

GAP 4

It is an increasing tendency in travel behaviour analysis to replace traditional travel diaries with GPS loggers and smartphone applications, which provide accurate longitudinal data about respondents' activity. Collecting this type of data can be costly, lead to small sample sizes and require long times for the data collection design and app development, when needed. At the same time, a large amount of GPS data is collected from individuals from research and commercial bodies for purposes other than choice modelling. This is not only true for travel behaviour, but also other choices, such as communication or purchase behaviour, that are recorded through mobile phones or fidelity cards. Often privacy and corporate confidentiality are a substantial constraint, but in other cases the data can be accessed. While not originally collected with the aim of performing choice modelling, and therefore potentially challenging to model, these data could constitute an invaluable resource as they could provide low (or zero) cost, high resolution RP data for choice modelling. Nevertheless, there has been very little effort from choice modellers towards exploring ways to make these alternative data sources usable for their research.

GAP 5

A limited number of surveys, some of which are exploited for the analyses in this thesis, have collected in-depth real-life longitudinal information from respondents. The existing literature lacks a comprehensive dataset that contains information about travel and other life-course choices, attitudes and social network as well as a GPS tracking element to look at the short term travel and activity behaviour of people. Such a dataset would allow us to make important progress in the areas discussed in this thesis as well as on many other behavioural questions in choice modelling, including the interactions between long term as short-term choices, the interrelationships between different decisions and the the role of feedback on behavioural change.

3 Objectives

This thesis pursues objectives both in terms of choice modelling methodology, innovative applications and data collection. The specific objectives of this work are described below, divided in these three categories.

Methodological

M1: Modelling inter and intra-agent heterogeneity in longitudinal data

Recent years have seen increasing interest in modelling intra-agent heterogeneity. Such applications often made use of stated preference data (Hess and Giergiczny, 2015; Hess and Rose, 2009), with very limited applications using RP panel data, where the example of Yáñez et al. (2011) also uses a simplified implementation (cf. Hess and Train, 2011). This work aims at investigating inter and intra-agent heterogeneity in a social network setting where behaviour is observed at multiple points in time, proposing a hybrid modelling approach which is applicable to other contexts as well and which helps disentangle the sources of heterogeneity.

M2: Modelling complex correlation patterns in discrete-continuous models and recognising their role in forecasting

The state-of-the-art MDCEV framework is particularly suitable to model time allocation decisions, but it does not allow to accommodate complex correlation patterns across days and activities which characterise real-life behaviour. Existing alternative approaches are difficult to apply and rarely used. This thesis aims at suggesting practical solutions to account for such correlations both in model estimation and forecasting.

M3: Capturing the latent aspects of alternative availability and consideration in high resolution data

The use of high resolution data, such as GPS travel diary data, can imply benefits and challenges. A key issue relates to choice set formation at the individual choice level. This work aims to explore the benefits of capturing alternative availability and consideration in travel mode choice models, in particular where panel GPS data are used.

Applied

A1: Novel applications to high resolution and/or longitudinal data and exploitation of non-traditional data sources

This thesis aims to make use of multiple RP datasets to propose innovative applications to help understand real-life behaviour while exploiting the full potential of the different data sources, using advanced modelling tools. In particular, this work aims to exploit longitudinal time use diaries to investigate the different determinants of time allocation and the correlations across activities as well as using GPS mobility data to model travel mode choice. The latter are also used with the objective to understand the necessary steps to take to make such non-traditional data usable and to investigate the modelling techniques to apply to accommodate the behavioural realism implied by this type of data.

A2: Applying advanced choice models in the area of social networks

This thesis aims to apply choice models to analyse three different aspects in the context of social networks. We first look at social interactions within individual social networks, i.e. modelling how respondents communicate with their social contacts. We next look at the evolution of the network over time, i.e. whether social contacts are maintained in the network or lost over time. This is studied making use of longitudinal data. With literature arguing that the social context has an effect on different types of choices, this thesis also aims to investigate the possible links between time allocation decisions and the social context, using rich RP data.

Data

D1: Highlighting issues with existing datasets and guidance for integrated data collection efforts

Data that is not collected for choice modelling can often be exploited for it, as shown in our work. For this thesis, different data sources are exploited. They often have limitations and require taking actions in order to make them usable for our analysis. We seek to identify and highlight these gaps and present solutions for addressing these issues in existing data. The work in this thesis aims to offer insights about different issues related to capturing and modelling the complexity of real-life behaviour. Examples are the treatment of heterogeneity in the work on social network and on time use, and the study of the possible links between time allocation decisions and the social context. It is clear that there are links across these dimensions, and a unified data collection effort is needed. We seek to outline the requirements of such a survey effort, implement it, and conduct initial analyses on the data.

4 Thesis outline and contributions

Given the format of this thesis, this section outlines the content of each Chapter by presenting each paper, briefly summarising its aim and contents and stating its original contribution. The order of the papers will follow the one of the four themes outlined in Section 2, i.e. the influence of social networks on decisions, the acknowledgment of a discrete and a continuous dimension of choice (although this is present from the first paper), the awareness of the interrelations between choices, both across time and across choices, and the emergence of more detailed RP data.

Chapter 2 presents a paper entitled "Modelling contact mode and frequency of interaction with social network members using the multiple discrete-continuous extreme value model". This Chapter aims to understand the determinants of the communication patterns between individuals and their social network members. It represents an application of the MDCEV model to a new area of analysis, namely the mode and frequency of social interactions. While previous research efforts looking at this decision mainly used multi-level models or multi-level path analysis, our approach exploits a more suitable framework that jointly deals with the continuous and discrete choice dimension and can accommodate corner solutions. Our framework also allows us to measure satiation from different modes, something that was not accommodated in previous studies. Our findings show that both the respondent's (ego) characteristics as well as those of the relationship between him/her and each social contact (ego-alter) have a significant impact on communication patterns. In particular, differently from similar studies which made use of social network data, the simultaneous modelling technique adopted in the present paper allows us to observe that dyad level variables have a much more significant effect on communication frequency than ego-level ones, a result that supports the need to make use of measures related to the similarities and differences between egos and alters to understand interaction patterns. We find that the strong underlying preference for face-to-face contact (especially in the maintenance of core contacts) is an important conclusion given the on-going debate on potential substitution effects between ICT based modes of communication and most traditional ones. A brief illustrative forecasting example also shows how a model of the type used here can be used to gain insights into the likely changes in travel patterns resulting from changes in the composition and characteristics of a social network.

Chapter 3 presents a paper entitled "Modelling the loss and retention of contacts in social networks: the role of tie strength and dyad-level heterogeneity". This paper aims at modelling the evolution of personal social networks over the course of 4 years. In particular, it looks at whether each social network contact has been retained or lost over time. This binary outcome is modelled as a function of socio-demographic characteristics and life course changes of the ego as well as of ego-alter characteristics in the first wave. The emotional strength of a relationship is treated as a latent component within a hybrid choice model. We show how this allows us to separately account for different layers of heterogeneity, both at the level of the ego and across the alters. Our findings on a typical name generator dataset underline the relevance of random ego-level heterogeneity in retention, as well as both ego and ego-alter level heterogeneity in strength. The former means that some egos will retain more social contacts than others, while the latter implies that some egos will be more prone to establishing strong relationships than others (variation across egos) and that even within a specific ego's network, certain ties will be stronger than others (variation across alters, for an ego). Not only is this work one of the first to apply choice modelling to study social network evolution, but also it does so by developing a comprehensive framework allowing for an appropriate treatment of relationship strength and random heterogeneity. The methodological framework proposed is suitable for other applications using longitudinal data with indicators.

Chapter 4 presents a paper entitled "Does the social context help with understanding and predicting the choice of activity type and duration? An application of the Multiple Discrete-Continuous Nested Extreme Value model to activity diary data". This paper proposes an application of the nested version of the MDCEV model (MDCNEV) to two-day time allocation data from Chile. Activity choice and time allocation are explained on the basis of individual socio-demographics and social network variables, although definitive interpretations about the directionality of the latter effects cannot be given. Previous studies looking at the relationship between social networks and activity engagement mostly focused on leisure and social activities, while in this work all the activities that people engage in are considered. The MDCNEV model, that had been previously applied only in a very limited number of cases, is found to provide a better fit than the simple MDCEV. Higher levels of correlation between the unobserved portion of utility of the activities are found in either nest (in home and out of home activities) with respect to previous studies. Moreover, a simple and effective method to approximate draws from a GEV distribution is proposed and forecasting with the MDCNEV model is successfully performed, showing how the time allocation changes according to the nesting structure.

Chapter 5 presents a paper entitled "Accommodating correlation across days in multiple-discrete continuous models for activity scheduling: estimation and forecasting considerations". In this paper, it is recognised that the standard formulation of the MDCEV model is not adequate to model time allocation when multiple days of data are available for each individual. The theoretical accommodation of these effects is not straightforward (especially when the budget constraints both at the day-level and multi-day level). Therefore, a mixed MDCEV model with multi-variate distributions is applied allowing for correlation between activities at the within-day and between-day level. The standard Pinjari and Bhat (2010) forecasting approach generally used for the MDCEV model cannot accommodate "links" across days, therefore two different adaptations of this algorithm that relax the 24 hour constraint in forecasting and then reinstate it through rescaling are proposed. The issue and the methods are illustrated using two different time use datasets. Our estimation work confirms the presence of deterministic and random heterogeneity, and crucially in the context of the present paper, correlations both at the within-day and between-day level. We then test the proposed forecasting approaches, showing that they lead to more behaviourally meaningful results than the simple day-level forecasts. We also show that the loss in terms of utility of these "alternative" approaches is relatively small when compared to the theoretically correct model. The fact that consistent insights from two different datasets are obtained adds further empirical weight to this work.

Chapter 6 presents a paper entitled "Mode choice with latent availability and consideration: theory and a case study". The focus of this paper is the investigation of whether and how GPS data collected for purposes other than modelling can be used for our analyses. As mentioned above, there is very limited work in choice modeling making use of such data sources. We also partly aim to investigate how analysts can better accommodate mode availability and consideration when working with GPS data. We address this by proposing a latent class approach which treats mode availability and consideration in a probabilistic manner, with the former being at the person level and the latter at the trip level. We show that if special care is taken in understanding, cleaning and enriching and handling the data, at least in this case, successful modelling could be performed. Due to missing information about availability, this has to be inferred through other available socio-demographics, a method that proved not only effective but superior to using stated availability. Moreover, the inclusion of consideration sets provided improvements in model fit. Reasonable values of model coefficients and values of travel time were obtained, with the models including probabilistic availability and consideration sets providing more realistic figures.

Chapter 7 presents a paper entitled "We want it all: experiences from a survey seeking to capture social network structures, lifetime events and short term travel and activity planning". This paper describes a data collection effort aimed at collecting in-depth RP data about a wide range of decisions, both long-term and short-term. As highlighted in section 2, such comprehensive data collection efforts are very rare and we are not aware of such a detailed effort in the literature. This survey is composed of a detailed background questionnaire, asking respondents about their socio-demographics, residential location, energy, travel and expenditure choices, followed by a life-course calendar, which records their important past choices and by a name generator, which collects information about their social network. After completing the survey, respondents are asked to use a tracking smartphone app for two weeks, which includes short surveys to collect detailed information about trips and activities. In the paper, we provide a detailed description of the survey design and protocol and we present descriptive statistics of the sample. The collected data is of high quality and can be used to model a wide range of decisions and interrelations amongst them. The novelty of the paper comes in the unified data collection effort and the guidance it provides for future similar studies.

Chapter 8 of this thesis presents a discussion and conclusions from the work presented in the body of the thesis, linking together the different contributions. It also outlines possible next steps for this research.

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Chapter 2

Modelling contact mode and frequency of interactions with social network members using the multiple discrete-continuous extreme value model

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Abstract

Communication patterns are an integral component of activity patterns and the travel induced by these activities. The present study aims to understand the determinants of the communication patterns (by the modes face-to-face, phone, e-mail and SMS) between people and their social network members. The aim is for this to eventually provide further insights into travel behaviour for social and leisure purposes. A social network perspective brings value to the study and modelling of activity patterns since leisure activities are influenced not only by traditional trip measures such as time and cost but also motivated extensively by the people involved in the activity. By using a multiple discrete-continuous extreme value model (Bhat, 2005), we can investigate the means of communication chosen to interact with a given social network member (multiple discrete choices) and the frequency of interaction by each mode (treated as continuous) at the same time. The model also allows us to investigate satiation effects for different modes of communication. Our findings show that in spite of people having increasingly geographically widespread

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networks and more diverse communication technologies, a strong underlying preference for face-to-face contact remains. In contrast with some of the existing work, we show that travel-related variables at the ego *level are less important than specific social determinants which can be considered while making use of social network data.*

1 Introduction

In the activity-travel perspective, travel is a derived demand due to activities (Ortuzar and Willumsen, 2002). Individuals connect the activities in their lives by travel because they bring value to their life. This is because activities "satisfy a particular need or requirement" (Ortuzar and Willumsen, 2002, p.473). The need to socialise is a basic human need and travel serves to bring individuals together through face-to-face interaction. Carrasco and Miller (2006, 2009) developed conceptual models of social activity generation and social network structure and information and communication technology (ICT) interaction. Habib and Carrasco (2011) declare that their work suggests that "activity scheduling models should explicitly include the role of social networks" (p. 2). Lin and Wang (2014) found that emotional support from family led to more joint travel trips as compared to emotional support from non-family friends and acquaintances. Castiglione et al. (2015) note that activity-based models at the academic level have considered full social networks in joint travel decisions and in generating and scheduling daily tours, but their use in practice-ready activity-based models has not been implemented yet.

This need for socialising can also be achieved by other forms of communication. Often, these communication patterns are correlated by different modes of communication and travel (van den Berg et al., 2012; Frei and Axhausen, 2009; Kowald, 2013; Lin and Wang, 2014; Schaap et al., 2016; Tillema et al., 2010). Thus, communication patterns are an integral component of activity patterns and the travel induced by these activities. Understanding the determinants of communication patterns between people and their social network members is critical for gaining further insights into travel behaviour for social purposes. A social network perspective brings value to the study and modelling of activity patterns since social activities are influenced not only by traditional trip measures such as time and cost but also motivated extensively by the people involved in the activity (Ryley and Zanni, 2013). Van den Berg et al. (2012) provide an extensive review connecting social networks, ICT use for social interaction and communication patterns:

- The majority of social network studies in transportation use egocentric social network data. These approaches prompt users with a name generator to create a list of relevant contacts. By following this up with questions about the given contacts, measures of an individual's social network can be formed including network-wide measures (e.g. centrality, density, between-ness) as well as dyad-level measures (characteristics of the linkage between two individuals).

- There is still limited research on the impacts of ICT use on social activity generation. Support for the substitution hypothesis of ICT use replacing all face-to-face communication is limited. In contrast, studies have found a complementarity between ICT use and social activity generation.

- Communication mode and frequency have been found to be impacted by not only individual characteristics, but also by dyad-level attributes such as tie type and relationship, tie strength and geographic distance.

For example, previous research has found relationships between face-to-face social activity and online social activities (Schaap et al., 2016). In research by Schaap et al. (2016), increasing internet usage was correlated with increasing network sizes, distances between friends, and increasing travel distances for social activities. But they also found that increasing online social activities reduced some specific types of social travel (e.g. out-of-home entertainment). The authors conclude that these effects are not simple or one-directional and that "the complexity of the activity and the context-dependency lead to a complex set of simultaneous effects" (p. 12).

Previous research mainly used multi-level models (Frei and Ohnmacht, 2016) to address the complexities in communication mode choice and frequency. This hierarchical structure accommodates different "levels" with different dependent variables, namely the frequency of interaction, the *ego*-level characteristics and the *ego-alter* dyad ones. van den Berg et al. (2012) used multilevel path analysis to describe mode-specific communication frequencies and correlations between modes. Their results indicated a complementary relationship between the communication frequencies between the modes. The authors state that "the contact frequencies of the different modes, especially face-to-face and telephone, can also be largely explained by the *ego*'s personal characteristics and the type of relationship and the distance between *ego* and *alter*" (p.125). Axhausen (2007); Frei and Axhausen (2007) perform a similar multilevel path analysis to describe communication mode and frequency relationships. Frei (2012) notes a limitation of path analysis techniques in that the models are fitted on sample covariance rather than sample values.

In contrast, a multivariate regression approach can be used to fit a model on sample values. Frei (2012) and Kowald (2013) used multivariate multilevel linear regression models of dyad-level communication patterns. Frei (2012)'s results showed that:

- Increases in distance correspond to decreases in face-to-face and phone contact frequency while e-mail frequency is unaffected.
- *Ego*-level socio-demographics were more influential than dyad-level (*ego-alter*) characteristics.
- "The interaction of the different contact modes and face-to-face meetings are complementary" (p. 137).

Kowald (2013) also reports similar results and additionally found that nuclear family members and close social ties were contacted more frequently than other contacts. But the multivariate linear regressions used in that work have limitations due to the skewness in mode frequency data. This is due to high incidences of no communication via a mode and because some contact frequencies occur at very high levels. In these studies, the authors dealt with this concern by either removing observations (mode-level) for an *ego-alter* communication mode if no communication was performed via that mode (Kowald, 2013), or using a log-transformation with a residual maximum likelihood estimator and setting communication frequencies of zero to the minimum positive frequency for that mode (Frei and Ohnmacht, 2016). Either of these approaches is unsatisfactory and this is a further motivation for the approach used in our work.

Neither the path analysis approach nor the multivariate regression approach account for behavioural conditions that lead to zero communication frequency. Overall, these prior models are unable to describe why individuals would choose to not communicate by a certain mode, but only describe how much communication occurred if the mode was chosen.

The present study aims to account for this limitation by explicitly modelling the selection of communication mode and its corresponding communication frequency. In our work, we simultaneously take into account potential determinants of the decision at both the *ego* and the *ego-alter* level. By using a multiple discrete-continuous extreme value model (Bhat, 2005), we can simultaneously investigate the mode of communication chosen to interact with a given network member and the frequency of interaction by each mode. The model further allows us to investigate satiation effects from different modes of communication. The multiple discrete component of the model accommodates the fact that each ego potentially communicates with multiple *alters* and using different modes of communication. The continuous component of the model accommodates the fact that for each *alter* and mode and communication, there is the possibility of either 0, one, or multiple interactions. Of course, the number of times an *ego* communicates with an *alter* using a given mode is an integer value in the data, and the use of a continuous response model thus represents somewhat of an abstraction from reality. This is however no different in regression work.

The paper is organised as follows. The next section introduces the dataset used for the study. Section 3 provides an overview of the modelling framework, with an emphasis on the role of the different utility function parameters, before presenting the specification used in our analysis. The fourth section presents the results of the model estimation and provides an interpretation of the specific coefficients and their impact on behaviour, while the fifth section shows a simple forecast example on the basis of the estimated model. The final section draws conclusions and implications for travel behaviour analysis and outlines the next steps to be taken in the study of this topic.

2 Data

2.1 Survey overview

Over the past decade, the field of transport planning has been using methods from social network analysis to approach and explain leisure travel (see van den Berg et al., 2009; Carrasco and Miller, 2006; Kowald, 2013; Larsen et al., 2006). The selection of this methodological approach is based on the recognition of leisure travel as being primarily undertaken to join others in leisure activities. For this reason, leisure travel is also referred to as "social' or "activity" travel. Existing work analysed correlations between characteristics of network topology (for example the number of social contacts and geographical distances between people) and aspects of travel activity, resulting in new empirical findings (Carrasco et al., 2008a; Frei and Axhausen, 2007; Kowald and Axhausen, 2014; Larsen et al., 2006; Silvis and D'Souza, 2006) as well as suggesting advances to overcome the challenges in data collection and modelling (Axhausen, 2007; Carrasco et al., 2008b; Frei and Axhausen, 2007; Hogan et al., 2007). These studies though did not try to survey a population-wide "global" leisure network, but only looked at individual "egocentric" networks. Knowledge of the wider network structure connecting personal networks to form a population-wide one allows more generalizable analyses as well as the implementation of a "global" leisure network in agent-based travel demand simulations.

The Institute for Transport Planning and Systems (IVT) of ETH Zurich conducted a survey between January 2009 and March 2011 to investigate this global leisure network topology, as part of a joint project with the Institute for Sea- and Land-Transport (ILS) of TU Berlin. One way of obtaining a population-wide leisure network is to sample respondents by means of a "chain method", in which some initial respondents are asked to report their social contacts and these contacts are in turn used to enlarge the network sampled. The survey implemented to collect the data used in this paper makes use of one of the best-known chain methods, "snowball sampling", which implies asking initial respondents, called "seeds", to report their social contacts. These social contacts are then again asked to report their social contacts and invite them to take part in the study, a procedure that can be repeated for a predefined number of iterations. With the exception of the seeds, all respondents in a snowball sample are reported by former respondents. An illustration of a network obtained by a snowball chain is given in Figure 2.1.

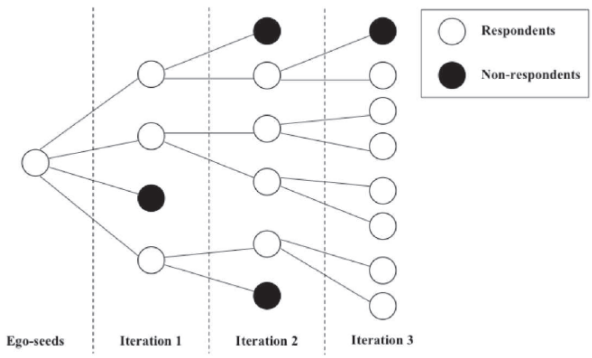

Fig. 2.1: An illustration of a three-iteration snowball chain. Source: Kowald and Axhausen (2012)

Snowball chains were started with 40 *ego*-seeds drawn from a stratified random sample of the Canton Zurich population. Half of the seeds got to the second iteration of *egos* (who named *alters* constituting the third iteration). The remaining 20 chains included iteration 3 *egos*, and the researchers who collected the data were planning to let the snowball chain continue until iteration 4. Respondents can report social contacts anywhere, so that recruitment is not geographically limited.

The survey instrument was made up of four sections.

- The first section included questions about respondents' socio-demographics and mobility biography, i.e. a report of the places where they lived and worked throughout their lives.
- The second section was made up of two name generators. Name generators are questions, generally in the form of tables, which ask people to report names of their social contacts. The wording of the question makes use of specific stimulus to help respondents focus on the part of their social network of interest to a study and recall all the relevant names (Campbell and Lee, 1991; Marsden, 1990). The use of two name generators is motivated by the need to use different stimulus for a complete and more accurate recall of the social network of interest.

The first name generator asks explicitly for leisure contacts providing examples related to leisure interactions, which should guide respondents in distinguishing whether a relationship fits to the requirements or not. The second name generator applies a different approach, as it asks respondents to mention the people with whom they discuss important problems. The question asked in relation to the second name generator differs from the one used in the first one in that it uses an affective perspective instead of a stimulus about the context of social interactions. Although the latter might be subject to individual interpretation, contacts from both name generators can trigger leisure travel and are therefore relevant given the scope of the study. The social network reported through the two name generators could not exceed the size of 40 contacts, but participants were encouraged to use additional sheets of paper if needed. In most analyses of the present dataset (Illenberger et al., 2011; Kowald and Axhausen, 2012), including the one in the present paper, we only make use of the first 40 contacts to avoid potential bias deriving from the extra effort some participants made to report names in a non-survey form.

- The third instrument used in the survey was a "name interpreter", where *egos* were asked to enrich the list of names reported in the name generators by adding *alters*' socio-demographics as well as information related to the *ego–alter* relationship, e.g. duration and circumstances of first meeting. To ensure continuation of the snowball recruitment, named social contacts' addresses were collected so that the survey and an optional invitation card could be sent to them. Only a paper version of the survey was in fact administered, therefore physical addresses were necessary to communicate with participants.

- The fourth section of the survey was a "sociogram", a tool used to indicate whether, among the social contacts mentioned in the name generators, there were groups of people who know each other and generally spend time together. The information collected through this last section is not used for the current work.

As this type of survey could appear quite unusual to respondents, special care was taken of question formulation, so that potential sources of misinterpretations were avoided. Where a risk of misunderstandings was identified, examples were provided to clarify the question. Another potential problem with this type of survey is that respondents might not be comfortable with providing information (especially home addresses) about their social contacts. Several measures to establish trust between respondents and the survey promoters were adopted. *Egos* were asked to sign an invitation card to be sent to their *alters* by the research team (for more details see (Kowald et al., 2009), and once they had agreed to take part, the survey instrument was sent to them together with a 20 CHF (approximately €19 in 2015) monetary incentive. A response rate of 26% was achieved and considered satisfying by the promoters. Although some fatigue effects are present in the responses, the share of missing values is low, around 3% for *egos*' and 13% for *alters*' characteristics (for details see Kowald et al. (2010)). As mentioned above, the sample had no predetermined geographical limits, but despite this setting most respondents were from the German speaking part of Switzerland. Although data cleaning and censoring somewhat limited its representativeness, the originally collected sample matched the characteristics of the Swiss population well. For further information and details about the data collection protocol, see Kowald and Axhausen (2014).

2.2 Sample characteristics

We excluded from the analysis all the *egos* who did not report any frequency of communication with any of their network members. We also excluded *egos* for whom most of the basic socio-demographic information were missing. Our final sample is made up of 638 *egos*, who named 13,500 *alters*. The socio-demographic and economic characteristics of the *egos* are reported in Table 2.1.

Note that we consider as an *ego* any respondent who has completed the entire survey and named her (or his) *alters*, no matter the wave in which she was recruited. In this sense, we virtually make use of *egocentric* data despite the fact that the dataset has been collected as a snowball sample.

The independent variables included in the modelling work are characteristics of both *ego* and dyad, i.e. features of the relationship between the *ego* and each *alter*. The list of *ego-alter* measures used in the model (excluding missing values) is given in Tables 2.2 and 2.3. Table 2.2 reports continuous measures and their basic statistics, while Table 2.3 reports categorical variables. Note that the statistics for distance between ego and alter includes only “positive” distances, i.e. people who live together are excluded from this table. As stated above, missing values are also excluded from these tables (this is why the percentages do not sum to 100%) although a specific treatment has been adopted in the modelling, as detailed in section 4.2.

3 Methodology

3.1 MDCEV framework

The family of MDCEV models first proposed by Bhat (2005) and extended in different directions (Bhat, 2008; Castro et al., 2012; Pinjari and Bhat, 2010b) represents the state of the art in modelling multiple discrete-continuous choices.

	N	%		N	%
Age			*Sex*		
Age = 18	4	1%	Male	245	38%
Age 19-30	47	7%	Female	389	61%
Age 31-45	149	23%	*Employment status*		
Age 46-60	258	40%	Student	19	3%
Age > 60	149	23%	Employed full time (FT)	210	33%
Car availability			Employed part time (PT)	231	36%
Always	60	9%	Homemaker	70	11%
Often	90	14%	Retired	96	15%
Seldom	46	7%	Looking for work	10	2%
Never	21	3%	Unfit to work	1	0%
Citizenship			*Household income (CHF)*		
Switzerland	576	90%	Min	0	-
Germany	18	3%	Max	18000	-
Italy	11	2%	Average	10320	-
Austria	5	1%	*Education duration (years)*		
France	4	1%	Min	0	-
Other	21	3%	Max	35	-
Civil status			Average	14.94	-
Married	461	72%	*Network size (number of contacts)*		
Divorced	51	8%	Min	40	-
Living separately	8	1%	Max	1	-
Single	90	14%	Average	21.16	-
Widowed	27	4%			

Table 2.1: Descriptive statistics of the sample

	Mean	**Median**
Distance (km)		
	2,817.57	8.68
Age difference (years)		
	16.51	15
Relationship duration (years)		
	21.27	19

Table 2.2: Continuous dyad measures

The initial exponential utility function proposed in Bhat (2005) was later replaced in most applications by a Box-Cox specification which presents several advantages, as described in Bhat (2008); in particular, the continuity of the Box-Cox form with respect to the exponent, even for values near zero, turned out to be important in our work.

The Multiple Discrete Continuous Extreme Value (MDCEV) model and

	N	%
Sex homophily		
Both male	2981	22%
Both female	5810	43%
Different sex	4269	32%
Help&Discuss		
Ask for help	4474	33%
Discuss problems	7120	53%
Type of relationship		
Spouse	308	2%
Relative 1st degree	1845	14%
Other relative	819	6%
Married into family	705	5%
Friend	5685	42%
Acquaintance	3717	28%
Citizenship homophily		
Same citizenship	10935	81%
Different citizenship	1263	9%
Education homophily		
Same level	6729	50%
Different level	4430	33%

Table 2.3: Categorical dyad measures

its various extensions have been applied to several empirical contexts, mainly related to the study of travel behaviour. Examples are applications to the choice of vehicle type and mileage (Bhat and Sen, 2006; Sen, 2006),), to the type or timing and duration of activities (Bhat, 2005; Srinivasan and Bhat, 2005) and to vacation-related decisions (Pinjari and Sivaraman, 2013). The model has also been used in applications other than transport. For example, Lu et al. (2016) have applied it to the case of multi-buy alcohol promotions. Woo et al. (2014) used the model to understand how the use of traditional media (e.g. television, radio, newspaper) had been affected by new ones, such as in-home and mobile internet. Another application to media use is Block and Schultz (2015), focussed on understanding the time spent on each medium (television, radio, print, internet) by American consumers. The present paper represents the first application of the present modelling framework to investigate patterns of social interaction between people and their social contacts.

The model is derived coherently with the random utility maximisation theory, and it differs from traditional choice models in the fact that, by allowing the choice of multiple products, it relaxes the assumption of the alternatives being mutually exclusive. The additive but non-linear formulation of the utility function guarantees that the consumption of one good does not affect the utility of the others and that these goods are imperfect substitutes. The non-linear specification allows estimation of the satiation experienced from each good by allowing for diminishing marginal returns. The derivation of probabilities also differs from standard choice models.

The presence of both a discrete and a continuous choice dimension allows the modelling of the behaviour of people choosing a number of different options at the same time (for example varieties of products sold on the market) and, for each of them, a continuous amount to consume, for example money or time spent making use of them. They make their consumption decisions in order to maximise a direct utility function $U(x)$ where x is a vector of non-negative quantities of consumption for each of the goods, $x = (x_1, \ldots x_K)$. The expenditure that an individual can allocate to the purchase of the goods is subject to a budget constraint $xp = E$, where E is the budget, and p is the vector of prices. In most applied work, as well as in our case, x includes a unit-priced outside good to represent expenditure on a good that is always consumed in a positive quantity by all the individuals in the sample. This can have a specific interpretation or simply represent the consumption of all the other goods on the market.

The functional form of the direct utility is a generalised variant of the translated CES function, additive with respect to the different products but non-linear to allow diminishing marginal returns, i.e. that the benefit of an additional unit purchased of a given good decreases with increasing consumption of that good. The utility formulation, introduced by Bhat (2008), assumes the presence of K goods and assumes good 1 to be the outside good, although this choice is fully arbitrary. The utility function is as follows.

$$U(x) = \frac{1}{\alpha_1}\psi_1 {x_1}^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k}\psi_k \left(\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right) \tag{2.1}$$

so that $U(x)$ is a quasi-concave, increasing and continuously differentiable with respect to x and ψ_k, γ_k and α_k are parameters relating to good k.

The specific role of these parameters is as follows.

- ψ_k is the defined as the "baseline utility of good k". It is in fact the marginal utility of the good at the point of zero consumption. A higher baseline utility makes corner solutions (i.e. zero consumption of a good) less likely. ψ_k is a function of observed characteristics z_k associated with good k and the decision maker. z_k also includes a constant reflecting the generic preference for good k. The random form of the utility is obtained by introducing an exponential multiplicative random element. This, together with an exponential form of the deterministic component of utility, ensures the positivity of the utility, which can be written as: $\psi_k(z_k, \epsilon_k) = e^{\beta' z_k + \epsilon_k}$, where ϵ_k is an extreme value error term, and β is an estimated vector of parameters. For identification, we set the deterministic part of the log baseline utility for one good to zero, say the outside good.

- The γ parameters in the model have several roles. First, they are translation parameters that allow for corner solutions, so that for any good (other than the outside good) it is possible to evaluate the model with $x = 0$. Second, γ defines a scale for each good. Third, because γ defines a scale, it also affects the satiation, as a higher γ_k implies that more consumption of the corresponding x_k is needed to obtain the saturation effect. It is this last role of γ that makes separate identification of γ and α difficult.

- α_k is a "pure" satiation parameter. By exponentiating the consumption quantity of good k, it reduces the utility of any additional unit consumed. α_k can take any value smaller or equal to 1. Low α_k means faster satiation. In our model, we bound $0 \leq \alpha_k \leq 1$ as suggested by Bhat (2008). When $\alpha_k \to 0$, the utility form above collapses to a linear expenditure system (Bhat, 2008). Conversely, $\alpha_k = 1$ would reproduce the case of "traditional" choice models, i.e. with constant marginal utility of consumption and no satiation effects allowed.

As mentioned above, both α_k and γ_k control satiation although through different mechanisms, as the former does so by exponentiating the consumption quantity while the latter by translating it. Bhat (2008) argues that the two effects are very hard to disentangle in empirical analysis, and for this reason some form of normalisation is generally needed. Indeed, he claims only three different versions of the stochastic model, obtained by fixing some of the parameters, are empirically estimable. In the present application, we have made use of the γ-profile (c.f. Bhat, 2008), which estimates the α parameter for the outside good only with other α parameters taking the zero limit and all γ_k, $k > 1$.

The probability that an individual consumes $x_1^*, x_2^*, \ldots, x_M^*, 0, \ldots, 0$, where M of the K goods are consumed in positive amounts, is given by (see Bhat, 2008)

$$P(x_1{}^*, x_2{}^*, \ldots, x_M{}^*, 0, \ldots, 0)$$
$$= \frac{1}{p_1} \frac{1}{\sigma^{M-1}} \left(\prod_{m=1}^{M} f_m \right) \left(\sum_{m=1}^{M} \frac{p_m}{f_m} \right) \left(\frac{\prod_{m=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma} \right)^M} \right) (M-1)! \tag{2.2}$$

where σ is an estimated scale parameter and where $f_m = \frac{1-\alpha_m}{x_m{}^* + \gamma_m}$

3.2 Application to social network data

The MDCEV model can accommodate the fact that people choose simultaneously between different products, in our case the means of communication with every member of their social network (face-to-face, phone, e-mail, SMS) and the quantity of each, in our case the frequency of interaction. We believe that this framework is more adequate than previous approaches to represent real-world behaviour in this specific case. The choice of how and how frequently to stay in touch with someone requires joint consideration of the *ego* and *alter* characteristics, and the understanding of underlying behaviour would be limited without considering the substitution effects that are likely to be present in this context.

The dependent variable of our model is the frequency of interaction by each communication mode with each social network member per year. As there are 4 possible modes of communication (face-to-face, phone, e-mail, SMS) and each *ego* can have at most 40 social contacts, the number of "products" in our model is $4 * 40 = 160$. As not all the *egos* have named 40 social contacts, in the case in which someone has reported a lower number, say n, the remaining $40 - n$ contacts are considered to be unavailable to her. The outside good, that in the present context represents all the activities other than communication, takes the total number of products to 161.

As described above, the model framework assumes the presence of a budget constraint. Typically, this has been treated either as a time budget (Bernardo et al., 2015; Bhat, 2005; Salem and Nurul Habib, 2015; Sener and Bhat, 2012), a money budget (Ferdous et al., 2010; Lu et al., 2016; Rajagopalan and Srinivasan, 2008; Yu and Zhang, 2015; Yu et al., 2011) or even separate time and money budgets (Castro et al., 2012; Pinjari and Sivaraman, 2013). Authors are increasingly recognising the difficulty with the definition of money budgets, where a simple hard constraint such as 24 hours a day for a time budget does not apply. Indeed, individuals may for example have different mental accounts for different products. The situation is further complicated in the case of work using stated preference data (such as in Lu et al. (2016)) where arguments can be made that the expenditure observed for a given respondent may well be below their budget constraint (if the scenarios presented were not varied enough) or may be above the real world budget constraint (by being based on hypothetical choices). Recent work by Augustin et al. (2015) has put forward the idea of using regression approaches to estimate a latent budget for vehicle miles travelled, while Dumont et al. (2013) proposed a latent budget approach for money budgets.

For our specific case study, we use a slightly different approach. Firstly, as neither costs nor durations for the different types of interactions are available, the definition of time or money budgets would be difficult. Secondly, the use of such an approach would be geared at aiming to model (and then predict) the overall level of interaction an *ego* undertakes. In our work, we focus instead on understanding how, with the overall annual number of communications being determined exogenously, an *ego* distributes these across *alters* and across modes of communication.

In the specification of the model, we need to specify costs for each "product", and an overall budget. In our final specification, given the above, we use a unit cost for each "product", i.e. the same cost applies to one phone call as to one face-to-face meeting, for example. The budget for a given *ego* is then simply given by the total annual number of communications that we observe for that *ego* in the data, across all *alters* and all modes. We maintain an outside good in our model specification and simply assign one unit of the budget for the outside good[5].

We are aware of the simplification implied by assuming a joint budget for all four communication modes, with the same unit cost for each mode. In reality, the cost (time and money) of face-to-face interactions, especially when two people live far away from each other, is likely to be much higher than the cost of sending that person an e-mail. To test the impact of these simplifying assumptions, we also estimated models with a number of different specifications for costs and the budget. We first tested the impact of the unit cost assumptions, by making face-to-face the most expensive mode, ahead of phone, sms and e-mail. We still allocated one unit to the outside good. Secondly, we tested the impact of the budget assumption and specifically the allocation to the outside good, where we estimated a model in which a generic fixed amount is allocated to the budget for each individual. The full details of these tests are reported in Appendix A. Neither of these departures had a significant impact on our overall findings, and we thus maintained the unit cost assumption, and a budget given by total expenditure across inside goods plus one unit for the outside good.

The final specification of the model has been obtained by first testing the performance of the different specifications that can be empirically estimated (according to Bhat (2008)). As mentioned above, we adopt the "γ-profile" of the model in estimation, i.e. we only estimate the γ_k for $k = 1, 2, \ldots, n$ and α_1 for the outside good. . This profile provides better statistical fit than either the "α-profile" or the "$\alpha - \gamma$-profile" in this specific empirical application. As α_1 presented an extremely small and insignificant value in all the model specifications we estimated, we decided to fix it to zero in order to avoid computational problems. As an example, in the latest model specification where it was estimated, its value was 0.001 with a t-statistic of 0.878. In

[5]This is for econometric reasons alone, as it is helpful to have one good that is always chosen

very simple specifications, for example where only the structural parameters of the models, the constants and the distance coefficients were estimated, α_1 was equal to 0.000005 with a t-statistic of 0.057. As explained in Bhat (2008), $\alpha_k \rightarrow 0$, implies that the utility form collapses to a linear expenditure system, i.e. to a log utility formulation.

Moreover, as it would have been impossible to estimate a γ_k for each of the 160 inside goods, we only estimated four of them, one for each mode of communication, which were then reused across *alters*. In estimation, to ensure positive values, we work with $\gamma_k = e^{log(\gamma_k)}$, with $log(\gamma_k)$ being estimated. For the presentation of the results, we then apply the transform, and report γ_k.

4 Empirical results

We started off by estimating a base version of the model and systematically adding and combining variables on the basis of statistical significance, intuition and guidelines from previous studies. Our results are displayed in Table 2.4, where the estimates and t-statistics of coefficients are presented. A detailed presentation and interpretation of results follows.

4.1 Core results

4.1.1 Baseline constants & γ parameters

The δ_k parameters represent the baseline preference constant component of the utility of each alternative, where they enter through an exponential into ψ_k. A higher value for δ_k thus leads to an increase in the baseline utility of alternative k. The γ_k parameters in turn determine, jointly with the baseline utilities ψ_k, the impact that each additional unit of consumption has on the contribution that the consumption of good k makes to the overall utility. All else being equal, including the socio-demographic effects being the same across products, we could state that increases in δ_k will lead to bigger increases in utility for each additional unit being consumed, while for γ_k, the opposite applies. What we then see from our results is that, if the socio-demographic impacts on baseline utilities are the same across modes (a point we will return to below), a face-to-face contact has more impact on the utility function than a contact by phone ($\delta_{face-to-face} > \delta_{phone}$ and $\gamma_{face-to-face} < \gamma_{phone}$). The impacts of an interaction either face-to-face or by phone is also stronger than that of e-mail or SMS. However, for the latter two, the ordering is less clear cut, as $\delta_{e-mail} < \delta_{sms}$ and $\gamma_{e-mail} < \gamma_{sms}$. With $\alpha_k \rightarrow 0$ in our models, the utility component $\frac{\gamma_k}{\alpha_k}\psi_k\left(\left(\frac{x_k}{\gamma_k}+1\right)^{\alpha_k}-1\right)$ reduces to a log specification, with $\gamma_k\psi_k\ln\left(\frac{x_k}{\gamma_k}+1\right)$. Ignoring the socio-demographic

	face-to-face		*phone*		*e-mail*		*sms*	
	est	t-stat	est	t-stat	est	t-stat	est	t-stat
Gamma parameters (γ)	0.5567	23.92	3.0200	51.67	5.6150	47.34	7.7260	43.35
Baseline constants (δ)	4.3710	14.92	1.4810	5.06	-0.1050	0.34	0.4197	1.37
Ego characteristics								
Age								
Age = 18	0.0712	0.12	-0.0372	0.06	-2.1840	3.38	0.7791	1.26
Age 19-30	-0.1515	0.61	-0.4043	1.62	-0.5198	2.04	0.7626	2.99
Age 31-45	-0.0415	0.25	-0.0942	0.57	0.0703	0.42	0.5786	3.37
Age 46-60	-0.0999	0.63	-0.1928	1.21	-0.0300	0.18	0.4215	2.52
Education duration (years)	-0.0141	1.25	-0.0101	0.88	0.0311	2.69	-0.0211	1.80
Civil status								
Married	-0.0744	0.51	-0.2604	1.77	-0.4053	2.72	-0.5950	3.99
Widowed	-0.0827	0.33	-0.3542	1.39	-0.9495	3.54	-0.4597	1.74
Divorced	-0.1570	0.78	-0.2907	1.43	-0.5044	2.44	-0.4056	1.96
Living separately	-0.2679	0.67	-0.0515	0.13	-0.6754	1.66	-0.3348	0.82
Employment status								
Student	0.3020	0.98	-0.1467	0.47	0.4092	1.31	0.1495	0.48
Homemaker	-0.0506	0.36	-0.0711	0.51	-0.2290	1.59	-0.1590	1.10
Retired	-0.1903	1.05	-0.1912	1.05	-0.4997	2.68	-0.4710	2.43
Looking for work	-0.2901	0.87	-0.0433	0.13	0.1712	0.50	-0.0467	0.14
Number of contacts	-0.0083	2.05	-0.0130	3.20	-0.0016	0.39	-0.0001	0.02
Ego-alter characteristics								
Distance	-0.3250	43.40	-0.075	10.28	0.063	7.47	-0.054	0.01
Distance=0	0.3900	5.22	-0.6403	8.51	-0.0005	0.00	-0.0462	0.51
Relationship duration	-0.2360	17.94	0.0436	3.01	-0.1078	6.18	-0.2271	12.27
Sex homophily								
Both male	0.0667	2.33	0.0672	2.19	0.3242	8.92	-0.2741	6.28
Both female	0.0093	0.04	0.2510	9.79	0.0858	2.64	0.4698	13.82
Age difference	0.010	10.15	0.0054	4.94	-0.0122	8.06	-0.0101	6.52
Help & Problems								
Ask for help	0.2733	5.01	0.4673	8.11	0.3353	4.61	0.3069	3.73
Discuss problems	0.2373	9.06	0.4483	16.03	0.2305	6.64	0.4947	13.07
Ask for help x Discuss problems	0.1545	2.59	-0.0668	1.06	-0.1434	1.81	-0.1391	1.58
Type of relationship								
Spouse	2.1530	26.86	1.1950	15.22	0.2216	2.24	0.9860	10.35
Relative 1st degree	0.5001	14.47	0.5084	14.04	0.0112	0.24	0.3530	7.23
Relative	-0.0291	0.68	0.0608	1.36	-0.3955	6.16	-0.0786	1.19
Married into family	0.1171	2.65	0.1381	2.96	-0.5771	8.33	-0.3397	4.68
Acquaintance	-0.2245	8.82	-0.3868	13.85	-0.1176	3.53	-0.5809	14.90
Same level of education	-0.0433	2.00	-0.0242	1.05	0.1246	4.28	0.1092	3.51
Same citizenship	0.1085	3.91	0.0285	0.94	0.0272	0.75	0.1069	2.64
Missing values coefficients								
Ego education duration	0.7742	1.35	-0.4215	0.73	0.8407	1.43	-0.4971	0.82
Distance	-0.9766	27.85	-0.2386	6.70	-0.0416	0.98	-0.1308	2.89
Relationship duration	-0.5914	6.22	0.3452	3.61	-0.7104	5.55	-0.9118	7.25
Age difference	-0.4591	7.05	-0.4893	6.94	0.4654	5.28	0.0283	0.29
Ask for help	0.1899	1.58	0.3669	2.82	-0.4536	2.48	-0.4743	2.16
Discuss problems	0.3971	2.92	-0.1233	0.81	0.3689	1.98	-0.6967	2.59
Type of relationship	-0.0217	0.19	-0.1860	1.44	-0.1018	0.63	-0.0272	0.17
Same level of education	-0.1045	2.70	-0.1653	4.13	0.0453	0.97	-0.0830	1.65
Log-likelihood: -162,036.9								

Table 2.4: Model results

effects and setting $\psi_k = e^{\delta}_{k}$, we can then see that the impact of a SMS is always stronger than the impact of an e-mail. With bigger consumption, this difference increases. This is a direct result of the fact that satiation is stronger with lower γ_k. We then also note that satiation approaches more rapidly for a given number of contacts when they are by phone and especially face-to-face. Intuitively this appears reasonable, as people exhaust all the activities/communication they want to undertake with an *alter* in fewer face-to-face meetings than with other forms of communication, followed by phone. The γ parameters could also be thought of, to some extent, as representing the amount of time and the cost of setting up the communication by each mode.

4.1.2 Effect of ego-level characteristics

The *ego* level characteristics are in general not strongly significant, possibly indicating that measures of the attributes of just one of the two people involved in the interactions are not sufficient in explaining the communication frequency. Nevertheless, we will try to interpret the significant coefficients for each of the variables. For each *ego*-level variable, we estimated four coefficients, one for each communication mode. This approach allows us to observe the impact of that variable on mode-specific frequency of communication.

Age A categorical variable represents the age of *egos*, as shown in Table 2.1. The category including people more than 60 years old is used as a base. The significant coefficients give some interesting insights: the e-mail coefficient for the youngest category is negative and significant, meaning that teenagers are less likely to use e-mail than people who are over 60. This result may seem counter-intuitive if we think about the familiarity of younger generations with ICT, but existing studies (e.g. Agosto et al., 2012) found that teenagers make a reduced use of e-mails and see it only as a mode to communicate with adults or in particularly formal communication.

People in their twenties resulted being less likely to communicate by phone (although the significance level is only 90%) and rather surprisingly also by e-mail than people more than 60 years old, while they are significantly more likely to send SMS with respect to the oldest group. The last point is also true for the 31-45 and the 46-60 years old categories, confirming that this mode is probably not used much by those over 60.

Education duration A log transformation is applied to the years spent in education. As concluded by previous studies (Frei and Ohnmacht, 2016), this variable is not particularly relevant in explaining the frequency of social interaction. The only significant coefficient shows that the longer the time spent in education, the more likely someone is to communicate via e-mail. This could be motivated by the fact that people with a higher level of education often hold "office jobs" or have in general higher IT literacy due to their engagement in further education, and therefore are more likely to use their computer as a way to communicate.

Relationship status The different categories considered for the *ego*'s relationship status are "single", "married", "widowed", "divorced" and "married but living separately". "Single" is used as a base, so all the coefficients should be interpreted as effects relative to this category. In line with results of studies on the impact of marriage on social life and contact with the family of origin (e.g. Sarkisian and Gerstel, 2008), we find that married people are significantly less likely to communicate by e-mail and SMS than single people. Although the literature also suggests an effect on physical interactions, we do not find the impact on face-to-face meetings as significant. Both widowed and divorced people get a lower benefit from communicating via SMS than singles. We also find a negative effect on communication via e-mail for widows. Although several explanations for this could be possible, one interpretation could be that widowed people are believed to intensify phone and face-to-face contacts to overcome their loss and reduce their use of impersonal communication for social purposes, especially in late stages of life (Utz et al., 2002).

Employment status This variable specifies whether the *ego* is a student, looking for a job, a homemaker, a retiree or is employed (full or part time). The last "employed" category is our base. Most of the coefficients are not significant, but we observe that retired people are significantly less likely to use e-mail and SMS than those in employment. This result does not contradict the findings reported in the "Age" section above, as the effect of the latter and that of employment status are separately controlled for, and the two categories of "retired" and "over 60" are not necessarily coinciding. The higher propensity to communicate of those who are in employment with respect to those who are not has been found in previous research (Frei and Ohnmacht, 2016).

Number of social network contacts In line with previous findings (Dunbar, 2003; Frei and Ohnmacht, 2016) all the mode-specific coefficients show that the higher the number of social contacts in the network, the less the utility that the *ego* accrues by communicating by any mode. The intuitive explanation is that social contacts require maintenance, so the bigger the network, the lower the number of interactions that people can have with each of their network members.

Ego characteristics excluded from the model Several *ego*-level variables that previous studies have found to be relevant for social interactions have proved to be non-significant in our model. As an example, differently from Carrasco and Miller (2009), we did not include network measures in our final specifications, as even the most commonly used ones, such as degree centrality, betweenness and density, did not have a significant effect on communication frequency. We believe that this is due to the fact that the actual pattern of communication is mainly determined by characteristics of the two individuals involved in it, not necessarily by the overall network structure. Different transformations were applied to the income variable to investigate potential effects but we never found it to be a significant determinant. We do not find this result too unexpected. We appreciate that face-to-face contact with people who live far away could be rather costly, but lacking information on the spatial arena of each interaction, it would have been difficult to expect a specific effect.

We also excluded the variable indicating the availability of a car to the *ego* as we found no significant effects on patterns of communication. This variable had four levels (i.e. a car could always, often, seldom or never be available), and we attempted various specifications with these levels but no effect was found. We also tested possible interactions of this variable with others, namely civil status, employment status, level of education, presence of children in the household and number of social contacts, but no significant effect was found. This finding may be surprising, but a review of the existing literature reveals the lack of robust evidence about this effect. Frei and Axhausen (2009) and Frei and Ohnmacht (2016) find relatively weak positive effects of car availability on face-to-face interaction, while Tillema et al. (2010) and Sharmeen et al. (2014) find an effect of the number of cars on frequency of interaction. Other studies reached conclusions in line with ours, i.e. they do not find significant effects (van den Berg and Timmermans, 2015; Carrasco, 2011) or highlighted that car availability can have an effect on decisions other than frequency in the domain of social interactions, such as the decision of whether to interact (van den Berg and Timmermans, 2015) and the number of trips for social purposes (van den Berg et al., 2013). Moreover, Van den Berg et al. (2012) found that car ownership has no effect on frequency of interaction and only has a weak impact on the choice to communicate by phone. One possible interpretation of our findings could be related to the fact that the public transportation system in Switzerland is very efficient and relatively inexpensive. Somewhat surprisingly, the ownership of a public transport pass also did not significantly affect the frequency of interaction by any mode. Respondents could state whether they owned a half-price ticket or a full exemption for all Swiss transport, a regional pass or a pass for a specific route. These categories were tested separately as well as aggregated in a dummy corresponding to owning a pass versus not owning it. No effect at the 0.05 significance level was found. Similar conclusions were reached, for example, by van den Berg and Timmermans (2015). While acknowledging that some of these results may be due to intrinsic characteristics or limitations of the specific dataset/context, with a high share of respondents owning a public transport pass, we believe that this and other results may suggest that dyad-level variables can be more important determinants of communication patterns than *ego* socio-demographics and characteristics related to the transport system.

4.1.3 Effects of ego-alter (dyad) characteristics

The coefficients estimated for the variables expressing dyad characteristics are substantially more significant than those described in the previous section. A detailed interpretation of these coefficients follows.

Distance This continuous variable represents the distance (measured as a straight line, in kilometres) between the *ego*'s and each *alter*'s home location. It enters the model in 2 different levels, i.e. positive distance (in logs, given the strongly skewed distribution, evident from mean and median statistics reported in Table 2.2) and zero distance, i.e. dyads living together. 74% of the *ego-alter* pairs present positive distance between their homes, while 3% of them live together.

In line with previous findings (Carrasco and Miller, 2009; Frei and Ohnmacht, 2016; Kowald, 2013) and with basic intuition, the effect of distance on interactions is very significant, and in particular we find that higher distances are related to lower face-to-face social interactions. In Figure 2.2, we simulate the impact of increasing distance between *ego*'s and *alters*' home locations on utility for distances between zero and 500 km. This is computed by adding the mode-specific baseline constants to the values of utility computed considering only the effect of distance.

We observe that the impact of distance on face-to-face is larger than on the other modes. In particular, the second strongest effect on utility is for SMS contact, then for phone and e-mail, although the order of the two latter modes is reversed for distances higher than approximately 90 km. The utility accrued by face-to-face communication is substantially lower for people who live far away than for people living close by. Utility decreases with distance also in the case of contact via phone and SMS, while in the case of e-mail we observe the opposite effect: the utility people get from this type of interaction increases with distance. This pattern in the signs of coefficients is not only observed in the case of distance and it seems to suggest that e-mail is a mode of communication that is used for different purposes and with different people with respect to the other three modes. This finding is supported by previous evidence that tackled the same research question (Frei and Ohnmacht, 2016).

As mentioned above, the "zero distance" category is treated separately, as we use a specific dummy variable for people who live together. In this case, we observe significant coefficients only for face-to-face and phone interactions. Although the former is positive (as expected), the phone coefficient is negative. This could either reflect the fact the people who live together, as they see each other very often, tend not to talk often on the phone more than they do with other people, or be the result of a recalling effect: sometimes when there is a strongly prevalent mode of interaction for a specific person, people may overestimate its frequency and underestimate the frequency of other modes when reporting these figures.

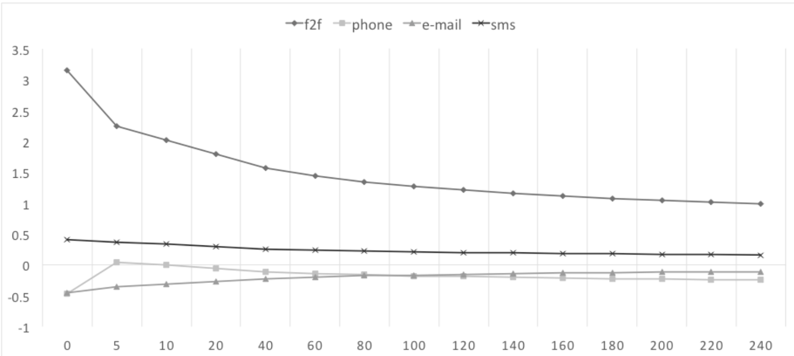

Fig. 2.2: Effect of distance on utility

Relationship duration This variable indicates for how many years the *ego* and each *alter* have known each other. A log transformation is applied to the values. The coefficients for all the modes are significant and negative except for the phone one, which is positive. This implies that people who have known each other for a long time are more likely to interact via phone than people who have met more recently. Conversely, communication by e-mail, face-to-face and SMS (the coefficients for the last two modes are nearly identical) provides less utility for longer-term relationships than for recently formed ones. It is likely that people who have known each other for long may have relocated to different parts of the city/country, which makes interaction by phone a preferable mode, as it is not as impersonal as other modes but not much affected by distance. Another explanation could be that both people are rather old and will therefore prefer to use the phone. In general, the negative coefficients should not be surprising, as generally long term relationships seem to display lower and lower communication frequencies as time goes by (Frei and Ohnmacht, 2016; Kowald and Axhausen, 2012).

Overall, face-to-face is the preferred mode of communication. This can be clearly seen in Figure 2.3, where we represent the effect of relationship duration on utility given the estimated parameters, analogously to the relationship with distance in Figure 2.2.

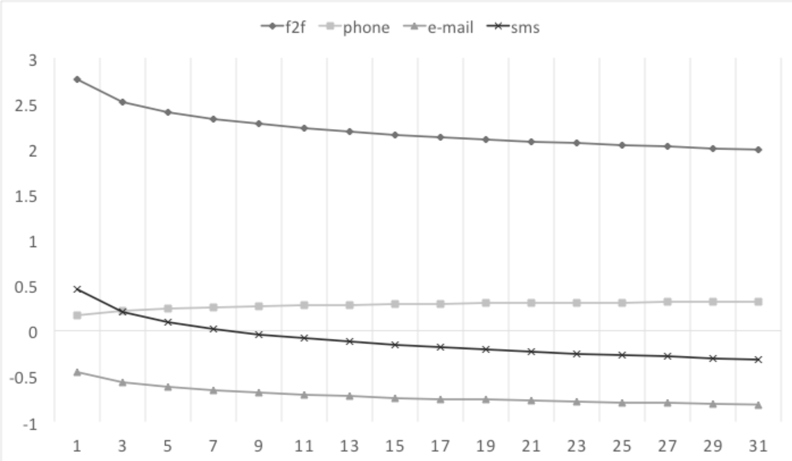

Fig. 2.3: Effect of relationship duration on utility

Age difference This variable indicates the absolute value of the age difference (in years) between the *ego* and each *alter*. All the coefficients are significant. From the graph in Figure 2.4, we can observe that the larger the age difference, the more likely it is that two people will make use of the phone and see each other face-to-face and the less likely it is that they exchange e-mails and SMS. Clearly, when the age difference is large one of the two people is likely to be rather old and not to make large use of new technologies such as computers and mobile phones. As we did for the other continuous exogenous variables, the described dynamics can be graphically visualised by simulating different levels of the variable. In this case the magnitude of the age difference coefficients is rather small for all the modes, so the main effect observed is the one highlighting the comparative preference for the different modes, determined by the alternative specific constants.

Core social contacts These two dummy variables report the response of the *ego* to the questions "Would you ask the person for help in urgent situations (e.g. when in need of money)?" and "Would you discuss important personal problems with the person (e.g. personal relationships, illness)?" This can be considered a question to detect the people who are very "close" to the *ego*, as she considers them someone to rely on. Respondents could answer Yes (coded as 1) or No (coded as 0). As expected, all the mode-specific coefficients are positive and significant, possibly indicating that people are more likely to interact by any mode with "core" contacts than with people they are not so emotionally close to. The magnitude of the coefficients is generally quite small and mode-specific coefficients are similar for the two variables.

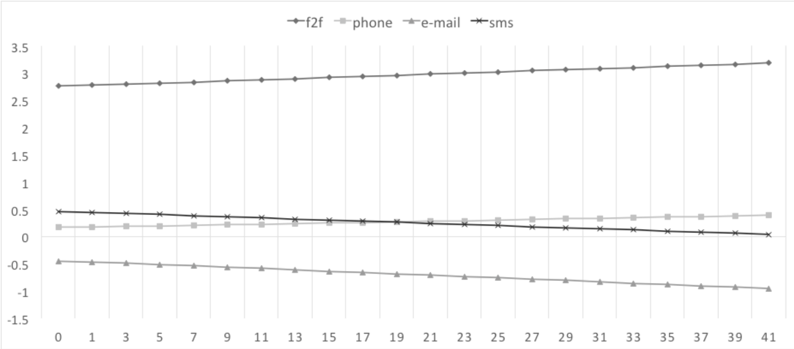

Fig. 2.4: Effect of age difference on utility

We also included an interaction term between these two variables, to consider the very strong contacts, i.e. the people that the *ego* would both ask for help and discuss problems with. In this case, only the face-to-face coefficient is significant and has positive sign, indicating a more likely interaction with this group of people with respect to others only in person. This finding is in line with the results obtained by Carrasco and Miller (2009).

Sex homophily We include two different dummy variables related to sex homophily, indicating if both *ego* and *alter* are male and if they are both female. Different sex is used as a base category, as in previous versions of the model it proved not to be significantly different from the case where the value for this variable was missing. We find that if both *ego* and *alter* are male, they are more likely to communicate by any mode except SMS than in communication with the opposite sex. If both are female, they use more phone, e-mail and SMS than when they communicate with the opposite sex, while the face-to-face coefficient is not significant. These results are difficult to compare with most of the other studies which used multilevel models, as they would observe the impact of the *ego* and *alter* socio-economic characteristics in different levels of the model, i.e. for example Kowald (2013) considers *ego* sex in Level 3 and *alter* sex in Level 2.

Type of relationship A number of dummy variables are employed to specify whether each *alter* is the *ego*'s spouse, relative of first degree, another relative, someone married into the family, acquaintance or friend. The latter is used as a base category. We observe a strong significant effect of almost all these variables on communication patterns. The "spouse" coefficients are all positive, implying that *egos* are more likely to communicate by all means with their spouses than with their friends. The face-to-face and phone coefficients are particularly large in magnitude.

Positive signs of all coefficients are also observed in the case of 1^{st} degree relatives, i.e. someone's parents, siblings or children. For more distant relatives and people married into the family we observe lower likelihood of making use of e-mail and SMS than with friends and but more likelihood of using phone. In the case of people married into the family, the face-to-face coefficient is also positive. It is in fact intuitive that contact with family members who are not immediate family will be mostly maintained through occasional phone calls and face-to-face meetings at family gatherings. Our results also reflect previous findings in the sense that SMS seems to be used mainly with very close contacts (like spouses) or family members than with friends (Tillema et al., 2010). The same holds for face-to-face, suggesting the presence of potential complementarities between the two modes. We also observe that although e-mails are likely to be used with very strong contacts like spouses, they are more likely to be used with friends than with not very close relatives and acquaintances.

Education homophily As mentioned above and highlighted by previous studies, the level of education does not seem to be a determinant of communication frequency. When looking at whether the *ego* and *alter* have the same level of education, we observe that those with the same level tend to interact by e-mail and SMS more than those with a different level. The opposite holds for face-to-face, suggesting that it is more likely for two people with a different level of education to meet in person than for people with the same level. Communicating with someone with a different level of education could be relatively more difficult, and the richness of expression possible with face-to-face can be a way to overcome such difficulty.

Citizenship homophily Most of the respondents have been recruited in the Zurich area, but not all their social contacts are Swiss citizens. We therefore added a variable to assess the influence of being citizens of the same country, which also implies being native speakers of the same language, on communication. The nationalities reported by participants were Swiss, German, Austrian, Italian, French and Other. Evidence of a preference for co-nationals is not completely unexpected, and is also supported by recent work on residential location choices in the Swiss city of Lugano (Ibraimovic and Hess, 2016) We observed that this variable is only significant (and positive) in the case of face-to-face and SMS, giving us a hint on possible complementarities between these two modes.

4.2 Missing value analysis

The name generator technique applied to collect the data used for the present study presents a number of issues when it comes to the reliability of the information reported by respondents. One problem which has been addressed by previous research is the accuracy of the reported network composition, as people are more likely to remember those social contacts who are emotionally closer to them (Bell et al., 2007; Marin, 2004).

Another often observed problem is the difficulty encountered by respondents when it comes to recalling information about the *alters* that they name, for example because of fatigue or satisficing behaviour (Pustejovsky and Spillane, 2009) or simply lack of knowledge of the requested information.

We hypothesised that the presence of missing values might not have been random in the dataset, and that by modelling these values as a separate category of exogenous variables we could have tried to interpret results and understand the reasons behind non-reporting. In addition, elimination of all the *egos* who reported missing information for at least one of their *alters* would have resulted in massive loss of observations.

It is sometimes relatively easy to provide an interpretation of the coefficients estimated for the dummy variables indicating a missing value, while in other occasions this is not the case. Most of the missing values were due to lack of information about *alters*, with the only exception of *ego* years of education. The corresponding coefficients are reported in the first line of the "Missing values coefficients" section of Table 2.4 (although they are not significant), followed by a number of dyad measures.

In the case in which the ego did not report his or an *alter*'s home location, it was not possible to compute the distance and the variable was treated as missing. In this case, we find significant and negative coefficients for communication face-to-face, by phone and via SMS, meaning that people who do not provide addresses are less likely to communicate by these modes than those who do. As most of the missing values were at the *alter*-level, this could be interpreted by hypothesising that if an *ego* does not know where the *alter* lives he either does not know this person very well, or the person lives too far for the *ego* to provide an accurate address. If this is true, it would make sense to imagine that there will not be intensive communication between them.

A similar interpretation seems to be applicable in several other cases, for example in the case of education homophily, where the ego is asked to report both his and the *alters*' level of education. It is reasonable that the *alter*'s education level is not known by the *ego* for loose social network members. Also in the case of missing values for age difference (generally implying that the *alter*' age is not reported) it makes sense to observe that those are people with whom there is no intensive face-to-face or phone interaction. The positive coefficient on e-mail might indicate that there is more likely to be "distant" or maybe work-related interaction by e-mail with these people with respect to the ones whose personal information such as age are known to the *ego*.

In the case of relationship duration, we observe that the coefficients in the missing values case present the same signs as the case when values are stated, although the absolute magnitudes are slightly higher in the first case. A possible reason for non-reporting this piece of information is that the *ego* could have known the *alter* for a long time and could not be able or willing to recall the exact number of years, as this is the way the question was posed. If this is the case, a similar effect on utility in the two cases would not be very surprising. In some cases, like when the type of relationship with the *alter* is not specified by the *ego*, there is no intuitive interpretation of the missing values coefficients, as all the possible categories were included in the multiple-choice question. In our case, none of the coefficients are significant. Also, the missing values in the simple Yes/No questions asking *egos* whether they ask a given *alter* for help or discuss problems with them are not easy to interpret. One possible interpretation is that participants decided to skip this question in cases it required them to much thinking/recalling, i.e. in cases when the *alter* was neither someone very emotionally close to them, nor an acquaintance. This would explain the positive face-to-face coefficient for "Discuss problems" and the positive phone one for "Ask for help", meaning that these are people who are in touch with the *ego* but not too closely. The opposite signs of the e-mail coefficients and the negative one for the SMS ones are more open to different interpretations. The separate modelling of the missing values is an important approach in our application. Not only we can learn more about the phenomenon that we are investigating, i.e. the communication patterns, but we can also infer recommendations about survey design, as these coefficients can suggest, for example, that one should not aim at collecting too large and loose networks because the quality and availability of information about the *alters* decreases the more "affectively distant" they are from the *ego*. This approach is also the most appropriate in terms of modelling: we have indeed tested whether separate coefficients for the missing values were to be necessarily included or if the implied values were not significantly different from the mean (in the case of continuous variables). It was not the case, and therefore we had to treat them separately, also given that many of them were significant.

5 Model Forecast

An interesting question related to the topic studied in the present paper is to what extent the pattern of communication between an *ego* and her social contacts changes if there is a change in the characteristics of one of the *alters*, for example if a friend moves further away from the *ego*. In order to investigate this issue, we applied the forecasting procedure for MDCEV models proposed by Pinjari and Bhat (2010a).

In particular, we selected a subsample of our dataset that only includes *egos* who reported a friend who lives less than 5 km away from them (excluding friends who live with them). If more than one contact with these characteristics existed, we only considered one of them, in particular, the first one reported in the name generator. This resulted in a sample of 398 people. Following Pinjari and Bhat (2010a), we computed the frequencies of interaction with all the *alters* in the base scenario and in the forecasting scenario, when the selected friend's distance to the *ego* is increased by 10%.

In order to summarise the effect of the change, the forecasting results were used to compute elasticities of the frequency of interaction and of distance travelled across the sample of respondents. These are displayed in Table 2.5.

Elasticities of the frequency of interaction by each mode	
face-to-face	-0.004
phone	0.002
e-mail	0.008
SMS	0.003
Elasticities of the frequency of interaction with relocated alter by each mode	
face-to-face	-0.162
phone	-0.037
e-mail	0.052
SMS	-0.028
Overall elasticity of the frequency of interaction	-8.00E-06
Elasticity of the frequency of interaction with the relocated alter	-0.075
Elasticity of consumption of the outside good	0.006
Distance elasticity	0.007
Distance elasticity for relocated alter	-0.011

Table 2.5: Elasticities of frequency of interaction and distance

These results provide some important insights. First of all, we can observe that the overall frequency of interaction with social contacts is inelastic with respect this change. The elasticities of the frequency of interaction by each mode also underline that a change in distance will cause a reduction of overall face-to-face contact only, as obviously increased distance will mainly impact this type of interaction. Overall distance travelled is computed for each *ego* by multiplying the *ego-alter* distance for the number of yearly face-to-face contacts and dividing by 2. We are aware that this is an approximation, but as previously stated the data do not contain any information about meeting locations. The computed distance elasticity is small and negative for the relocated *alter*, meaning that the *ego* will travel less to see this *alter*. However, the overall elasticity is positive (though also small), meaning that there is a positive overall impact on the overall distance travelled, so that the *ego* compensates the drop in travel to the affected *alter* with more travel to other *alters*.

As expected, we observe a greater value for the elasticities of the frequency of interaction with the relocated social contact. Not only face-to-face interactions are sensitive to the increase in distance, but also the variation in phone and SMS, although smaller, is found to be negative. This finding potentially highlights the role of the latter two modes as complementary to face-to-face and as being used mainly for coordination purposes with contacts who live close by. E-mail frequency, in line with the overall findings of the model, seems to be likely to increase following an increase in distance. These results hint at the potential presence of substitution effects between face-to-face and ICT, which Sharmeen et al. (2013) already suggested to be strongly related to distance. Finally, we observe that the overall elasticity of interactions with the relocated *alter* is negative, meaning that overall, the *ego* will interact less with this person. Differently from our findings, Sharmeen et al. (2014) suggested a positive coefficient for interactions with a relocated *alter*, though acknowledging the counterintuitive result. Moreover, the authors tested the effect of a neighbour relocation, while our case concerns friends: these findings could highlight the importance of considering dyad-level characteristics such as relationship type to capture an accurate behavioural picture.

Although these results provide interesting insights about the sensitivity of the frequency of interaction to a change in distance between two people, it is important to point out that our forecasts are based on a model estimated on cross-sectional data. Over time, an *ego* has put together a network of *alters* that he/she interacts with and the specific pattern of interactions has evolved over that time. This in turn means that the impact distance has on frequency of interaction in the data is reflecting interaction patterns in some continuously evolving and partially stable situation. If an *alter* moves further away from the *ego*, then this may reduce interaction, but the effect may be more or less than the difference in the level of interaction at the "partially stable state" with two *alters* who are otherwise identical but live at different distances from the *ego*. Only the availability of longitudinal data with some location changes by *alters* or *egos* would allow us to truly understand the impact that changes in distance will have on interaction patterns. For this reason, the present exercise is likely to overstate the impact, at least in the short term.

As reported in section 3.2, we estimated versions of the model where the budget was increased by the same amount for the entire sample, and when the prices differed across modes. We applied the forecasting routine also to these models to check whether these different assumptions about the budget and prices would affect elasticities. The results, presented in Appendix A, show that there are no substantial differences in the elasticities obtained from the models where different assumptions on the budget and the prices are applied.

6 Conclusions and future research

Our study investigated the determinants of communication frequency by four modes (face-to-face, phone, e-mail, and SMS) between people and their social network members.

Its findings contribute not only to a better understanding of social networks, but also provide interesting insights for the analysis of travel behaviour for social and leisure purposes.

In terms of understanding communication patterns, we gave a detailed picture of mode-specific determinants of communication, advancing the study of this topic by using a model which simultaneously examines the contribution to utility of communication of both individual and *ego-alter* characteristics. On top of showing the detailed effect of each of these variables, we provide a picture of satiation effects from different communication modes, showing that despite face-to-face meetings remaining the most preferred type of communication, a lower number of interactions are demanded for each network member with respect to the other modes.

Our work also provides interesting insights into the modelling of travel behaviour, as understanding the pattern of interaction between leisure network members helps to understand travel for social and leisure purposes. The confirmation of the presence of a strong underlying preference for face-to-face contact (especially in the maintenance of core contacts) is an important conclusion given the ongoing debate on potential substitution effects between ICT based modes of communication and most traditional ones.

Additionally, we have shown that while some of the results linking socio-demographics to social interactions patterns are in line with results from previous work, other findings highlight differences that are particularly interesting for travel behaviour analysis. In particular, according to our results, the availability of specific travel modes or public transport passes does not seem to significantly affect the frequency of communication. Previous studies do not present clear-cut evidence on the significance of these factors for the patterns of social interactions, so we acknowledge that our findings could be partially related to the specific context where the data was collected as well as to the lack of detailed information about the transport network. These results could also possibly suggest that some of the existing travel behaviour work mainly focussing on travel-related variables and *ego*-level characteristics as determinants of decisions about social activity travel might not have fully considered other important aspects that can be investigated while making use of social network data. Moreover, differently from similar studies which made use of social network data, the simultaneous modelling technique adopted in the present paper allows us to observe that dyad level variables have a much more significant effect on communication frequency than *ego*-level ones, a result that supports the need to make use of measures related to the similarities and differences between *egos* and *alters* to understand interaction patterns. A brief illustrative forecasting example also shows how a model of the type used here can be used to gain insights into the likely changes in travel patterns resulting from changes in the composition and characteristics of a social network.

The findings and the modelling framework also has implications for the design of activity-based models (ABMs). As previous research and this work have shown, face-to-face meetings depend on communication patterns at the level of an individual's social network. Thus, these communication models can be used to determine the probability of an individual generating social activities in their daily activity patterns. Additionally, the communication model gives an indication of what types of in and out-of-household contacts are likely take place and the frequency of these contacts. Thus, the model also helps to enhance ABMs that include the coordination of joint inter- and intra-household activities. These enhancements will have important considerations as segments of society move toward less car ownership and vehicle sharing.

The present work constitutes a first step in the use of MDCEV models in the investigation of communication frequencies, and several improvements and more flexible structures can be suggested to better represent this specific behavioural process.

A first issue that we raised is the use of this model when the budget specification is not clear-cut. Both investigating the use of simplified approaches like in this paper and the attempt to derive prices and budgets which are not observed can constitute an interesting next step in this work.

In this paper, we estimated one γ parameter for each mode of communication to avoid explosion in the number of parameters. Nevertheless, heterogeneity in satiation could be accommodated in ways other than estimating one γ for each product. A possible option would be to parameterise the four mode-specific γs as a function of observed *ego*- and dyad-level characteristics to investigate whether these can affect satiation. We aim to perform a detailed investigation of this research question in future work on this topic.

Moreover, as mentioned while presenting the model results, we have observed that the signs and magnitudes of coefficients suggest the possible presence of complementarities between different modes while in other cases the substitution effects were more evident. The limiting case of perfect substitution between different modes can also not be excluded. The presence of these complex patterns is supported by existing literature, e.g. Sharmeen et al. (2013). The current version of the model, by only allowing the consideration of imperfect substitute goods, does not allow us to test these hypotheses. An extension of the present work to test for more flexible complementarity and substitution patterns is an important area for future work. This could involve developing a nested version of the current model, or relying on model extensions such as Bhat et al. (2015). Finally, as highlighted in the forecasting example, an important next step would be the use of longitudinal data in a study of this type.

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Chapter 3

Modelling the loss and retention of contacts in social networks: the role of tie strength and dyad-level heterogeneity

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Abstract

Social networks have attracted attention in different fields of research in recent years and choice modellers have engaged with the discipline by looking at the role that social networks play in shaping decisions across a variety of contexts. With work in choice modelling increasingly looking at long-term decisions, the incorporation of the social dimension in choice models creates the need for understanding how social networks evolve over time and in particular which social contacts (alters) are retained over time by an individual (ego). Existing work fails to capture the full extent of ego-level and ego-alter level heterogeneity in these processes. We propose the use a hybrid model framework which is based on the notion of a latent strength of relationship. The resulting model allows for heterogeneity in the latent strength both across individuals in our data and across their different relationships. In addition, we allow for heterogeneity not linked to the latent strength concept. We demonstrate the benefits of the approach using data from Chile, showing the presence of extensive variations both at the ego and ego-alter level, only some of which can be linked to observed characteristics.

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1 Introduction

Social networks have attracted substantial attention across different research fields in recent years, looking for example at information diffusion (e.g. Bakshy et al., 2012) and social influence (e.g. Kempe et al., 2003). Choice modellers have engaged with this discipline by looking at the potential effects that social networks may have on decisions across a variety of contexts, including time use (Calastri et al., 2017a), telecommuting (Páez and Scott, 2007) and evacuation stategies (Sadri et al., 2017) and by modelling decisions related to social interactions (Calastri et al., 2017b). Several contributions focused on addressing the issue of how to capture social influence (Dugundji and Walker, 2005; Maness et al., 2015), with some also dealing with the issue of endogeneity that might be implied by including such effects (Walker et al., 2011).

A key characteristic of social networks is that they are not static but evolve over time. With the work in choice modelling increasingly looking at the use of longitudinal data and modelling longer term decisions, any incorporation of a social dimension in choice models thus also creates a need for understanding how social networks evolve over time. Some first attempts to model social network dynamics and their interaction with life-cycle events have been made by (Chávez et al., 2017; Sharmeen et al., 2014, 2015, 2016). While these papers have modelled the changes in social networks over time, more can be done to accommodate the extent of the heterogeneity involved in this process at the respondent and at the dyad level.

Researchers in the social sciences have studied characteristics and processes inherent to social networks themselves, i.e. how they are formed and how they can be represented. The process of network formation and change over time is complex and depends on the characteristics of the different individuals involved, and its study requires adequate data. In particular, when the aim of the study is to investigate network changes over time, longitudinal data, inclusive of information about individuals and their attributes, are needed. Such data are rare and most examples in the social network literature are mainly for small groups (e.g. Wasserman and Faust, 1994), while studies using larger groups have mainly focused on cross-sectional analyses.

Given the generally limited sample sizes, qualitative methods have often been applied to investigate the determinants of social network evolution. Interviewing a sample of 33 people from Toronto in 1968 and then in 1978, Wellman et al. (1997) analysed the change in personal networks, trying to understand what the influence of personal circumstances and measures of homophily might have had on it. The results of this study show that frequent telephone interactions and social support increase the likelihood of retaining contacts over time, while changes in marital status (especially for women) may involve losing friends. A strong turnover in the network is reported, except for a stable core component. The latter finding is confirmed by Mollenhorst et al. (2014), who study the changes occurred over seven years in the social network of Dutch people aged 18 to 65 (although they use a larger sample). High average numbers of social contacts lost over time are reported in particular in association with important life course events. This is especially apparent in a study surveying young French people (Degenne and Lebeaux, 2005), showing dramatic changes in their network as they undergo life-course changes.

Choice modelling techniques provide a suitable tool for the study of how social networks evolve, and in particular to explain whether a given social contact is maintained over time. As with many other decisions, there is scope for extensive heterogeneity, both deterministic and random. Crucially, this is an area where the heterogeneity may be especially strong at the individual level, so that the likelihood of retaining people in one's network varies extensively across individuals, but there is further (and possibly even larger) heterogeneity across the individual members of a network. This is line with the work on network evolution which often refers to "core" ties, identified as the ones who are emotionally closer to the surveyed individual, and which are also the ones that are generally more likely to be retained over time. These are often identified as the closest friends or family members, or through questions asking for the names of the people who provide more support. This creates the notion of relationship strength, which has been the object of studies linking it to frequency of interaction, amount of time spent together and reciprocal services (for a discussion, see Marsden and Campbell 1984).

In the present paper, we put forward the idea of modelling this notion of strength of a relationship as a latent component within a hybrid choice model. We show how this allows us to separately account for different layers of heterogeneity, both at the level of individual survey respondents (which we call egos) and across the different members of their network (alters). We demonstrate this approach using data from a typical name generator survey conducted in Chile. Our findings can be operationalized to dynamically predict the composition of the social network as well as the strength of the ties, both of which can lead to more realistic modelling of activity, travel and other choices.

This paper is organised as follows. Section 2 introduces the data collection protocol and describes the sample used for analysis. Sections 3, 4 and 5 introduce the methodological framework and report the estimation results of each set of estimated models. In particular, section 3 focuses on the simple binary models for retention of social contacts, section 4 discusses the treatment of the strength of relationship as a latent concept and reports the estimation results of the measurement models, while section 5 introduces the latent strength in the binary model, showing a number of different model specification with different levels of heterogeneity both at the level of the latent variable and in the retention model. Finally, we draw conclusions about the modelling work performed in the paper.

2 Data

2.1 Survey and data collection

For the present analysis, we use longitudinal network data collected in two waves (2008 and 2012) within the Communities in Concepción project, in the city of Concepción, Chile. The project, aimed at understanding multiple aspects of the life of the respondents, included a very rich questionnaire, a name generator and name interpreter and a time use diary.

The questionnaire, which presented only minor differences in the two waves, asked respondents to provide information about themselves and their household, their housing arrangements as well as their past education and job history.

We make use of multiple parts of the questionnaire, although the crucial elements for our study are the *name generator* and the *name interpreter*. A name generator is a survey question, usually in the form of a table, asking respondent to list the names of the people in their social network (Campbell and Lee, 1991; Marsden, 1990). Different studies use different types of stimuli to help respondents recall the relevant social network. For example, some studies are more interested in business networks, while others ask people to recall the names of those with whom they spend their free time. In the case of the present study, the instrument is based on Carrasco et al. (2008b). Two different name generators were presented to respondents. Both asked them to report names of people outside of their household (could be friends, family members, neighbours etc.), dividing those who are emotionally very close from those who are "somewhat close", although not mere acquaintances. On top of providing the names of the alters, egos were asked to enrich this list by answering questions about them: some basic socio-demographic characteristics (sex, age, occupation, residential location) as well as some information concerning the relationship between the two are asked. In particular, egos are asked to specify for how for long they had known each alter (less than a year, 1-10 years or more than 10 years) and how they would define their relationship (immediate family, other family, neighbour, friend, colleague, someone from a club or organisation). Egos were also asked to report the frequency of interaction by different modes of communication with each alter. As in most social network surveys, respondents were given a separate table to report these additional information about each alter, referred to as the name interpreter.

The name generator was not the only part of the survey related to the social environment. A social capital section listed different "types of help" (e.g. advice on important matters, borrowing small amounts of money, assisting when ill...), and for each of them asked the egos to identify one or more alters to whom/from whom they could grant/receive this type of help. Several Likert-scale questions about the ego's personality traits and subjective well-being were also included.

Finally, respondents are asked to fill in a time use diary for two days, a week day and a week-end day. Start and end times as well as activity type, place and people involved had to be specified.

The data were collected by an interviewer at the respondents' homes, except for the time diary, which respondents were given instructions about and let free to complete on the chosen days.

2.2 Sample characteristics

Participants were recruited by post using their home address. This implies that a certain number of respondents from the original (2008) sample of 240 were lost due to relocation or unresponsiveness. 102 people took part in both waves. Due to the specific nature of our study, we excluded from this sample the participants who did not complete the name generator in either wave or who did not have any overlap in their network, as we assumed that this was due to severe recall issues. The usable sample for analysis was made up of 94 respondents, who named a total of 1912 alters in 2008 (20.34 each, on average). Table 3.1 reports the socio-demographic characteristics of the egos as of 2008 (first wave) as well as some statistics about the life course events occurred between the two waves and network size statistics. Although the selection of the subsample for this analysis somewhat limited its representativeness, the originally collected sample matched the characteristics of the local population well (Carrasco and Cid-Aguayo, 2012).

As it can be observed from Table 3.1, while in the case of the egos we can make use of both waves of data and infer life-course changes that could be relevant for social network-related behaviour, the same cannot be done when it comes to the ego-alter level variables. In fact, while we are aware of socio-demographic changes about the alters who have been retained in 2012, we have no information about those who are no longer part of the egos' network. This is indeed a potential limitation of the present work that we will come back to later on in the paper, as the outcome that we are focusing on is likely to depend not only on characteristics and events related to the ego's life, but also to those related to the alters.

Table 3.2 reports ego-alter characteristics. We can observe that for *Sex Homophily*, *Age Homophily* and *Time known each other*, the categories are of course mutually exclusive, while egos could classify a given alter as (say) both a colleague and a friend. This happens in a limited number of cases

Table 3.1: Ego characteristics

Number of egos	**94**	
Number of ego-alter pairs	**1912**	
	Freq	**%**
Sex		
Male	33	35%
Age		
18-30	25	27%
31-40	16	17%
41-50	18	19%
51-60	17	18%
over 61	18	19%
Education		
Elementary School	15	16%
Medium School	37	39%
Technical School	8	9%
Undergraduate Degree	25	27%
Postgraduate Degree	9	10%
Employment status		
Employed	49	52%
Unemployed	9	10%
Student	6	6%
Homemaker	17	18%
Retired	8	9%
other	5	5%
Mobility		
Driving licence	31	33%
Communication tools ownership		
Landline	61	65%
Mobile phone	80	85%
Internet connection	51	54%
Life course events 2008-2012		
Went to University	6	6%
Finished University	2	2%
Started a new job	4	4%
Quit a job	4	4%
Divorced	3	3%
Got married	12	13%
Had a child	14	15%
Network size		
Min	7	-
Max	44	-
Average	20.34	-
Median	19	-

(230 out of 1912), not sufficient to create interaction effects in our models.

Table 3.2: Ego-alter characteristics

Number of ego-alter pairs	**1912**	
	Freq.	%
Sex homophily		
both male	388	20%
both female	802	42%
different sex	722	38%
Age homophily		
Under 30	390	20%
30-60	135	7%
Over 60	161	8%
Different age	1222	64%
Type of relationship		
Immediate family	369	19%
Other family	460	24%
Neighbour	352	18%
Colleague	171	9%
Club/ Organisation	107	6%
Friend	690	36%
Time known each other		
Less than 1 year	173	9%
1-10 years	1081	57%
More than 10 year	397	21%
NA	261	14%

3 Binary models for retention of social contacts

We observe E separate egos that participate in both the 2008 and 2012 survey, where for a given ego e, we have a set A_e of different alters named in 2008. The objective of our modelling work is to explain the retention or loss of a given alter by a given ego[3]. For this, we specify y_{a_e} to be the dependent variable of a binary model, which takes the value 1 if and only if ego e retains alter a_e in his/her network of named social contacts.

3.1 Model specification

[3]It is important to note that there are potential recall issues associated with the use of name generators, so although we attempt to model loss, what we can model, given the potential measurement error, is recall.

3.1.1 Base model

As a first step, we model the retention of an alter as a function of the characteristics of the ego and alter in 2008 ($z_{e,a_e,2008}$) and any changes in the characteristics of the ego between 2008 and 2012 ($z_{e,2008-2012}$). Using a simple binary logit model, we would then write the utility of retention as:

$$U_{e,a_e} = V_{e,a_e} + \varepsilon_{e,a_e} = \delta + f\left(\beta, z_{e,a_e,2008}, z_{e,2008-2012}\right) + \varepsilon_{e,a_e} \tag{3.1}$$

where δ is an estimated constant, β is a vector of parameters measuring the impact of $z_{e,a_e,2008}$ and $z_{e,2008-2012}$ on V_{e,a_e} and ε_{e,a_e} is an *i.i.d.* extreme value error term. The probability of the observed outcome would then be:

$$P_{y_{a_e}}\left(\delta, \beta\right) = \frac{e^{y_{a_e} \cdot V_{e,a_e}}}{1 + e^{V_{e,a_e}}}, \tag{3.2}$$

and the likelihood of the sequence of outcomes for ego e would be given by:

$$L_e\left(\delta, \beta\right) = \prod_{a_e \in A_e} P_{y_{a_e}}\left(\delta, \beta\right), \tag{3.3}$$

where $\prod_{a_e \in A_e}$ is a product over all alters named by ego e in 2008.

3.1.2 Introduction of random heterogeneity in binary choice model

The simple base model in Section 3.1.1 accounts for some of the differences across egos and across ego-alter pairs in the probability of retention by linking this to observed characteristics. However, there is clearly scope for additional unexplained variation both at the level of an individual ego (affecting his/her probability of retention equally across all alters) as well as the ego-alter level. This latter component of random heterogeneity is potentially especially important given that the retention in a social network is driven not just by the ego but also by the alter, where an added source for this is the lack of data on changes in alters' characteristics/circumstances between 2008 and 2012 (given that this is of course only available for retained alters).

Random heterogeneity at the ego level is relatively easy to deal with by making δ_e ego-specific in Equation 3.1, and allowing it to be distributed randomly across egos with $\delta_e \sim h\left(\delta_e \mid \mu_\delta, \sigma_\delta\right)$, using for example a Normal distribution. Equation 3.3 then becomes a binary mixed logit model, with:

$$L_e\left(\mu_\delta, \sigma_\delta, \beta\right) = \int_{\delta_e} L_e\left(\delta_e, \beta\right) h\left(\delta_e \mid \mu_\delta, \sigma_\delta\right) \mathrm{d}\delta_e, \tag{3.4}$$

where the integration is carried out at the level of an ego, recognising that we are dealing with ego level heterogeneity.

The binary mixed logit model in Equation 3.4 will capture differences in the probability of retention across the individual egos in the estimation sample. Such differences are likely to exist both as a result of unobserved characteristics of the ego as well as unobserved characteristics in his/her circumstances. It is also likely that some egos are more likely to name the same alters in 2012 and 2008 than others, i.e. some are more prone to forgetting some alters than others.

While ego-level heterogeneity obviously plays a role in the retention of social contacts, there is also substantial scope for ego-alter level heterogeneity - to put it colloquially *"it takes two to tango"*. Some of this heterogeneity can again be linked to the characteristics of the alter in 2008 and the differences/similarities between the ego and alter characteristics in 2008. However, there is substantial scope for additional unobserved heterogeneity. While such observation level random heterogeneity has received growing interest in choice modelling in recent years (Hess and Rose, 2009; Hess and Train, 2011), in the simple binary case faced here, any random heterogeneity in δ at the ego-alter level would be very difficult (or impossible) to disentangle from the extreme value error term in Equation 3.1[4]. This forms the motivation for the remainder of our methodological discussion in sections 4 and 5.

3.2 Estimation results

The models were coded and estimated using R (R Core Team, 2016), and estimation results for the binary models are presented in Table 3.3, where we refer to the simple base model as A_1 and the model with added random heterogeneity as A_2. In all models including random heterogeneity, we made use of 100 Halton draws (Halton, 1960) for each random parameter. Going beyond 100 draws in the full model rapidly led to memory issues but separate tests showed stable results with varying numbers of draws. We see that A_2 provides better fit according to the log-likelihood (LL) and Bayesian Information Criterion (BIC). This is also confirmed by a likelihood ratio test between the two models, where $p \sim 1.9 * 10^{-9}$. The μ_δ parameter is negative and significant in both models, indicating that egos are overall more likely to lose their social contacts over time. When estimated, σ_δ is highly significant, confirming the presence of heterogeneity in retention at the ego level.

As explained above, in A_1 only characteristics of the ego and of ego-alter relationships are used to explain retention. For each effect, we report the estimate (est.) and the robust t-ratio (rob t). In our final specifications, we only retain those variables that have a statistically significant effect, where this list was arrived at after an extensive specification search. All available ego-level socio-demographic effects were tested in the model, in a linear fashion and, where relevant, with non-linear transformations. These included age, sex, level of education, income, different life course changes such as get-

[4] Some weak empirical identification would only be possible thanks to differences between the distribution used for δ (say a Normal) and the extreme value distribution.

Table 3.3: Estimation results for binary retention models

	Model A_1	**Model A_2**
Final LL	-1,020.19	-1,000.90
adj. ρ^2	0.23	0.24
BIC	2,115.93	2,087.50

	est.	**rob t**	**est.**	**rob t**
μ_δ	-1.866	-9.94	-1.9882	-9.83
σ_δ	-	-	0.58	7.47
$\beta_{ego\,landline}$	0.4132	2.25	0.4123	2.13
$\beta_{ego\,student}$	-0.4903	-1.5	-0.5355	-1.6
$\beta_{ego\,divorced\,2008-2012}$	0.517	2.11	0.5584	2.23
$\beta_{ego-alter\,both\,male}$	0.4243	2.81	0.4827	3.12
$\beta_{ego-alter\,both\,female}$	0.4868	3.06	0.5377	3.36
$\beta_{ego-alter\,immediate family}$	1.0467	5.94	1.1385	6.14
$\beta_{ego-alter\,organisation}$	-0.5951	-2.38	-0.5466	-2.45
$\beta_{ego-alter\,known\,under\,one\,year}$	-0.4694	-1.52	-0.489	-1.7
$\beta_{ego-alter\,network\,betweenness}$	0.0185	2.9	0.0217	3.22

ting married, divorcing or having a child, as well as different social network measures such as network density, number of isolates and different measures of centrality (degree, betweenness and closeness). Ego-alter variables were also tested, including homophily measures, such as same sex or same age, as well as type of relationship between the ego and the alter.

As mentioned in Section 2.1, information about the residential location of alters was also available. Previous research in social network analysis suggests that distance is an important element when it comes to social interactions and establishing social links (e.g. Carrasco et al., 2008a). For this reason, while the change in distance between the ego's and the alters' residential locations was only available for those alters who had been retained in the network, we attempted to develop a model to infer the same information for the alters that were not retained. Unfortunately, due to the small sample and the high level of missing information, as well as to the complexities in the development of such a model, this attempt was not successful. We believe that a similar effort with more suitable data could lead to better results.

Table 3.3 first reports the ego-level characteristics that help explain the retention of social contacts. In particular, we find that having a landline in 2008 increases the probability of retaining social contacts, while being a student decreases it. The latter effect could be related to the fact that students and their social contacts are more likely to experience life changes that might result in losing touch.

At the ego-alter level, we find that gender homophily makes relationships more likely to last over time. A strong positive effect is found for immediate family members, while people met through clubs and organisations are more likely to be removed from the network. Moreover, alters who have been only known to the ego for one year or less are less likely to be retained than those who have been known for longer. Betweenness centrality is conceptualised as a measure of "control" of the flow of resources in a network (Wasserman and Faust, 1994), and in the context of social activities is normally seen as the level of contact between a node and the rest of the network. The alters with a higher level of betweenness centrality are more likely to be maintained, likely because they have a more important role in the network structure.

4 Strength of relationship as a latent concept

The work in Section 3 has highlighted the presence of heterogeneity across egos in the probability of retaining alters and has also shown how some ego-alter level characteristics influence that outcome. In this section, we delve deeper into the possible reasons for retention. Specifically, we hypothesise that a key driver in the retention of an alter a_e in ego e's network is the strength of that relationship.

4.1 Model specification

4.1.1 Latent strength

We define α_{a_e} to be a latent variable which describes the strength of the relationship between ego e and alter a_e. We hypothesise that this latent strength depends on the characteristics of the ego and alter in 2008, i.e. $z_{e,a_e,2008}$. We exclude $z_{e,2008-2012}$ from the structural equation of this latent variable as it is used to explain the strength of the relationship in 2008. We then write:

$$\alpha_{a_e} = g\left(\gamma, z_{e,a_e,2008}\right) + \eta_e + \eta_{a_e} \tag{3.5}$$

where γ takes a role similar to β in Equation 3.1. This structural equation for the latent strength includes two random error terms, one distributed across egos (η_e) and one distributed across alters and egos (η_{a_e}). Both are specified to follow Normal distributions with a mean of 0, where, for normalisation, we set σ_{a_e}=1 and estimate σ_e. The rationale for two separate error terms is that we assume that the strength of a relationship varies both across egos and across alters for that ego. This means that we allow for the fact that some egos will be more prone to establishing strong relationships than others (variation across egos) and that even within a specific ego's network, certain ties will be stronger than others (variation across alters, for an ego).

4.1.2 Measurement models

The latent strength concept is explored in a number of measurement model components which use this variable to explain an ego's answers to a number of subjective questions, which we treat as indicators of the latent variable. This set of indicators I_e for ego e includes seven binary responses and one ordered response. The binary items were from survey questions where the ego had to specify the names of the alters he/she was exchanging support with, in particular: giving advice on important matters and about job opportunities, lending and borrowing small amounts of money, receiving help in terms of mobility in times of need and whether or not the ego and alter participate in joint social activities; in addition, each alter could be reported in a different name generator depending on how emotionally close he/she was perceived: we use this as a measure of closeness. The ordered response related to the frequency of face-to-face contact. The selection of these statements as indicators of the latent variable was guided by studies in the field of sociology. Granovetter (1973) defines the strength of a tie as a "(probably linear) combination of the amount of time, the intimacy (mutual confiding) and the reciprocal services (...)". Some studies talk about "multiplexity", i.e. argue that the co-presence of multiple elements constitutes a strong tie (e.g Kapferer, 1969), while others consider the possibility that ties with only one content or with diffuse content might also be strong (Simmel, 1950). In our case, we did not have any measure of intimacy, but we did have measures of reciprocal services (the so-called social capital or support questions). We decided to also use the involvement in social activities as a measure of time voluntarily spent together.

We use binary logit models to explain the answers to the first seven items, and an ordered logit model for the frequency of interaction. Each time, we estimate a parameter ζ_i that measures the impact of the latent variable on the indicator, along with a mean parameter in the binary logit model and four threshold parameters for the ordered logit model (for the 5-level indicator).

Under the error assumptions made in Equation 3.5, the probability of the observed set of answers to these questions for a given ego e across all his/her alters is then given by:

$$LI_e\left(\gamma,\sigma_e,\mu_I,\zeta_I\right)=\int_{\eta_e}\prod_{a_e\in A_e}\int_{\eta_{a_e}}\prod_{i=1}^{8}PI_{a_e,i}\left(\alpha_{a_e},\mu_I,\zeta_I\right)\phi\left(\eta_{a_e}\right)\mathrm{d}\eta_{a_e}\phi\left(\eta_e\right)\mathrm{d}\eta_e, \tag{3.6}$$

where $\phi\left(\eta_{a_e}\right)$ and $\phi\left(\eta_e\right)$ are Normal density functions with mean 0 and where, as mentioned above, the variance of η_{a_e} is normalised to 1. The probability $PI_{a_e,i}\left(\alpha_{a_e}\right)$ for the observed response for indicator i for ego-alter pair a_e is conditional on the latent strength, with the functional form for this probability being either binary logit or ordered logit. This leads to the estimation of two vectors of parameters for the measurement models (μ_I and ζ_I) in addition to the parameters of the structural equation for α_{a_e}, namely γ and σ_e.

Equation 3.6 involves integration at two separate levels, leading to an ability to separate out the two layers of heterogeneity (ego and ego-alter level), albeit at a high computational cost (Hess and Train, 2011). The estimate of σ_e relative to the normalised σ_{a_e} gives an indication of the relative importance of the two layers of heterogeneity.

Two simplifications of this model arise. In the first, we allow for only ego-level random heterogeneity (but still deterministic ego-alter level heterogeneity through γ), meaning that we set $\eta_{a_e} = 0$ in Equation 3.5 and then normalise σ_e to 1. We then rewrite Equation 3.6 as:

$$LI_e\left(\gamma, \mu_I, \zeta_I\right) = \int_{\eta_e} \prod_{a_e \in A_e} \prod_{i=1}^{8} PI_{a_e,i}\left(\alpha_{a_e}, \mu_I, \zeta_I\right) \phi\left(\eta_e\right) \mathrm{d}\eta_e. \tag{3.7}$$

While this model is substantially easier to estimate, it led to slightly poorer performance, confirming the presence of extensive levels of random ego-alter heterogeneity.

It is similarly possible to estimate a version with only ego-alter level heterogeneity, thus setting $\eta_e = 0$ in Equation 3.5 and rewriting Equation 3.6 as:

$$LI_e\left(\gamma, \mu_I, \zeta_I\right) = \prod_{a_e \in A_e} \int_{\eta_{a_e}} \prod_{i=1}^{8} PI_{a_e,i}\left(\alpha_{a_e}, \mu_I, \zeta_I\right) \phi\left(\eta_{a_e}\right) \mathrm{d}\eta_{a_e}. \tag{3.8}$$

This model now has random heterogeneity only at the ego-alter level, but the estimation of this (in contrast with the binary choice model) is made possible by the presence of multiple indicators at the ego-alter level, just as in Equation 3.6.

4.2 Estimation results

The models were again coded and estimated using R (R Core Team, 2016), where parallel processing was used to deal with the complexity especially of the models with two layers of integration. Simulated maximum likelihood was used. Table 3.4 reports the estimation results for the measurement models. As specified in the table, the first model (B_1) only includes heterogeneity at the ego level, the second one (B_2) only at the ego-alter level, while the last one (B_3) includes both, so that σ_e is estimated while σ_{a_e} is set to 1, as explained in Section 4.1. The model including both the ego and ego-alter heterogeneity performs better than the other two. The p-value for the likelihood ratio test comparing B_3 to B_1 is $p \sim 1.4 * 10^{-35}$ while the comparison between B_3 and B_2 results in $p \sim 1.2 * 10^{-16}$. B_1 and B_2 have the same number of parameters, so the test cannot be performed, but both the LL and BIC are better for B_2. This makes intuitive sense, as we would expect most of the heterogeneity in strength to be at the ego-alter level, and that serves as a motivation for attempting to include such ego-alter level heterogeneity also in the choice model, which is only possible in the hybrid structure discussed in Section 5.

For each of the binary indicators used in the measurement model, we report a mean (μ_I), estimated from the binary logit model. For example, $\mu_{I,receive\,advice\,on\,work\,opportunities}$ is negative and significant in all the models, indicating that most egos in the sample do not receive advice about new jobs from most of their social contacts. Frequency of face-to-face interaction is the only non-binary indicator used: respondents could state that they never see the alter face-to-face, that they do so at least once a year, at least once a month, at least once a week, or multiple times per week. We estimate four thresholds in an ordered logit model $t^1 - t^4_{I,face\,to\,face}$, so that the probability that a person answers "never" is the probability that the utility is less than -3.5628 (in model B_1) and so on. The impact of the latent strength on the indicators is captured by the ζ_I parameters. We see that the latent variable positively affects all the indicators, confirming that α_{a_e} might indeed be measuring relationship strength.

After this first set of estimated parameters, we report the σ terms, which reflect the heterogeneity at the ego and at the ego-alter level, as discussed above. σ_e is significant and its value is less than 1, confirming the presence of heterogeneity in strength at the ego level, but also indicating that there is higher heterogeneity at the ego-alter level.

The set of γ reported in the lower part of the tables represent the significant coefficients of the covariates included in equation 3.5. We have included these covariates to explore possible correlations, but the work in sociology looking at relationship strength has mainly relied on using indicators of this purely latent construct, rather than modelling it as a dependent variable. Nevertheless, we believe that some of the effects we obtain are intuitive. Some ego-level socio-demographics were significant, although their effect are the most difficult to interpret. For example, the age of egos is included as a continuous variable and is negatively related to relationship strength. Being unemployed or a homemaker is also negatively related with having stronger relationships. Having lived for many years in the same neighbourhood is related with less strong social connections, a result which is somewhat counter-intuitive. The larger the network size of an ego, the less strong his/her individual relationships will tend to be. This result is intuitive, as a larger network will require more resources such as time and other types of effort to maintain, and each node will receive less "care" so that many nodes can be active.

The two measures of network density and network centrality (also referred to as graph centrality) were found to have opposite effects on strength, the first one being negative and the second one positive. Network density is computed as the ratio between the actual connections in a network and the potential connections. The effect is rather weak in all the models. Network centrality denotes the variations in the point centralities in the network, which in turn represent a measure indicating whether each alter is directly connected with a large proportion of network members. So in networks with high variations in the point centralities, egos are more likely to have strong social contacts, although the effect is only significant in model B_2. In terms of ego-alter measures, we observe that if the alter is an immediate family member, the relationship is more likely to be strong. The opposite is true if the ego and the alter have known each other for less than one year or were both students in 2008. As expected, alters with higher level of betweenness are also more likely to be strong contacts. Finally, we found that a higher level of ego-alter degree centrality, or "point centrality" is associated with stronger ties. These alters are likely to be crucial nodes in the network, and therefore it is to be expected that they will be important for the ego.

5 Introduction of latent strength in binary choice model

We now exploit the concept of latent strength introduced in Section 4 to allow for ego-alter level heterogeneity in the retention model. We do this by jointly estimating the binary choice model and the various measurement models, allowing for a joint influence on both by the latent strength variable.

5.1 Model specification

We first rewrite the utility in the choice model as:

$$U_{e,a_e} = V_{e,a_e} + \varepsilon_{e,a_e} = \delta_e + f\left(\beta, z_{e,a_e,2008}, z_{e,2008-2012}\right) + \tau\alpha_{a_e} + \varepsilon_{e,a_e} \quad (3.9)$$

This utility specification retains the randomly distributed δ_e from Section 3.1.2 but in addition allows for an impact of the latent strength variable through the estimation of τ.

The joint likelihood of the observed retention patterns and answers to the indicator questions for ego e with this model is now given by:

$$LJ_e\left(\mu_\delta, \sigma_\delta, \beta, \tau, \gamma, \sigma_e, \mu_I, \zeta_I\right) = \int_{\delta_e}\int_{\eta_e}\prod_{a_e\in A_e}\int_{\eta_{a_e}} P_{y_{a_e}}\left(\delta_e, \beta, \tau, \alpha_{a_e}\right)\prod_{i=1}^{8} PI_{a_e,i}\left(\alpha_{a_e}\right)\phi\left(\eta_{a_e}\right)\mathrm{d}\eta_{a_e}\phi\left(\eta_e\right)\mathrm{d}\eta_e h\left(\delta_e \mid \mu_\delta, \sigma_\delta\right)\mathrm{d}\delta_e. \quad (3.10)$$

Table 3.4: Estimation results for measurement models for latent strength

	Model B_1		**Model B_2**		**Model B_3**	
ego-level heterogeneity	yes		no		yes	
ego-alter-level heterogeneity	no		yes		yes	
Final LL	-7,829.65		-7,786.42		-7,752.16	
BIC	15,893.53		15,807.07		15,738.55	
	est.	**rob t**	**est.**	**rob t**	**est.**	**rob t**
$\mu_{I,give\,advice\,on\,important\,matters}$	-0.4587	-1.17	-0.3699	-1.78	-0.4463	-1.23
$\zeta_{I,give\,advice\,on\,important\,matters}$	0.3215	3.37	0.701	8.64	0.6254	4.1
$\mu_{I,receive\,advice\,on\,work\,opportunities}$	-2.1992	-3.41	-2.1987	-9.15	-2.2848	-4.63
$\zeta_{I,receive\,advice\,on\,work\,opportunities}$	0.3431	1.57	0.7443	5.52	0.6627	2.23
$\mu_{I,give\,emergency\,financial\,support}$	-0.5666	-0.7	-0.8405	-2.57	-0.8929	-1.23
$\zeta_{I,give\,emergency\,financial\,support}$	0.677	2.89	1.1636	8.22	1.2	3.41
$\mu_{I,receive\,emergency\,financial\,support}$	-1.2446	-1.71	-1.3155	-3.35	-1.4807	-1.93
$\zeta_{I,receive\,emergency\,financial\,support}$	0.5868	3.2	1.4206	8.1	1.2952	4.19
$\mu_{I,receive\,emergency\,transport\,support}$	-1.2513	-1.85	-1.3837	-4.09	-1.513	-2.22
$\zeta_{I,receive\,emergency\,transport\,support}$	0.5824	2.98	1.2157	7.62	1.1368	2.94
$\mu_{I,stated\,closeness}$	1.1509	3.22	1.4996	6.15	1.2387	3.26
$\zeta_{I,stated\,closeness}$	0.3629	4.58	0.8597	8.05	0.6719	3.99
$\mu_{I,conduct\,joint\,social\,activities}$	-0.2243	-0.87	0.0022	0.01	-0.1237	-0.47
$\zeta_{I,conduct\,joint\,social\,activities}$	0.2236	3.45	0.5803	7.95	0.4725	3.78
$t^1_{I,face\,to\,face}$	-0.4425	-2.1	-0.2729	-1.81	-0.362	-1.62
$t^2_{I,face\,to\,face}$	1.1252	4.92	1.3687	8.28	1.265	5.07
$t^3_{I,face\,to\,face}$	2.1211	8.66	2.4015	13.57	2.2902	8.43
$t^4_{I,face\,to\,face}$	3.5684	11.93	3.8759	18.78	3.7595	11.41
$\zeta_{I,face\,to\,face}$	0.1776	3.47	0.4484	7.17	0.3714	3.79
σ_e	1	-	0	-	0.5309	5.4
σ_{a_e}	0	-	1	-	1	-
$\gamma_{ego\,age}$	-0.0195	-2.35	-0.0126	-4.63	-0.0122	-2.44
$\gamma_{ego\,homemaker}$	-1.0937	-2.89	-0.6515	-5.18	-0.6582	-3
$\gamma_{ego\,unemployed}$	-0.5809	-1.95	-0.345	-3.61	-0.3565	-1.88
$\gamma_{ego\,years\,in\,neighbourhood}$	-1.0184	-2	-0.5875	-4.53	-0.6072	-2.05
$\gamma_{ego\,network\,size}$	-0.0835	-3.68	-0.0415	-5.85	-0.0467	-3.92
$\gamma_{ego\,network\,density}$	-1.6053	-1.52	-0.6619	-1.83	-0.7615	-1.21
$\gamma_{ego\,network\,centrality}$	1.2502	1.4	0.7863	2.3	0.8324	1.65
$\gamma_{ego-alter\,immediate family}$	2.0717	4.74	1.1318	9.46	1.2106	5.67
$\gamma_{ego-alter\,known\,under\,one\,year}$	-0.7188	-1.85	-0.5016	-3.16	-0.4466	-2.16
$\gamma_{ego-alter\,both\,students}$	-1.364	-2.3	-0.9561	-2.67	-0.8482	-2.29
$\gamma_{ego-alter\,network\,betweenness}$	0.0475	3.87	0.0284	6.52	0.0295	4.8
$\gamma_{ego-alter\,network\,degree\,centrality}$	0.1231	3.31	0.0601	5.51	0.0662	3.14

The resulting model jointly explains the retention pattern for ego e across all his/her alters as well as the answers to the 8 indicator questions, again for each alter. For a given ego e, this model thus explains A_e binary outcomes of retention, along with the answers to $7 \cdot A_e$ binary and A_e ordered questions. This wealth of data for each ego allows us to incorporate not just detailed patterns of deterministic heterogeneity (both directly in the choice model as well as in the structural equation for the latent strength), but also random heterogeneity across egos in both the baseline retention utilities (δ_e) and the latent strength variable and across ego-alters in the latent strength variable. This model is of course much more complex to estimate than either the binary choice models or the measurement models, and again involves integration on two different levels. Figure 3.1 represents the modelling framework described in this section. As discussed, all the ego and ego-alter characteristics affect the utility of retention, while the latent variable is only affected by the ego and ego-alter characteristics in 2008. While the stated (emotional) closeness, participation in social activities (binary) and the frequency of face-to-face interactions (ordered) are explicitly reported in the graph, the different types of help that the ego and the alter can exchange are grouped into a single category ("social capital").

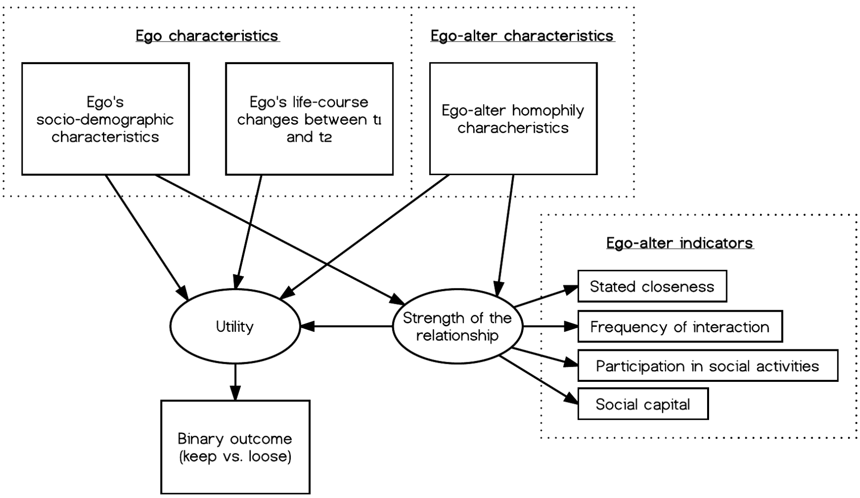

Fig. 3.1: Modelling framework

A number of simplifications of this model are possible. Following the experience with the measurement models, it is clear that making the random heterogeneity in the latent strength purely ego-specific makes little sense, and as such a specification excluding η_{a_e} is not advisable. On the other hand, it is possible to estimate models which exclude the ego-level random heterogeneity in the latent strength (i.e. using only η_{a_e}) as well as models which exclude the additional ego level heterogeneity in the binary choice model by using a fixed δ in Equation 3.9, i.e. setting $\sigma_\delta = 0$.

5.2 Estimation results

As described above, we report the results for different versions of the hybrid model, where we jointly estimate the binary choice model and the various measurement models, in Tables 3.5 and 3.6. The specific assumptions in terms of heterogeneity in each of the models are specified in the top 3 rows of the table. In the first 3 models, all the heterogeneity is linked to the latent variable α. In C_1, this heterogeneity is only at the ego level, in C_2 it is only at the ego-alter level, while in C_3 it is in both. The likelihood ratio test comparing C_3 to C_1 shows a strongly significant improvement ($p \sim 6.5{*}10^{-49}$) as well as in the case where C_3 is compared to C_2 ($p \sim 3.1{*}10^{-16}$), confirming the need to accommodate the heterogeneity in strength both at the ego and at the ego-alter level. Models C_4 to C_6 include additional ego level heterogeneity in retention not linked to the latent variable, while in order from C_4 to C_6, they use the same specification of the latent variable heterogeneity as in C_1 to C_3. C_6 is therefore the most complex model, including both ego and ego-alter heterogeneity in the latent variable, as well as ego level heterogeneity in retention. We again see that the most complex model, C_6, offers significant improvements over C_4 and C_5, with p-values of the likelihood ratio tests of $p \sim 2.2 * 10^{-51}$ and $p \sim 4.4 * 10^{-15}$, respectively. We can also compare the models that have the same pattern of heterogeneity in the latent variable but differ in terms of heterogeneity in the retention part of the model. Model C_4 provides a significant improvement over C_1 ($p \sim 7.3 * 10^{-7}$), as does C_5 over C_2 ($p \sim 1.4 * 10^{-10}$) and C_6 over C_3 ($p \sim 2.1 * 10^{-9}$). Finally, we always see that using ego-alter level heterogeneity in the latent variable is better than ego-level heterogeneity (C_1 and C_2, and C_4 and C_5). These results show, as expected, that allowing for additional random heterogeneity in both retention and latent strength, both at the ego and at the ego-alter level, significantly improves model fit.

Table 3.5 reports the results related to the retention part of the model (although of course the two parts of the model were jointly estimated). Where present, the heterogeneity in retention in the choice model (σ_δ) is significant, meaning that there are differences across egos in retention independent of the latent strength variable, even when the latent strength incorporates heterogeneity at the ego level. The τ parameters represents the impact of the latent variable α_{a_e} on the outcome of retention. The estimated coefficient is positive and significant in all the specifications, although it is worth noting that it is weaker (the coefficient is smaller in absolute value and less significant) in models C_1 and C_4, i.e. where we do not allow for ego-alter heterogeneity in strength. Given the discussion in Section 4.2 about the interpretation of the latent variable, a positive τ means that a higher value in the latent variable has a positive impact on the likelihood of contact retention. The actual sign of this can only be interpreted together with the findings from the measurement model in Table 3.6. We see that all ζ parameters are again positive, confirming the directionality of the latent variable as a positive strength. This shows that a higher latent strength increases the likelihood of retaining a social contact in the choice model (positive τ). In terms of random heterogeneity introduced by the latent strength into the choice models, all models except C_1 and C_4 introduce significant heterogeneity at the ego-alter level, something that was not possible with the binary choice models alone.

The socio-demographic and network characteristics also need to be jointly studied in the two model components, given that for numerous variables, a significant effect arises in both[5]. Some effects matter only in the choice model. This includes a positive impact on retention for egos who have a landline in 2008 (although this is only weakly significant in model C_2), a negative impact for students in 2008 or those who went to university between 2008 and 2012 and a positive impact if both ego and alter are male. Similarly, some effects are only present through the latent strength variable. This includes reduced relationship strength for older respondents, those not employed and homemakers. Network size and density have a negative impact on latent strength, while ego network centrality has a positive impact, as has ego-alter network betweenness. There is increased strength if both ego and alter are aged over 60 or if both are professionals, with reduced strength for newer acquaintances.

The most interesting findings arise when looking at those variables present in both model components. Here we need to look at the sum of $\beta + \tau\gamma$. While we see positive signs for both β and γ for female gender homophily and for immediate family, the same is not the case for three other measures. We see that, like in the measurement models alone, having lived in a neighbourhood for longer reduces the latent strength, and this outweighs the positive sign for β in the choice model alone, for all the models. If both ego and alter are students, this reduces the latent strength, but the final impact on the utility of retention remains small but positive ($1.0243 + 0.8681 \cdot -0.9187 = 0.3317$ for model C_6). Finally, the positive effect of ego-alter network centrality in the latent variable is dampened in the choice model by the less strong β, so that the effect is almost cancelled out from the choice model. These results validate our approach of testing the role of these variables in both models

[5] With the exception of changes in ego characteristics between 2008 and 2012, which should not affect latent strength in 2008, we tested the impact of all measures both in the choice model and the structural equation for the latent variable, thus reduced the risk of misattribution of effects (Vij and Walker, 2016)

where the inclusion in only the structural equation would have assumed a common impact on latent strength and retention, while the inclusion in only the choice model would have prevented us from understanding the drivers of latent strength.

The ζ_I parameters for the measurement models showed in Table 3.6 are weaker (the coefficients are smaller in absolute value and less significant) in models C_1 and C_4, i.e. where we do not allow for ego-alter heterogeneity in strength. The signs are still as expected, so the interpretation does not change. σ_e, when estimated (in models C_3 and C_6) is significant and smaller than 1, suggesting that there is higher heterogeneity at the ego-alter level than at the ego level.

6 Conclusions

Our study investigated social networks dynamics over time, with a particular focus on the retention in the social network (vs. loss) of social contacts over a four-year interval. Our results unveil interesting insights, showing that both ego socio-demographics and life-course changes, as well as ego-alter characteristics, have a significant impact on retention.

The key contribution of our work comes in attempts to disentangle sources of heterogeneity and in particular to allow for ego-alter level random heterogeneity. This is important due to a key limitation of the type of data collected for social network evolution. Indeed, the vast majority of such data are collected from the point of view of the ego, and the analyst can only rely on information provided by one of the *dancers*, if we use the metaphor *"it takes two to tango"*. This already creates significant scope for heterogeneity at the ego-alter level. As an example, a relationship might have ended not because the ego moved, but because the alter did. Explaining such an outcome on the basis of ego-level only data is problematic and creates clear scope for the type of heterogeneity we introduce in our models.

We accommodate this ego-alter level random heterogeneity through a hybrid framework in which we develop a latent variable for relationship strength, which varies both across egos and across ego-alter pairs. We use this to explain a number of indicators of relationship strength as well as accommodating heterogeneity in the choice model (on top of independent heterogeneity).

Our findings on a typical name generator dataset underline the relevance of random ego-level heterogeneity in retention, as well as both ego and ego-alter level heterogeneity in strength. The former means that some egos will retain more social contacts than others, while the latter implies that some egos will be more prone to establishing strong relationships than others (variation across egos) and that even within a specific ego's network, certain ties will be stronger than others (variation across alters, for an ego).

Table 3.5: Estimation results for hybrid models (retention part)

	model C_1		**model C_2**		**model C_3**		**model C_4**		**model C_5**		**model C_6**	
ego-level heterogeneity in α	yes		no		yes		yes		no		yes	
ego-alter-level heterogeneity in α	no		yes		yes		no		yes		yes	
ego-level heterogeneity in δ	no		no		no		yes		yes		yes	
Final LL	-8,828.55		-8,753.89		-8,720.52		-8,816.29		-8,733.33		-8,702.57	
BIC	18,012.23		17,847.79		17,788.61		17,995.25		17,814.23		17,760.27	
	est.	**rob *t***	**est.**	**rob *t***	**est.**	**rob *t***	**est.**	**rob *t***	**est.**	**rob *t***	**est.**	**rob *t***
μ_δ	-0.8634	-1.81	-0.4964	-1.64	-0.5301	-1.14	-0.8711	-1.98	-0.2786	-0.48	-0.3339	-0.7
σ_δ	-	-	-	-	-	-	0.499	6.87	0.6408	6.69	0.6655	7.38
τ	0.2917	3.51	0.7997	8.31	0.714	6.07	0.3058	4.34	0.9422	7.93	0.8681	7.68
$\beta_{ego\,landline}$	0.2735	1.42	0.3475	2.47	0.3141	1.51	0.2022	1.05	0.2537	1.12	0.2673	1.26
$\beta_{ego\,years\,in\,neighbourhood}$	0.1929	0.65	0.367	1.81	0.3428	1.06	0.0789	0.27	0.234	0.58	0.1784	0.53
$\beta_{ego\,student}$	-0.8936	-2.88	-1.0376	-3.89	-1.0128	-3.05	-0.9064	-3.01	-1.1433	-3.12	-1.2043	-3.42
$\beta_{ego\,went\,to\,university\,2008-2012}$	-0.9837	-3.21	-0.9202	-3.22	-1.1014	-4.26	-1.1156	-3.31	-1.036	-3.15	-1.0465	-3.08
$\beta_{ego-alter\,both\,male}$	0.4479	2.88	0.4602	2.76	0.4591	2.78	0.4751	3	0.5155	2.89	0.5421	3.13
$\beta_{ego-alter\,both\,female}$	0.3727	2.48	0.3766	2.67	0.3633	2.11	0.4162	2.73	0.4273	2.31	0.4048	2.23
$\beta_{ego-alter\,immediate\,family}$	0.4461	1.85	0.2161	1.26	0.2353	1.21	0.5021	2.14	0.2014	0.9	0.2015	0.94
$\beta_{ego-alter\,both\,students}$	0.5136	1.19	0.7547	1.62	0.7806	1.85	0.6543	1.35	1.0428	2.03	1.0243	1.98
$\beta_{ego-alter\,network\,degree\,centrality}$	-0.0288	-2.52	-0.0399	-3.98	-0.0384	-3.42	-0.0182	-1.19	-0.0313	-1.89	-0.0293	-1.71

Table 3.6: Estimation results for hybrid models (latent strength and measurement model part)

	model C_1		**model C_2**		**model C_3**		**model C_4**		**model C_5**		**model C_6**	
	est.	**rob t**	**est.**	**rob t**	**est.**	**rob t**	**est.**	**rob t**	**est.**	**rob t**	**est.**	**rob t**
$\mu_{I,give\,advice\,on\,important\,matters}$	-0.5397	-1.36	-0.3913	-1.83	-0.4674	-1.31	-0.502	-1.31	-0.3408	-0.84	-0.4307	-1.24
$\zeta_{I,give\,advice\,on\,important\,matters}$	0.3483	3.57	0.7271	9.01	0.6414	4.74	0.3602	3.51	0.722	5.43	0.6476	4.65
$\mu_{I,receive\,advice\,on\,work\,opportunities}$	-2.2817	-4.02	-2.2441	-9.73	-2.3004	-5.3	-2.2617	-3.83	-2.1743	-4.46	-2.2675	-4.77
$\zeta_{I,receive\,advice\,on\,work\,opportunities}$	0.3817	1.62	0.7535	5.61	0.6987	2.46	0.3841	1.65	0.7732	3.13	0.6983	2.38
$\mu_{I,give\,emergency\,financial\,support}$	-0.8377	-1.06	-0.9416	-2.96	-0.9847	-1.51	-0.7911	-1.04	-0.8672	-1.28	-0.936	-1.56
$\zeta_{I,give\,emergency\,financial\,support}$	0.6736	2.91	1.1224	8.45	1.1222	3.88	0.6878	2.86	1.1084	4.63	1.1297	3.76
$\mu_{I,receive\,emergency\,financial\,support}$	-1.4362	-1.9	-1.3978	-3.47	-1.5212	-1.95	-1.4072	-1.97	-1.296	-1.52	-1.4764	-2.09
$\zeta_{I,receive\,emergency\,financial\,support}$	0.6209	3.2	1.4809	8	1.4178	4.41	0.6223	3.16	1.4624	5.54	1.3951	4.28
$\mu_{I,receive\,emergency\,transport\,support}$	-1.4687	-2.23	-1.4751	-4.57	-1.5605	-2.58	-1.4419	-2.15	-1.3771	-2.08	-1.5041	-2.4
$\zeta_{I,receive\,emergency\,transport\,support}$	0.5902	2.6	1.1851	7.63	1.1379	3.3	0.5905	2.76	1.2154	4.58	1.1659	3.2
$\mu_{I,stated\,closeness}$	1.0193	2.78	1.4888	6.14	1.2664	3.54	1.0288	2.8	1.5153	3.63	1.2615	3.59
$\zeta_{I,stated\,closeness}$	0.373	4.88	0.8909	9.04	0.7167	4.33	0.3716	4.62	0.8639	5.04	0.6952	4.43
$\mu_{I,conduct\,joint\,social\,activities}$	-0.2658	-0.98	-0.028	-0.16	-0.1111	-0.42	-0.2589	-1	-0.0013	0	-0.1021	-0.41
$\zeta_{I,conduct\,joint\,social\,activities}$	0.2471	3.66	0.5887	8.34	0.5051	4.31	0.2461	3.61	0.5739	4.7	0.4944	4.25
$t^1_{I,face\,to\,face}$	-3.5231	-12.23	-3.8676	-19.65	-3.7981	-12.06	-3.5326	-12.18	-3.9115	-11.47	-3.8223	-12.14
$t^2_{I,face\,to\,face}$	-2.0741	-8.92	-2.3899	-14.24	-2.322	-9.25	-2.0842	-8.78	-2.4326	-8.69	-2.3475	-9.01
$t^3_{I,face\,to\,face}$	-1.0772	-4.84	-1.3554	-8.59	-1.2906	-5.48	-1.0874	-4.84	-1.3967	-5.24	-1.314	-5.48
$t^4_{I,face\,to\,face}$	0.4928	2.42	0.2894	2	0.3464	1.65	0.4831	2.35	0.2505	1.03	0.3248	1.52
$\zeta_{I,face\,to\,face}$	0.1884	3.49	0.4605	7.58	0.4016	4.43	0.1892	3.62	0.462	5.28	0.4044	4.48
σ_e	1	-	0	-	0.5057	5.93	1	-	0	-	0.5079	5.68
σ_{a_e}	0	-	1	-	1	-	0	-	1	-	1	-
$\gamma_{ego\,age}$	-0.0198	-1.9	-0.0154	-5.25	-0.0152	-2.86	-0.0195	-1.86	-0.0154	-3.07	-0.0156	-3.14
$\gamma_{ego\,homemaker}$	-0.9881	-2.32	-0.5996	-4.99	-0.6255	-3.09	-0.9594	-2.09	-0.6255	-3.42	-0.6428	-3.18
$\gamma_{ego\,unemployed}$	-0.562	-1.68	-0.3614	-3.87	-0.3919	-2.22	-0.4908	-1.32	-0.3868	-2.34	-0.3897	-2.16
$\gamma_{ego\,years\,in\,neighbourhood}$	-0.8212	-1.35	-0.5332	-3.97	-0.4994	-1.73	-0.8221	-1.38	-0.5381	-2.05	-0.4552	-1.68
$\gamma_{ego\,network\,size}$	-0.0877	-3.89	-0.0394	-5.84	-0.0471	-3.9	-0.092	-4.04	-0.0421	-3.97	-0.0493	-4.22
$\gamma_{ego\,network\,density}$	-1.7723	-1.62	-0.8846	-2.48	-1.0364	-1.82	-1.616	-1.44	-0.9149	-1.77	-0.9544	-1.62
$\gamma_{ego\,network\,centrality}$	1.3551	1.8	0.8705	2.75	0.9494	2.4	1.3029	1.48	0.9031	2.36	0.9077	2.18
$\gamma_{ego-alter\,both\,female}$	0.4496	2.39	0.1505	1.88	0.2067	1.97	0.446	2.38	0.1428	1.33	0.2017	1.92
$\gamma_{ego-alter\,both\,over\,60}$	0.7821	1.92	0.3723	2.35	0.4389	1.9	0.8082	1.95	0.3816	1.6	0.4707	2
$\gamma_{ego-alter\,immediate\,family}$	2.0459	4.84	1.1409	9.92	1.2066	6.12	2.023	4.8	1.1364	6.1	1.1994	6.12
$\gamma_{ego-alter\,known\,under\,one\,year}$	-0.7685	-1.88	-0.5289	-3.55	-0.455	-2.3	-0.7797	-1.92	-0.5191	-3.24	-0.4539	-2.31
$\gamma_{ego-alter\,both\,students}$	-1.3021	-2.22	-0.9176	-2.67	-0.7753	-2.2	-1.2962	-2.21	-0.9517	-2.48	-0.7978	-2.28
$\gamma_{ego-alter\,both\,professionals}$	0.7224	1.55	0.2331	1.62	0.3558	1.72	0.6967	1.48	0.2194	1.18	0.3445	1.69
$\gamma_{ego-alter\,network\,betweenness}$	0.0452	3.8	0.0273	6.47	0.0281	4.65	0.0453	3.82	0.0277	4.54	0.0278	4.71
$\gamma_{ego-alter\,network\,degree\,centrality}$	0.1332	3.29	0.0647	5.93	0.0747	3.64	0.1292	3.24	0.067	4.4	0.0727	3.57

This paper has focused on understanding the process of retention of social contacts. The findings we presented could be operationalised to forecast the composition of social networks, as well as the strength of social networks, as they both depend on socio-demographic characteristics of the ego and the alter. This could allow analysts to produce better predictions of other decisions that are connected to an individual's social networks.

While our results are in line with expectation and provide interesting insights, we acknowledge some limitations of the current work due to the data used. We made use of a two-wave dataset from Chile, where social network data were collected by means of two name generators. Name generators have raised concerns due to potential recall biases (Bell et al., 2007), and in our case we are modelling whether egos recall each alter in the second wave, not whether the alter is still in the network. Collecting reliable social network data and efforts into exploring different data sources, especially panel, is a research area where further effort is needed. Similarly, a larger sample might provide more detailed insights as well as allowing for validation with out-of-sample prediction testing. Finally, an important area for future work is looking beyond which alters leave a network and also incorporate the arrival of new alters.

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Chapter 4

Does the social context help with understanding and predicting the choice of activity type and duration? An application of the Multiple Discrete-Continuous Nested Extreme Value model to activity diary data

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Abstract

An understanding of activity choices and duration is a key requirement for better policy making, in transport and beyond. Previous studies have failed to make the important link with individuals' social context. In this paper, the Multiple Discrete-Continuous Nested Extreme Value (MDCNEV) model is applied to the choice of activity type and duration over the course of two days, using data from the Chilean city of Concepción. In common with other studies, heterogeneity across decision makers is accommodated in the model by analysing the impact of different socio-demographic, mobility and residential location variables on both the activity choice and the time allocation decision. In addition, different social network and social capital measures are found to be significantly correlated with the choice and duration of different activities, and we show how these relationships seem to differ from the effects of socio-demographic variables. Finally, we perform a forecasting exercise using the MDCNEV model, highlighting the differences in substitution patterns from a

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standard MDCEV model.

1 Introduction

In recent years, activity-oriented approaches have gained considerable ground in the study of travel behaviour (Axhausen and Gärling, 1992). Travel demand is believed to be mainly a derived demand, directed at objectives such as going to work or performing recreational activities (Bhat et al., 2013; Ettema and Timmermans, 2003). The understanding of activity scheduling, which includes the decision of which specific activities to perform, with whom, for how long and using which transportation mode (Doherty et al., 2002; Gärling et al., 1998), can in turn lead to greater insights into the drivers of travel behaviour. Initial contributions to the literature treated the different dimensions of activity choice (such as type, timing and duration) separately, while in the last decade a growing amount of literature has highlighted the value of jointly investigating these aspects (Bowman and Ben-Akiva, 2001; Ettema et al., 2007).

The first econometric models accommodating both the discrete and continuous dimensions of choice were developed starting from the late 1950s by Tobin (1958), Heckman (1977), Dubin and McFadden (1984), Train (1986) and De Jong (1990). Starting by using a system of equations, each corresponding to one choice dimension (Bhat, 2001), Chandra Bhat and his co-authors gradually developed a more general and flexible framework to model the choice of multiple alternatives and a continuous amount associated with each of them, in the form of the Multiple Discrete-Continuous Extreme Value (MDCEV) model (Bhat, 2008). This model has been applied in several studies analysing activity choice and duration (e.g. Bhat, 2005; Bhat et al., 2006; Kapur and Bhat, 2007) and constitutes the state of the art in modelling multiple discrete-continuous choices. These studies concluded that socio-demographic characteristics of individuals and households, ownership and availability of mobility tools, accessibility and land use characteristics are significant determinants of the choice of the different activities. For example, Kapur and Bhat (2007) study weekend day activity engagement by participants in the 2004 American Time Use Survey. Their results show how low income households are more likely to perform in-home activities, such as in-home leisure or maintenance, a conclusion that reflects the financial constraints to performing the generally more expensive out-of-home activities. Individual socio-demographics also affect activity choice. Women are for example more likely to be involved in household maintenance, with the same applying to married as opposed to singlerespondents, while middle-age people (40-60) are found to be more likely to engage in arts and events. A limited number of studies applied the nested version of the model (MD-

CNEV) to study time allocation (Bernardo et al., 2015; Pinjari and Bhat, 2010b; Rajagopalan et al., 2009).

While most datasets collect information about respondents' socio-demographic characteristics alongside time use diaries, contextual information about the circumstances in which people make their choices is often not available. However, there is clear scope for a relationship between an individual's social environment and his/her travel and activity choices. Indeed, our earlier work has shown how the patterns in which people interact with other members of their social network varies across those members as a function of the characteristics of both individuals (Calastri et al., 2017). We are careful here in not positing a specific directionality of this relationship at the outset. Indeed, if a relationship between a large social network and the choice of out-of-home recreation is found, then it may of course be tempting to infer that the person conducts many such activities as a result of having many friends, However, it is similarly possible that the person developed a large social network to facilitate him/her performing out-of-home recreational activities. While the challenges in terms of causality remain, it is clearly still important to test for these effects in models to understand the relationship between the choices and the context in which they are made. This is one of the aims of the present paper. At the same time, it is also important to test for confounding between these contextual variables and other socio-demographic characteristics, another point we pay careful attention to.

The closest existing work has got to this issue has come in attempts to find an impact of the social dimension on leisure and social activities, specifically on their frequency (Carrasco and Miller, 2009) and duration (van den Berg et al., 2012), while some work has also jointly modelled several dimensions (Carrasco and Habib, 2009; Habib et al., 2008; Moore et al., 2013). These efforts showed the importance of considering the social dimension to explain engagement in social and leisure activities, highlighting the relevance of the cultural context examined (Kowald et al., 2013).

One of the aims of the present work is to investigate the broader relations of the social dimension with time use going beyond just leisure and social activities, by looking at the time allocation for entire days.

The remainder of this paper is organised as follows. The next section describes the data used for our analysis, followed by a discussion of the modelling framework. We then present our application and the different models we estimated. After describing our results, we forecast with the MDCEV and the MDCNEV models and discuss the implications of including the social network variables for model performance and forecasting. We conclude by drawing policy considerations and suggesting directions for future work.

2 Data

2.1 Survey and data collection

The dataset used for our analysis was collected in 2012 within the *Communities in Concepción* project, which involved people from four neighbourhoods of the Chilean city of Concepción. Concepción is located approximately 500 km south of the capital Santiago and with its 1 million population it constitutes the second largest urban centre of the country. Two of the neighbourhoods (*Agüita de la Perdiz* and *La Virgen*) are close to the city centre, with the first one being a medium-high income neighbourhood, and the second being a medium-low income one. The other two (*S. Sabina* and *Lomas S. Sebastian*) are further away from the city. Medium-low income households mainly populate the first one, while the second one is home to medium-high income people. The specific sampling approach adapted for this study implies that there is not enough variability to control for accessibility, walkability and other measures normally used to describe the built environment characteristics.

The data were collected face-to-face in respondents' homes. Participants were initially asked to complete a detailed socio-demographic questionnaire, including questions about themselves, their family composition and their mobility and communication tool ownership. They were then asked to complete a 2-day activity diary by filling a grid with detailed information about the activities they have been engaged in during one recent weekday and one recent weekend day, and during which time slots these took place.

In addition to these more traditional components, respondents were asked to elicit their social network by completing a so-called "name generator". This technique, extensively used in the sociology (Campbell and Lee, 1991) and travel behaviour (Carrasco et al., 2008; Kowald et al., 2010; Pike, 2014) literature, consists of asking people to recall their entire social network or parts of it. Respondents are generally presented with a table in which each row represents a person in the network, and each column refers to the information to be provided for each member, such as type of relationship, time they have known him/her, frequency and mode of interaction. Different studies use different "prompts" to help people recall the relevant network, depending on the scope of the research. In this case, the instrument is based on Carrasco et al. (2008), and uses an *affective approach*, i.e. it asks respondents to report first the people that they are emotionally close to, and then separately list those they are "somewhat close to". Respondents were also asked to specify the network members who would receive or grant some form of support, whether emotional, monetary or help with mobility or search for employment.

2.2 Sample characteristics and data cleaning

The initial sample of 241 respondents was reduced to 235 during cleaning, leading to a final sample of 4,092 activities, i.e. an average of 8.71 per respondent per day. Table 4.1 reports the socio-demographic characteristics of respondents. The ranges for the level of education have been organised according to the impact of this factor on social status and employment opportunities. Basic schooling includes all the compulsory levels of education, up to high school, which correspond to the qualifications necessary to apply for post-secondary education. Technical school corresponds to a 3-4 year post-secondary degree which does not require undergraduate diplomas. The quota sampling applied was based on the latest available census information at the neighbourhood level, making the sample reasonably representative of each neighbourhood.

Socio-demographic factor	*Ranges*	*Frequency*	*Percentage*
Gender	Female	147	63%
	Male	88	37%
Age	<26	31	13%
	26-40	84	36%
	40-60	83	35%
	Over 60	37	16%
Education	Basic Schooling	89	38%
	Technical School	23	10%
	University Drop-Out	25	11%
	University Degree	97	41%
Employment Status	Student	25	11%
	Employee	101	43%
	Graduate Job	63	27%
	Homemaker	33	14%
	Retired	13	6%
Relationship Status	Lives with partner (Married)	134	57%
	Single	101	43%
Children	No children	123	52%
	1 child	61	26%
	2 or more children	33	14%
Household Income	<400.000 CLP	81	34%
	400,000-2,000,000 CLP	80	34%
	>2,000,000 CLP	40	17%
Driving Licence	Has Licence	113	48%
	Does not have a licence	122	52%

Table 4.1: Socio-demographic characteristics of the sample

As we model the choice and duration of activities, the time use diary is the core part of the dataset for our analysis. We removed all the activities with unknown duration or missing description. In the case of reported activities exceeding 24 hours a day, we removed/shortened/reattributed the last activity(ies) reported. This was generally due to people including night activities that actually took place the following day.

People were allowed to freely describe the activities and we next had to reduce them to macro-categories used for the analysis, where we focussed on

12 categories, as listed in the first column of Table 4.2. Column 2 reports how many people choose each activity at least once; while column 3 shows the overall choice frequency, i.e. in how many separate occasions the activity is performed overall. The comparison between columns 3 and 5 (which contain the same information as 2 and 4, but in percentage terms) highlights that while everyone in the sample chooses the *Basic Needs* activity (which includes sleeping), the activity with the highest frequency is *Travel*. The last two columns show the overall number of hours spent by all people in the sample in the different activities, as well as the average only across those people who engage in a given activity.

Activities	*N. people who choose it*	*% of total sample*	*Overall choice frequency*	*% of all activities*	*Overall time spent (hrs)*	*Average time spent by those who choose it (hrs)*
Drop off- Pick Up	43	18%	78	2%	25.6	0.6
Family	43	19%	63	2%	178.5	4.1
Household Obligations	85	36%	183	4%	661.6	7.2
In-home Recreation	39	17%	98	2%	198.2	5.1
Out-of-home Recreation	85	36%	66	2%	191.5	2.3
Services	58	25%	71	2%	118.1	2.0
Social	164	70%	379	9%	932.6	5.7
Shopping	94	40%	141	3%	115.0	1.2
Study	52	22%	103	3%	263.7	5.1
Travel	226	96%	1601	39%	781.7	3.5
Work	138	59%	234	6%	1147.4	8.3
Basic needs (eat, sleep, stay home)	235	100%	1075	26%	6716.2	28.6

Table 4.2: Frequency and duration of activities in the sample

It is important to remember that the activities are performed over two days, one weekday and one weekend day. This explains figures such as the overall 8.3 hours spent working, or the high duration for *Basic Needs*, corresponding to sleeping, eating and simply staying at home. The 11 activities other than *Basic Needs* are "non-essential", explaining why only some people perform them. While the meaning of the different activities in Table 4.2 is generally self-evident, some clarifications are required. *Family* can be thought of as "time to support/attend family members in non-essential activities": this does not include obligatory activities such as washing or dressing children, or having in-home meals, but does include activities such as helping children with their homework or playing with them. *Household Obligations* includes cleaning/tiding up, taking care of pets, performing ordinary maintenance at home. Recreation activities were divided depending on whether they were performed at home or out of home, while *Services* include errands, such as going to the bank, the doctor or the hairdresser. *Social* activities are visits to/from friends and relatives and other activities specifically aimed at social interaction. *Travel* constitutes a single activity. This is one of the possible approaches that can be adopted, and it is particularly suitable in our case as it allows us to observe the impact of sociodemographic characteristics on activity choice and duration, as well as the correlations with social network measures. Alternative approaches are of course possible, such as adding this time to the out-of-home activity at destination. As evident from the third column of Table 4.2, nearly everyone travels, as each out-of-home activity implies going to the destination and back.

3 Model specification

3.1 Modelling framework

The family of MDCEV models initially developed by Bhat (2005) and subsequently extended in different directions (Bhat, 2008; Castro et al., 2012; Pinjari and Bhat, 2010b) represents the state of the art in modelling multiple discrete-continuous choices. Travel behaviour has been the main field of application of this modelling framework, for example in the study of the choice of vehicle type and mileage (Bhat and Sen, 2006), vacation-related decisions (Pinjari and Sivaraman, 2013) and to type and duration of activities (Bhat, 2005; Kapur and Bhat, 2007). The model used in the present application is the Multiple Discrete Continuous Nested Extreme Value (MDCNEV) model, proposed by Pinjari and Bhat (2010b) as an extension of the Multiple Discrete Continuous Extreme Value (MDCEV) model.

The model is derived coherently with the random utility maximisation theory, but relaxes the mutual exclusivity assumption inherent in traditional choice models. The additive but non-linear formulation of the utility function guarantees that the consumption of one good does not affect the utility of the others and that these goods are substitutes.

Both the MDCEV and the MDCNEV models are based on a direct utility function $U(x)$ that agents maximise by consuming a vector x of non-negative quantities of each of the K goods, $x = (x_1, \ldots, x_K)$. The choice of total consumption amounts is subject to a budget constraint $xp = E$, where E is the budget, and p is the vector of prices. The vector x generally includes a unit-priced outside good to represent expenditure on a good that is always consumed by all the individuals in the sample. In our case, this represents the time spent on *Basic Needs*.

The utility formulation, introduced by Bhat (2008) is given by:

$$U(x) = \frac{1}{\alpha_1}\psi_1 {x_1}^{\alpha_1} + \sum_{k=2}^{K} \frac{\gamma_k}{\alpha_k}\psi_k \left(\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right), \tag{4.1}$$

so that $U(x)$ is quasi-concave, increasing and continuously differentiable with respect to x and ψ. ψ_k is the baseline utility of good k, i.e. the marginal utility of the good at zero consumption. It is a function of observed characteristics of the decision maker and of good k, z_k, which also includes a constant representing the generic preference for good k.

The parameters γ_k and α_k relate to good k. The γ_k parameters are translation parameters that allow for corner solutions. They also affect satiation as a higher γ_k implies that more consumption of the corresponding x_k is needed to reach saturation. The α_k parameter is solely associated with the satiation effect.

Further details about the role of the different parameters and the implications for the model structure can be found in Bhat (2008).

The probability that an individual chooses a specific vector of consumption amounts $\langle {x_1}^*, {x_2}^*, \ldots, {x_M}^*, 0, \ldots, 0\rangle$, where M of the K goods are consumed, is given by:

$$\begin{aligned} & P({x_1}^*, {x_2}^*, \ldots, {x_M}^*, 0, \ldots, 0) \\ =& \frac{1}{p_1}\frac{1}{\sigma^{M-1}} \left(\prod_{m=1}^{M} f_m \right) \left(\sum_{m=1}^{M} \frac{p_m}{f_m} \right) \left(\frac{\prod_{m=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma} \right)^M} \right), \end{aligned} \tag{4.2}$$

where σ is an estimated scale parameter and where $f_m = \frac{1-\alpha_m}{{x_m}^* + \gamma_m}$.

The MDCEV probability formulation above is obtained when assuming an i.i.d. extreme value distribution for the stochastic part of utility. This assumption of an absence of correlation can however be unrealistic in many settings, just as in a discrete choice context. Pinjari and Bhat (2010b) introduce the nested version of MDCEV, MDCNEV. They solve the expenditure allocation problem through the Kuhn-Tucker conditions by assuming that the unobserved part of utility of the different activities has a joint extreme value distribution given by:

$$F(\varepsilon_1, \varepsilon_2, .., \varepsilon_K) = exp\left[-\sum_{s=1}^{S_K} \left(\sum_{i \in s^{th} nest} exp\left(-\frac{\varepsilon_i}{\theta_s} \right) \right)^{\theta_s} \right], \tag{4.3}$$

where s represents one of the S_K nests that the K alternatives belong to, where $S_K < K$, i.e. at least some of the alternatives are nested together.

The role of θ_s is that of a (dis)similarity parameter, i.e. a measure of the correlation between the stochastic components of the alternatives within a nest, with $0 < \theta_s \leq 1$. The MDCNEV model core parameters are the same as the MDCEV model except for the (dis)similarity parameters θ, where, if $\theta_s = 1\,\forall s$, the nested model collapses to the non-nested one (or indeed if $S_K = K$).

Following Pinjari and Bhat (2010b), we can let $1, 2, \ldots, S_M$ be the nests that contain the M chosen options and $q_1, q_2, \ldots, q_{S_M}$ be the number of chosen alternatives in each of the S_M nests, so that $q_1 + q_2 + \ldots + q_{S_M} = M$. Assuming the distribution of the random components specified in Equation 4.3 above, the probability expression for the MDCNEV model can be written as follows:

$$
\begin{aligned}
&P({x_1}^*, {x_2}^*, \ldots, {x_M}^*, 0, \ldots, 0) \\
&= |J| \frac{\prod\limits_{i \in \text{chosen alts}} e^{\frac{V_i}{\theta_i}}}{\prod\limits_{s=1}^{S_M} \left(\sum\limits_{i \in s^{th} nest} e^{\frac{V_i}{\theta_s}} \right)^{q_s}} \\
&\cdot \sum_{r_1=1}^{q_1} \ldots \sum_{r_s=1}^{q_s} \ldots \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{s=1}^{S_M} \left[\frac{\left(\sum\limits_{i \in s^{th} nest} e^{\frac{V_i}{\theta_s}} \right)^{\theta_s}}{\sum\limits_{s=1}^{S_k} \left\{ \left(\sum\limits_{i \in s^{th} nest} e^{\frac{V_i}{\theta_s}} \right)^{\theta_s} \right\}} \right]^{q_s - r_s + 1} \left(\prod_{s=1}^{S_M} sum(X_{rs}) \right) \left(\sum_{s=1}^{S_M} (q_s - r_s + 1) - 1 \right)! \right\},
\end{aligned}
\tag{4.4}
$$

where $sum(X_{rs})$ is the sum of the elements of a row matrix X_{rs}. A detailed description of the derivation of the probability expression above and the meaning of its different components is provided in Pinjari and Bhat (2010b).

3.2 Implementation for our time use data

In the present application of the model, people make a multiple discrete choice by choosing which activities to perform, and a continuous one by selecting the time allocated to each. As mentioned above, we need to make assumptions about the budget and specify the model including socio-demographic and social network characteristics in the utility and satiation from the different activities. Furthermore, an appropriate nesting structure needs to be implemented.

3.2.1 Budget

As mentioned in Subsection 3.1, utility is maximised subject to a budget constraint. In our case, the budget is defined as the total time available in the two days, i.e. $T = 48$ hours, and we consider only the time cost for each activity, so that the budget takes the form below:

$$\sum_{k=1}^{K} t_k = T, \quad t_1 > 0, \quad t_k \geq 0 \quad \forall k \quad (k = 2, \ldots, K), \tag{4.5}$$

where activity 1 is *Basic needs*, i.e. the *outside good* in our model (cf. Bhat, 2008).

3.2.2 Profile specification

In our work, we do not investigate methods to estimate a complete specification and adopt one of the 3 suggested by Bhat (2008). In particular, we make use of the "γ-profile", where we estimate only the γ_k parameters for $k = 2, 3, \ldots, 12$ (as we are modelling the choice between 11 alternatives on top of the outside good) and α_1 for the outside good. All the model specifications that we estimated displayed an extremely small and insignificant value of α_1, where, with $\alpha_1 \to 0$, the utility form collapses to a log utility formulation (cf. Bhat, 2008) with:

$$U(t) = \psi_1 \ln(t_1) + \sum_{k=2}^{12} \gamma_k \psi_k \ln\left(\frac{t_k}{\gamma_k} + 1\right) \tag{4.6}$$

This formulation implies that the direct utility increases with additional units of consumption in a logarithmic fashion, i.e. with diminishing returns. The only estimated parameters relating to satiation are the γ_k terms, which scale the consumption quantity of the *inside goods*.

3.2.3 Utility specification

Both socio-demographic and social network variables were included in the discrete part of the model through ψ_k, the alternative-specific baseline utility, where the majority of effects were included in the form of dummy variables. For example, age was divided into the ranges "less than 26", "26-40","40-60" and "Over 60", while, using different specifications, we also tested the effects of gender, level of education, marital status, number of children, type of job, driving licence holding, neighbourhood, and ownership of communication tools and income. The presence and number of children in the household was incorporated in the model using two dummy variables (one underage child and two or more), with those having no underage children used as the base. We also tried different specifications, for example directly including the number of children as well as having different dummy variables corresponding to the age of children in ranges, as suggested by Pinjari and Bhat (2010b).

In Chile, there is a strong correlation between the level of education and the type of job and consequently the level of income (Torche, 2005). Model specifications in which two or all these three variables were included clearly led to confounding effects, and it was therefore decided to retain only household income. This variable indicated the income perceived in the past six months and it was included in three levels, with the lowest being less than 400,000 Chilean Pesos (CLP), i.e. approximately $600, the medium level being between 400,001 and 2,000,000 CLP (i.e. between $600 and $3,000) and high income (used as a base in the model) corresponding to 2,000,001 CLP or more.

The survey also included information about the type of dwelling respondents lived in and its surroundings and information about their home arrangements, such as whether they rented or owned their home and how many people lived there. These variables were not found to significantly impact activity patterns. Information about the respondent's partner (where present) were also part of the questionnaire (e.g. type of job and residential and work location), but only the variable measuring whether the respondent lived with the partner (which in the present context is believed to be equivalent to being married) was found to have an effect, while the other variables were not significant.

As mentioned in Section 2, the survey also contained a *name generator* and a *name interpreter* where respondents ("egos") were asked to provide information about their personal social network members ("alters"). Several network measures can be computed from these tools and were used in our analysis.

One measure commonly used in the literature is the size of the social network, i.e. the number of people listed in the name generator. This was included in the model in a logarithmic specification (given the substantial variation across people) to test its relation with all the different activities. The information about the social network also allowed us to compute measures related to network composition. For example, we computed the share of different types of contacts (immediate family, friends, colleagues) as well as shares of people in the network having certain characteristics which made them similar to the respondent, such as having the same age, job, sex or income. These latter measures are commonly defined as *homophily* and commonly used in studies focusing on social interactions (Axhausen and Kowald, 2015).

The availability of both the "ego's" and each "alter's" residential location allowed the definition of a variable representing the share of emotionally strong contacts who live close to the "ego". Different geographical measures were attempted and we eventually chose a 1 km distance, partly because of its highly intuitive meaning of easily walkable distance. This measure could have arguably generated some confounding effects with the number/share of alters constituting the immediate family, but we checked and the magnitude of the coefficients measuring the latter effect did not change when this new variable was introduced.

We also explored some *heterophily* effects, i.e. the effect of higher shares of contacts who are different from the "ego" in one dimension. These effects have not been widely explored in the literature, therefore we can try to interpret these results but only deeper analyses will help in their understanding and differentiation from spurious correlations.

In addition, the questionnaire included some questions about different types of *social capital*, i.e. resources that can be provided or granted from/to other people within the social network. Respondents were given a table where the first column listed different types of help and the other two columns had to be filled in with names of people granting or receiving each type to/from the respondent. Examples are "Mobility for work", "Advice with important problems" and "Taking care of children".

We will describe the significant coefficients of these variables in Section 5.2.

3.2.4 Parametrisation of γ_k

In addition to identifying the determinants of the discrete choice, we allow for socio-demographic interactions in the continuous part of the model, i.e. through the γ_k parameters. To ensure positivity of the γ_k in estimation, we write $\gamma_k = exp(\mu_k + {\delta_k}'\omega_k)$, where ω_k is a vector of individual characteristics. The baseline value for γ_k (i.e. for a respondent in the base socio-demographic categories) is thus given by e^{μ_k}, while e.g. $e^{\delta_{k,l}}$ is a positive multiplier (greater or smaller than 1) on this baseline value for a respondent who possesses the socio-demographic characteristic identified by the l^{th} element in ω_k. This socio-demographic parameterisation allows the level of satiation and the position of the activity-specific indifference curve to be dependent on the respondent's characteristics.

In our specific case, the vector of socio-demographic characteristics ω_k enters the expression as: $\omega_k = (\omega_k^{base} - \omega_k^{mean})/\omega_k^{mean}$, so that the meaning of the δ_k parameters is related to the deviation of the value of the variable for a specific respondent from the rest of the sample. A positive value of the shift increases the translation parameter for alternative k, and therefore implies less rapid satiation and higher time investment in activity k. Differently, negative values imply a decrease in the translation parameter and more rapid satiation from activity k.

All the variables described in Subsection 3.2.3 were also tested as determinants of the satiation dynamics for the different activities.

4 Results

4.1 Nesting structure

With 12 activities in our dataset, many thousands of different possible nesting structures arise. In our work, we tested over 30 different structures, making informed decisions on which ones merited empirical testing. A subsample of ten diverse nesting structures (including the best fitting and most behaviourally interesting ones) is reported in Table 4.3, where the nesting is applied to the base model (i.e. only including the baseline constants and translation parameters). For each of these models, we describe the activities belonging to each nest as well as the estimated nesting parameters, where brackets are used when the nesting terms are not significantly different from the base value of 1 at a significance level of 95%.

The different specifications are ordered by their goodness of fit, measured by the Log-Likelihood (LL). We also include the Bayesian Information Criterion (BIC) value used to compare the models with each other. The base non-nested model had a log-likelihood of $-3,832.80$ and BIC of $7,785.71$.

The nesting structure testing process was guided by grouping activities according to intuition and findings from existing literature, although in some cases (e.g. specifications 8 and 10, where *Work* is grouped with *Shopping* and *Travel*), non-intuitive groupings were attempted in order to detect additional relationships. Although specification 10 provided the best fit, we decided to adopt specification 9, as it is a more parsimonious and behaviourally sensible structure, while being only marginally worse in terms of fit. This final structure, which is also shown in Figure 4.1, includes a nest for in-home and one for out-of-home activities, with only *Family* not belonging to any nest. A reason for this lack of correlation could be that *Family* is a relatively broad category including activities which can take place at home or elsewhere.

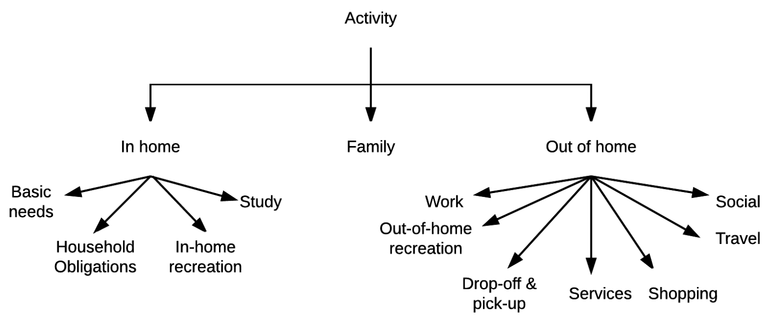

Fig. 4.1: Final nesting structure

The θ_s parameters related to the two (non-degenerate) nests in Figure 4.1

#	Nest 1	θ_1	Nest 2	θ_2	Nest 3	θ_3	Nest 4	θ_4	Non-nested activities	LL	BIC
1	*Solo activities* work, study	(0.9458)	*Social activities* family, OH recr., social	1	NA	NA	NA	NA	basic needs, IH recr., HH obligations shopping, travel	-3,832.45	7,795.92
2	*Discretionary* family, IH and OH recr., social	0.8893	*Compulsory activities* HH obligations, shopping, study, work	(0.9828)	NA	NA	NA	NA	basic needs. travel	-3,829.74	7,790.50
3	*Travel oriented* drop off-pick up, travel	(0.9999)	*Errands oriented* *shopping, services*	(0.9427)	*Leisure oriented* OH recr., social	0.8119	NA	NA	basic needs, HH obligations, IH recr., study, work	-3,829.16	7,794.80
4	*Home & Family* family, IH recr.	(0.9002)	*Work oriented* work, study	(1)	*Leisure oriented* OH recr., social	0.8203	NA	NA	drop off-pick up, HH obligations, service, shopping, travel	-3,828.22	7,792.93
5	*Home & Family* drop off-pick up, family	0.7875	*Errands oriented* shopping, services	(0.9437)	*Leisure oriented* OH recr., social	0.8217	NA	NA	basic needs, HH obligations, IH recr. travel, study, work	-3,824.58	7,785.65
6	*OH* drop off-pick up, OH recr., services, work shopping, social, travel	0.6921	*IH* HH obligations, IH recr.	(0.994)	NA	NA	NA	NA	basic needs, IH recr., HH obligations shopping, travel	-3,812.55	7,756.13
7	*Personal and home* basic needs, HH obligations	0.5206	*Family oriented* drop off-pick up, family	0.7869	*Errands oriented* shopping, services travel	(0.9998)	*Leisure oriented* *OH recr.,* social	0.8303	IH recr., study, work	-3,812.37	7,766.69
8	*IH* basic needs, HH obligations, IH recr.	0.4726	*Family oriented* drop off-pick up, family	0.7876	*Shopping and work* shopping, work	(0.9995)	*Leisure oriented* OH recr., social	0.8267	services, study,travel	-3,802.41	7,746.77
9	*IH* basic needs, HH obligations, IH recr., study	0.4661	*OH* drop off-pick up, services, OH recr., shopping, social, travel, work	0.764	NA	NA	NA	NA	family	-3,792.77	7,716.57
10	*IH* basic needs, HH obligations, IH recr., study	0.4360	*Family oriented* drop off-pick up, family	0.7871	*Travel and work* travel, work	0.7637	*Leisure oriented* OH recr., social	0.8358	services, shopping	-3,787.21	7,716.37

Table 4.3: Sample of the attempted nesting specifications (nesting parameters shown in brackets when not significant)

have values of 0.4316 for the "In-home" nest and 0.7366 for the "Out-of-home" nest, with both being highly significantly different from 1 (cf. Table 4.6). These results suggest that there is a heightened correlation between the unobserved portion of utility of the activities in either nest, which is stronger in the first group of activities. Intuitively, it makes sense to find correlation between the activities we group together, as an individual may be more likely to reallocate time between different in home activities or different out of home activities than across the two categories. The different magnitude of the two nesting parameters suggests that the choice is more deterministic across the alternatives belonging to the first nest. This result is intuitive, in the sense that there are likely fewer unobserved factors affecting the in home activities as opposed to the out-of-home ones. Interestingly, we find higher levels of correlation with respect to other applications of the same model to time use (Pinjari and Bhat, 2010b; Rajagopalan et al., 2009).

4.2 Overview of estimated models

The final specification of the MDCNEV model was obtained by starting off with a base model and progressively adding and combining variables on the basis of intuition, statistical significance and guidance from previous studies. All effects were tested as determinants of both the multiple discrete and continuous choice. The final specification was finally selected on the basis of better model fit and meaningfulness of the estimated effects, where it is worth noting that the differences in fit across different nesting structures remained largely unaffected by the inclusion of additional variables.

As stated above, one of the main objectives of the present work is to investigate the determinants of activity and travel behaviour and assess whether there is scope for confounding between social context and socio-demographic variables. To test for such confounding, we additionally estimated versions of the final model which included only the strictly socio-demographic effects and versions which include only the social context measures.

Table 4.4 reports measures of the goodness of fit for the base model (i.e. including only the baseline constants and satiation parameters), the two "partial" models discussed above and the full specification of the MDCEV and MDCNEV models. In all the specifications, the MDCNEV models present two extra estimated parameters, the θ for the two nests. The statistical tests reported in Table 4.4 show how adding socio-demographic and social context variables improves the base model, but also how the full specification provides a better fit than the two previous models, clearly suggesting that the socio-demographic and social network effects provide distinct insights into behaviour. We will return to the issue of potential confounding in Section 6, but for now focus on the results of the full specification. Finally, it is apparent that across all the different specifications, the introduction of the nesting structure results in a clear improvement in model fit.

		MDCEV	**MDCNEV**	LR-test (MDCNEV *vs* MDCEV)
Base specification	N. parameters	22	24	$80.1 \sim \chi^2_2$, $p < 10^{-17}$
	Log-Likelihood	-3,832.80	-3,792.77	
	AIC	7,709.61	7,633.54	
	BIC	7,785.72	7,716.57	
Socio-Demographics only	N. parameters	47	49	$109.6 \sim \chi^2_2$, $p < 10^{-23}$
	LL	-3,729.80	-3,675.02	
	AIC	7,536.80	7,444.05	
	BIC	7,699.41	7,7617.57	
	LR-test *vs* base	$206 \sim \chi^2_{25}$, $p < 10^{-29}$	$235.5 \sim \chi^2_{25}$, $p < 10^{-35}$	
Social Network only	N. parameters	42	44	$81.5 \sim \chi^2_2$, $p < 10^{-17}$
	LL	-3,742.913	-3,702.19	
	AIC	7,569.83	7,492.39	
	BIC	7,715.13	7,644.61	
	LR-test *vs* base	$179.8 \sim \chi^2_{20}$, $p < 10^{-26}$	$181.2 \sim \chi^2_{20}$, $p < 10^{-27}$	
Full specification	N. parameters	67	69	$90.8 \sim \chi^2_2$, $p < 10^{-19}$
	LL	-3,642.30	-3,596.88	
	AIC	7,418.61	7,331.77	
	BIC	7,650.40	7,570.48	
	LR-test *vs* base	$381 \sim \chi^2_{45}$, $p < 10^{-54}$	$391.8 \sim \chi^2_{45}$, $p < 10^{-56}$	
	LR-test *vs* socio	$175 \sim \chi^2_{20}$, $p < 10^{-26}$	$156.3 \sim \chi^2_{20}$, $p < 10^{-22}$	
	LR-test *vs* social	$201.2 \sim \chi^2_{25}$, $p < 10^{-28}$	$210.6 \sim \chi^2_{25}$, $p < 10^{-30}$	

Table 4.4: Comparison of goodness of fit measures

4.3 MDCNEV model results

The results of the final specification of the MDCNEV model are presented in Tables 4.5 and 4.6, alongside the results for the full specification of the MDCEV model. In what follows, a detailed description of our preferred model, the full MDCNEV model specification, is given, followed by a comparison with the MDCEV model results.

4.3.1 Baseline constants

The first 11 lines in Table 4.5 report the baseline preference constant components of the utility of each alternative, where they enter through an exponential into ψ_k. The negative value of these constants highlights the preference for the base alternative *Basic needs* with respect to any other activity. In the base model, where interaction effects are not included, the values of these parameters are in line with the discrete choice, i.e. how many people in the sample ever choose the activity.

4.3.2 Impact of socio-demographics on the baseline utilities

Several socio-demographic characteristics significantly affect the utility of the choice alternatives.

The only significant effect of the *Sex* variable was found on *Household Obligations*, an activity that men are less likely to perform than women. This is an expected result, as gender imbalance in household activities is found in most cultural contexts (Lachance-Grzela and Bouchard, 2010; Ruppanner, 2008). Less utility is derived from *In-home recreation* when decision makers

		Full Spec. MDCNEV		MDCEV		
	Activity	est	rob t-stat	est	rob t-stat	t-diff
Baseline utility constants	Drop-off/Pick-up	-6.1329	-14.5	-7.0995	-14.17	-1.47
	Family	-5.7346	-16.44	-5.7456	-16.61	-0.02
	Household obligations	-3.2715	-16.06	-3.3285	-8.7	-0.13
	Out-of-home recreation	-4.0542	-25.71	-4.3559	-23.31	-1.23
	In-home recreation	-4.6827	-16.58	-6.4392	-11.97	**-2.89**
	Services	-4.1466	-34.41	-4.4725	-32.48	-1.78
	Social	-3.9735	-8.38	-4.4709	-7.92	-0.67
	Shopping	-3.4295	-15.22	-3.5271	-12.38	-0.27
	Study	-5.0538	-9.83	-7.2027	-6.72	-1.81
	Travel	-3.9229	-4.41	-4.5610	-4.45	-0.47
	Work	-3.8267	-30.12	-4.0182	-26.51	-0.97
Sex=male	Household obligations	-0.4083	-2.88	-0.8788	-3.16	-1.51
Age < 26	Study	0.4205	1.93	0.9125	2.07	1.00
Age 26-40	Work	0.4491	2.87	0.5267	2.8	0.32
Age 40-60	In-home recreation	-0.7471	-2.91	-1.7587	-3.22	-1.68
1 underage child	Family	-1.0412	-2.8	-1.0382	-2.83	0.01
	Work	0.7590	3.32	0.9679	3.51	0.58
2+ underage children	Drop-off/Pick-up	1.1407	3.17	1.4831	3.08	0.57
	Family	1.7703	4.56	1.7843	4.65	0.03
Low income	Drop-off/Pick-up	1.0297	3.83	1.3163	3.82	0.66
	Family	0.4098	1.34	0.4369	1.45	0.06
	Household obligations	0.4264	3.35	0.8123	3.31	1.40
Agüita de la Perdiz	In-home recreation	0.8625	3.05	1.8448	3.02	1.46
	Social	0.2589	1.61	0.4258	2.28	0.68
La Virgen	In-home recreation	1.0926	3.85	2.3797	4.18	**2.02**
Driving Licence	Drop-off/Pick-up	0.7128	2.43	0.9155	2.5	0.43
Internet Access	Social	0.4019	1.92	0.6212	2.39	0.66
	Study	1.0547	2.19	2.2350	2.13	1.02
Lives with partner	Household obligations	0.3694	2.81	0.7755	3.05	1.42
	Shopping	0.4715	2.43	0.5955	2.42	0.40
Partner works	Drop-off/Pick-up	0.6484	2.04	0.8686	2.07	0.42
Social network size	Social	0.3039	1.85	0.4329	2.22	0.51
	Travel	1.4446	4.45	1.8634	4.87	0.83
Share of immediate family in the network	Household obligations	-1.0400	-2.96	-2.2341	-3.2	-1.53
Share of friends in the network	Household obligations	-0.8087	-2.85	-1.6903	-3.19	-1.47
Share of friends in the network	Shopping	-0.8578	-2.48	-1.1379	-2.55	-0.50
Social capital children X female	Drop-off/Pick-up	0.7740	2.83	1.0096	2.9	0.53
Social capital children X female	Study	0.3134	1.87	0.8541	2.51	1.43
Share of network in same age group (40-60)	Social	-0.6573	-2.31	-0.8342	-2.35	-0.39
Share of network with same work status (student)	Out-of-home recreation	1.2441	3.31	1.4771	3.09	0.38
Share of network with same work status (employed)	Work	1.4258	5.57	1.8881	6.84	1.23
Share of network employed when ego is student	Study	4.2603	4.13	7.3932	3.75	1.41
Share of close network members living within 1 km	Drop-off/Pick-up	-1.8379	-2.99	-2.2914	-3.01	-0.46
	Out-of-home recreation	-0.5204	-1.44	-0.6616	-1.42	-0.24
	In-home recreation	0.4135	1.47	1.0883	1.67	0.95
	Shopping	-0.8606	-2.39	-1.1000	-2.44	-0.41
	Travel	-1.4028	-2.28	-1.5739	-2.33	-0.19

Table 4.5: MDCNEV and MDCEV results - Utility parameters

	Activity	Full Spec. MDCNEV est	Full Spec. MDCNEV rob t-stat	MDCEV est	MDCEV rob t-stat	MDCEV t-diff vs A
Satiation parameters						
Baseline γ	Drop-off/Pick-up	0.3443	1.7	0.2306	1.12	-0.39
	Family	2.173	10.16	2.2297	10.35	0.19
	Household obligations	11.7755	53.86	4.0957	31.98	**-30.31**
	Out-of-home recreation	2.6369	18.12	1.8663	14.92	**-4.02**
	In-home recreation	7.9366	29.29	2.6165	12.56	**-15.57**
	Services	1.6599	9.52	1.1268	6.92	**-2.23**
	Social	2.6426	19.86	1.8293	16.14	**-4.65**
	Shopping	0.8574	6.33	0.5992	5.15	-1.45
	Study	5.774	23.69	1.8934	7.95	**-11.39**
	Travel	0.1695	0.55	0.1057	0.36	-0.15
	Work	5.8414	46.02	4.0355	38.25	**-10.94**
Shifts (log of baseline γ)						
Age < 26	Social	0.0541	1.55	0.0529	1.45	-0.02
Age 26-40	Household obligations	-0.1689	-2.04	-0.1383	-1.69	0.26
1 underage child	Work	-0.1898	-2.92	-0.1852	-2.77	0.05
2 underage children	Study	-0.4857	-2.88	-0.6457	-2.68	-0.54
Agüita de la Perdiz	Household obligations	-0.2482	-4.06	-0.1958	-3.58	0.64
Network size	Travel	-1.3054	-4.45	-1.5622	-4.69	-0.58
Social capital travel	Travel	-0.1691	-1.94	-0.1959	-2.22	-0.22
Share of close network members living within 1 km	Shopping	0.2167	1.89	0.2115	1.88	-0.03
	Travel	0.2798	1.58	0.3108	1.67	0.12
Nesting parameters						
In home		0.4356	-12.36	-	-	-
Out of home		0.7382	-6.48	-	-	-

Table 4.6: MDCNEV and MDCEV results - Translation and nesting parameters

are between 40 and 60 years old with respect to the "Over 60s", while the youngest group is more likely to study and the 26-40 group is the one getting more utility from *Work*.

People who have one underage child are found to be more likely to work. Somewhat surprisingly, one underage child relates to reduced occasions for *Family* time, differently from the case of two or more children, needing more support and a higher rate of being picked up and dropped off.

According to our results, the lowest level of income is associated with higher likelihood of performing *Household Obligations* and *Family*-oriented activities. The latter effect was retained for its intuitive meaning despite the low statistical significance. These findings are entirely reasonable in light of the fact that it is very common for medium and high income Chilean households to employ a housekeeper (Mora, 2006). Past studies (e.g. Bhat et al., 2006) argued that lower income household tend to be more likely to perform in-home activities due to the higher financial burden imposed by out-of-home recreation.

The effect of residential location was also tested, using the *Lomas S. Sebastian* neighbourhood (mid-high income, far from the centre) as a base. Living in the two neighbourhoods close to the city centre has a positive impact on

In-home recreation with respect to people living further away from town. A potential explanation for this result is the existence of a large shopping centre close to the neighbourhoods located further away from downtown, which serves as an important recreational facility. Among these two, respondents in the mid-high income neighbourhood have a higher probability of performing social activities. There might be confounding effects as variables such as income and neighbourhood could measure the same effect. In this case, the residents of the richer and more central areas could also have the resources for more social activities taking place downtown.

As expected, having a driving licence increases the likelihood of *Pick-up/Drop-off*. We further find that internet access has a positive impact on *Social* activities: this is in line with the literature on social networks and travel activities, which has often suggested the presence of complementarities between access to communication technology and travel for social purposes (Schaap et al., 2016). Access to the internet also positively impacts the utility of *Study*, an intuitive effect when we think about how important this has become in the search for sources of information. In this case, we acknowledge that there is a potential inverse causality, as we cannot exclude that someone would get access to the internet because they want to study.

People who live with a partner (which in the present context coincides with being married) are more likely to perform *Household Obligations* and *Shopping*. This could be due to sharing household duties on a daily basis, while people who live alone or with the family of origin might not perform these activities in the two days of observation. Kapur and Bhat (2007) motivate the higher involvement of married individuals in household maintenance activities on the basis of increased household responsibility.

In addition, people whose partner works are more likely to *Pick-up/Drop-off* other people, suggesting that the duty is probably split or mainly performed by the non-working partner. In an attempt to gain further insights about these effects, different interactions were tested (for example with sex or partner/respondent being employed) but they did not yield significant results.

4.3.3 Correlation between social network variables and baseline utilities

Several of the measures computed using the *name generator* and *name interpreter* data are found to be significantly related to activity patterns. These results are also displayed in Table 4.5, just below the socio-demographic effects, where it is again important to stress that we cannot assess the directionality of the impact with certainty.

Social network size is related to performing *Social* activities as well as to *Travel*. We did not find a strong link between network composition and recreational or social activities, but we found that people with higher shares of immediate family members and friends tend to engage in *Household obligations* less than others. Having high shares of friends is correlated with lowered utility from *Shopping* as well. The latter result could be linked to the potential trade-offs between friendship maintenance and other activities.

In terms of *social capital* measures, the only form of help which showed a significant correlation with the choice of an activity was "Taking care of children", mainly meaning baby-sitting. We find that, in interaction with being female, those who receive help are more likely to engage in *Drop-off/Pick-up* activities and in *Studying*. The first effect may reflect the need to drop children off and then pick them up from the people who take care of them. We find the second effect to be an interesting finding, as it potentially shows the importance of social capital in providing an opportunity to mothers of young children to find time for improving their education. As mentioned before, it is difficult to interpret the directionality of these effects, as it is similarly plausible that mothers with children would decide to include in their network people who can help them taking care of their children so that they can perform other activities, such as studying.

We find a negative relation between belonging to the 40-60 age category and having a high share of contacts in the same age group and being less likely to perform *Social* activities. On possible interpretation is that people in this group meet their peers mainly in other contexts, such as work. Homophily in employment status is also explored and we find that students with many contacts who are themselves students are more likely to perform *Out-of-Home Recreation*, probably because students tend to gather in groups and it is easier for them to do so outside of their homes, although again the opposite directionality is also possible. We also find that workers whose networks have high shares of people in the job market are more likely to perform *Work* activities.

Only one of the *heterophily* effects we tested remained strongly significant in the final specification: there is a correlation between someone being a student but with high shares of employed people in the network, and being likely to perform study activities. This could be interpreted as a student with this social context being particularly driven to finish his/her studies and enter the job market (and consequently lifestyle) of most of his/her peers, but further investigations would be needed, as evidence on heterophily measures and their impacts on behaviour is not present in the literature.

A higher share of emotionally close "alters" living close to the "ego" is associated with a lower likelihood of *Drop-off/Pick-up*, *Shopping* and *Travel*. With a low level of statistical significance, but intuitively interesting, we also observe a negative relationship with *Out-of-Home Recreation* and a positive one with *In-Home Recreation*. A closely clustered network of family or close friends can indeed imply more activities to happen close to home or at these people's homes, instead of outside, or (considering the opposite direction of causality) that a person with a preference for more local activities tends to compose his/her network of "alters" who live close to him/her.

4.3.4 Translation (γ_k) parameters

As mentioned above, the translation parameters of the model are further parameterised as $\gamma_k = exp(\mu_k + \delta_k{}'\omega_k)$ to accommodate heterogeneity in satiation across decision-makers. Table 4.6 shows the values of e^{μ_k} (reported as "Baseline γ_k"), which represent the baseline satiation from alternative k; and the values of δ_k, i.e. the shifts from the base values of γ_k, which show the effects of specific socio-demographic characteristics and social network measures on the satiation from different activities (in terms of the shift to the log of the baseline γ_k). As explained in subsection 3.2.4, a positive value of the shift increases the translation parameter for alternative k and implies less rapid satiation and higher time investment in activity k, while negative values decrease the translation parameter and imply more rapid satiation.

The coefficients shown in Table 4.6 suggest that respondents younger than 26 year old get less satiated by *Social* activities with respect to over 60s, i.e. the base category. Despite the robust t-statistics being only 1.55, we decided to retain this result because of its highly intuitive interpretation. People aged 26 to 40 are more satiated by *Household Obligations*, i.e. they tend to spend less time in these than older people. We also find that having 1 and 2 or more underage children results in higher satiation from, respectively, *Work* and *Study*: this is in line with the common practice of parents with young children to reduce the work/study time to take care of them.

We find that living in *Agüita de la Perdiz* is related to lower duration of *Household Obligations*, possibly due to the low complexity of these activities for low income groups.

Larger social networks are associated with reduced duration of *Travel*. A possible interpretation of this effect could be related to the need to reduce travel time to be able to gain interaction time with more people. The coefficient measuring the impact of social capital received for travelling on travel duration could suggest that interacting with many people implies travelling with them in a less costly and more efficient way. The opposite directionality is also plausible, i.e. people could choose to include in their network people who can offer them lifts or lend them transport tools so that their travel activities can be quicker.

Having a higher share of important people living no further than 1 km away from the ego is related to higher duration of *Shopping* activities, and (weakly significant) higher duration of *Travel*, potentially indicating that they conduct these activities jointly with people living close to them.

4.3.5 Impact of variables on both the discrete and the continuous choice

As shown above, the effect of the independent variables on the discrete and continuous part of the model can be isolated by including them, respectively, only in the utility specifications (i.e, as elements of the z_k vector in $\psi(z_k, \varepsilon_k)$, only in the specification of the translation parameters (i.e. as ω_k in $\gamma_k = exp(\mu_k + {\delta_k}'\omega_k)$), or in both. Interesting behavioural insights can be gained from the cases in which a specific effect is significant in both parts of the model for a given activity. For example, the likelihood of working is positively affected by having one underage child, but the duration of this activity is lower than in the case of people without young children. This could suggest that having one child is associated with the need to provide for him/her, but not worth one parent exiting the job market for childcare. At the same time, it is reasonable that people with a small child would either work part-time, or simply work less than people without children. This is a strategy recognised in sociological studies, e.g. Moen and Sweet (2003).

4.4 Comparison of MDCNEV and MDCEV results

Tables 4.5 and 4.6 report the model estimates and robust t-ratios. For the MDCEV model, we also display the t-statistics for the difference between this model's estimates and the corresponding one in the full specification of the MDCNEV, with significant differences shown in bold.

We observe that the main differences lie in the baseline constants for the different alternatives and in the baseline γ parameters. In addition, we can observe that while the sign of the coefficients is the same in the two models, both the *Baseline constants* and most interaction effects are smaller in magnitude in the MDCNEV with respect to the MDCEV. This can be explained by noting that the utility of alternatives belonging to one of the nests is divided by the respective θ_s in the probability expression, so all these coefficients are expected to be smaller, except in the case of *Family* activities, which does not belong to any nest. At the same time, we observe a larger magnitude of the γ_k parameters in the nested model. This can be understood by looking at the expression for the product-specific marginal indirect utility for the "γ-profile" (cfr. Bhat (2008)):

$$V_k = \beta' z_k - \ln\left(\frac{x_k^*}{\gamma_k} + 1\right) - \ln p_k, \quad (k \geq 2), \quad V_1 = (\alpha_1 - 1)\ln(x_1^*). \quad (4.7)$$

As V_k is negative in our case, if the components of the β vector are smaller, a compensation mechanism to leave the scale between x_k and z_k unaltered is needed. We thus observe values of the baseline γ_k which are higher than in the MDCEV model as they compensate for the scaled-down β parameters.

5 Model forecasting

Nested model structures, whether discrete choice or discrete-continuous, allow for correlations between individual alternatives. While the impacts of this correlation will manifest themselves in improvements in fit over non-nested models, and potential differences in other model parameters, the key benefit will be in changes to the substitution patterns between alternatives.

5.1 Approximating draws from a GEV distribution

For the standard MDCEV model, a simple and efficient forecasting algorithm exists (cf. Pinjari and Bhat, 2010a). This algorithm relies on the analyst producing draws from the underlying error structure, a process that is easy for the MDCEV model, which relies on type I extreme value draws, but substantially more complex for the MDCNEV model, which relies on generalised extreme value (GEV) draws (cf. Equation 4.3). Complex approaches to do so have been suggested by McFadden (1999) and Bhat (2009). We instead rely on a simpler approximation, as follows:

1. Compute the approximate correlations for each nest s as $1 - {\theta_s}^2$, and define an overall correlation matrix Ω.
2. Create (for each respondent) an Rx12 matrix with distribution $N(0, \Omega)$, where R is a number of draws chosen by the analyst. The correlation structure within this D_N matrix is easily created using a Cholesky factorisation.
3. Apply the inverse normal CDF transformation $D_U = F^{-1}(D_N)$ to transform the normally distributed draws into uniform draws.
4. Apply the transformation $D_E = -log(-log(D_U))$ to transform the uniform draws into extreme value draws.

We have shown in a number of tests that the approximation described above works correctly, as the resulting draws have a mean of around 0.577... (Euler's constant) and a standard deviation of about $\sqrt{\pi^2/6}$ (coherent with the extreme value distribution) and the approximate correlation structure implied by $1 - {\theta_s}^2$, i.e. Ω. In our forecasting runs, we use $1,000$ draws per individual.

5.2 Forecasting scenarios

We performed 3 different forecasting exercises, each time changing an attribute that was affecting an activity belonging to a different nest. This is a purely illustrative process, so the assumptions made are rather arbitrary.

In the first scenario, we made the assumption that everybody in the sample would behave as if they were women, where gender only affects the utility of *Household Obligations*, an activity contained in nest 1. A similar reasoning was applied in the second scenario, where it was assumed that nobody in the sample has a partner who works, where this variable only affects the utility of *Drop-off/Pick-up*, an activity contained in nest 2. As there was no single socio-demographic effect that exclusively affects *Family* activities, we decided to simply set to zero the coefficient measuring the impact of having low household income on this specific activity. This equates to testing the impact of making *Family* time as (un)attractive to low income people as others.

5.3 Forecasting results

The results of this process are summarised in Table 4.7, where we regroup the activities by nest. For each scenario, we report the average number of hours spent by respondents in the different activities. We show the "true" values from the sample, followed by the "base scenario", i.e. the consumption context reproduced by the algorithm that is used as a starting point, to which the forecasting routine is subsequently applied. This first step shows that time allocation is reproduced quite accurately by the algorithm both in the MDCEV and in the MDCNEV models. This provides a validation of the model.

We then show the forecasted average time allocation for each activity as well as the percentage change from the base scenario. As expected, in all the three scenarios we see a change in the "affected" activity (the sign of which depends on the sign of the model coefficient) that is compensated by a change of the opposite sign of the time invested in other activities. The impact of the nesting structure is clear to see. In the first scenario, for example, we see that, in the MDCNEV model, the increase in time allocated to *Household Obligation* is compensated by a reduction in all other activities, but the reduction is larger in time invested other in-home activities. A corresponding pattern is observed in Scenario 2. Finally, in Scenario 3, we do not observe major differences between the MDCEV and the MDCNEV forecasting scenarios, as in this case *Family* is nested on its own. These results show that the nesting structure matters in forecasting and its impact on time reallocation is in line with expectations.

6 Inclusion of social network variables

As stated above, one of the objectives of the present paper is to understand whether elements of the wider choice context, such as the social environment,

Scenario 1: everybody behaves as if they were women

			MDCEV			MDCNEV		
Nest	Activity	*Sample*	*Base scenario*	*Forecast*	*Change*	*Base scenario*	*Forecast*	*Change*
1	*Basic needs*	*28.6*	*26.55*	*26.21*	*-1.26%*	*26.09*	*25.74*	*-1.34%*
1	**Household obligations**	**2.6**	**2.65**	**3.30**	**24.42%**	**2.68**	**3.23**	**20.41%**
1	*In home recreation*	*0.8*	*0.78*	*0.77*	*-1.61%*	*0.79*	*0.76*	*-3.45%*
1	*Study*	*1.1*	*1.12*	*1.11*	*-1.24%*	*1.10*	*1.07*	*-2.83%*
2	Drop off/Pick up	0.1	0.17	0.17	-1.58%	0.17	0.17	-0.75%
2	Out-of-home recreation	0.8	1.01	0.99	-1.79%	1.13	1.12	-0.75%
2	Services	0.5	0.65	0.64	-1.87%	0.72	0.71	-0.80%
2	Social	4.0	4.13	4.06	-1.64%	4.36	4.33	-0.76%
2	Shopping	0.5	0.77	0.75	-2.23%	0.78	0.77	-0.99%
2	Travel	3.3	4.35	4.28	-1.53%	3.97	3.94	-0.75%
2	Work	4.9	5.06	4.97	-1.74%	5.39	5.35	-0.83%
3	Family	0.8	0.76	0.75	-1.85%	0.82	0.82	-0.92%

Scenario 2: everybody behaves as if no one had a partner who works

			MDCEV			nested MDCEV		
Nest		*Sample*	*Base scenario*	*Forecast*	*Change*	*Base scenario*	*Forecast*	*Change*
1	Basic needs (outside good)	28.6	26.55	26.58	0.14%	26.09	26.12	0.09%
1	Household obligations	2.6	2.65	2.66	0.22%	2.68	2.68	0.15%
1	In home recreation	0.8	0.78	0.79	0.15%	0.79	0.79	0.08%
1	Study	1.1	1.12	1.12	0.14%	1.10	1.10	0.08%
2	**Drop off/Pick up**	**0.1**	**0.17**	**0.09**	**-45.95%**	**0.17**	**0.10**	**-41.88%**
2	*Out-of-home recreation*	*0.8*	*1.01*	*1.01*	*0.20%*	*1.13*	*1.13*	*0.29%*
2	*Services*	*0.5*	*0.65*	*0.65*	*0.19%*	*0.72*	*0.72*	*0.33%*
2	*Social*	*4.0*	*4.13*	*4.14*	*0.19%*	*4.36*	*4.37*	*0.23%*
2	*Shopping*	*0.5*	*0.77*	*0.77*	*0.25%*	*0.78*	*0.78*	*0.32%*
2	*Travel*	*3.3*	*4.35*	*4.36*	*0.17%*	*3.97*	*3.98*	*0.20%*
2	*Work*	*4.9*	*5.06*	*5.07*	*0.21%*	*5.39*	*5.41*	*0.26%*
3	Family	0.8	0.76	0.77	0.33%	0.82	0.83	0.20%

Scenario 3: everybody behaves as if income level was high (impact on Family only)

			MDCEV			nested MDCEV		
Nest		*Sample*	*Base scenario*	*Forecast*	*Change*	*Base scenario*	*Forecast*	*Change*
1	Basic needs (outside good)	28.6	26.55	26.59	0.18%	26.09	26.14	0.18%
1	Household obligations	2.6	2.65	2.66	0.40%	2.68	2.69	0.42%
1	In home recreation	0.8	0.78	0.79	0.28%	0.79	0.79	0.28%
1	Study	1.1	1.12	1.12	0.21%	1.10	1.11	0.22%
2	Drop off/Pick up	0.1	0.17	0.17	0.45%	0.17	0.17	0.38%
2	Out-of-home recreation	0.8	1.01	1.01	0.24%	1.13	1.13	0.22%
2	Services	0.5	0.65	0.65	0.27%	0.72	0.72	0.26%
2	Social	4.0	4.13	4.14	0.26%	4.36	4.37	0.27%
2	Shopping	0.5	0.77	0.77	0.27%	0.78	0.78	0.25%
2	Travel	3.3	4.35	4.36	0.21%	3.97	3.98	0.19%
2	Work	4.9	5.06	5.07	0.30%	5.39	5.41	0.31%
3	**Family**	**0.8**	**0.76**	**0.66**	**-13.81%**	**0.82**	**0.72**	**-13.05%**

Table 4.7: Forecasting scenarios results

are related to time allocation decisions.

As already mentioned in Section 4.2, we want to test the presence of confounding effects between socio-demographics and social network measures by estimating models which include socio-demographics and social network measures only. Detailed results of these models are shown in Table 4.8 and 4.9. In line with what we did in Tables 4.5 and 4.6, we also present the t-difference to compare the parameters of the "partial" models (B and C in the Tables) to the full MDCNEV specification (A) as well as between themselves. When we compare the parameter estimates of these "partial" models with those of the full MDCNEV specification, which includes both socio-demographics and social network measures, we find no statistically significant differences in the interactions effects. This suggests that there are no confounding effects between social network measures and socio-demographics. The only differences are in the activity-specific baseline constants and in the baseline γ_k parameters, as expected. This is due to the fact that the base categories of respondents are different in the two models.

As shown in Table 4.4, the improvement due to the inclusion of the social network variables is nearly as large as the one resulting from the socio-demographics. But it is important to acknowledge the potential presence of endogeneity, and for this reason we performed model forecasts excluding the social network variables from the model. The forecasted time allocation obtained by applying the model specification that does not include social network variables are shown in Table 4.10. There are no substantial differences between these forecasts and the ones shown in Table 4.7. This is consistent with the lack of differences in the socio-demographic parameters between the models, and provides further reassurance that there is little or no confounding between the social network and other variables included in the model.

7 Conclusions

The present paper has aimed to contribute to the existing literature on choice of activity type and duration.

We successfully apply the MDCNEV model, finding significant correlations between activities and showing the importance of accommodating the nesting structure. Moreover, we propose a simple and effective method to approximate draws from a GEV distribution and successfully perform forecasting with the MDCNEV model, showing how the time allocation changes according to the nesting structure.

In terms of behavioural insights, we confirm the significant effect of several socio-demographic characteristics on activity type and duration choice. We also show the existence of significant relationships between social network variables and the choice of different activities. This extends to activities

	Activity	Full Spec. MDCNEV (A) est	rob t-stat	Only Socio-demographics - MDCNEV (B) est	rob t-stat	t-diff vs A	Only Social Network - MDCNEV (C) est	rob t-stat	t-diff vs A	t-diff vs B
Baseline utility constants	Drop-off/Pick-up	-6.1329	-14.5	-6.3119	-15.79	-0.31	-4.378	-21.44	**3.74**	**4.31**
	Family	-5.7346	-16.44	-5.7283	-16.42	0.01	-4.8006	-29.97	**2.43**	**2.42**
	Household obligations	-3.2715	-16.06	-3.8634	-29.06	**-2.43**	-2.9687	-17.34	1.14	**4.13**
	Out-of-home recreation	-4.0542	-25.71	-4.1182	-33.71	-0.32	-4.083	-25.58	-0.13	0.18
	In-home recreation	-4.6827	-16.58	-4.5869	-16.66	0.24	-4.1659	-27.8	1.62	1.34
	Services	-4.1466	-34.41	-4.1656	-34.78	-0.11	-4.1711	-33.97	-0.14	-0.03
	Social	-3.9735	-8.38	-3.308	-16.19	1.29	-3.5566	-7.94	0.64	-0.50
	Shopping	-3.4295	-15.22	-4.0442	-24.79	**-2.21**	-3.0681	-18.05	1.28	**4.14**
	Study	-5.0538	-9.83	-5.0171	-10.14	0.05	-4.0307	-34.1	**1.94**	**1.94**
	Travel	-3.9229	-4.41	-1.1809	-5.05	**2.98**	-3.9115	-4.44	0.01	**-3.00**
	Work	-3.8267	-30.12	-3.5555	-30.61	1.58	-3.4869	-33.76	**2.08**	0.44
Sex=male	Household obligations	-0.4083	-2.88	-0.3723	-2.68	0.18	-	-	-	-
Age < 26	Study	0.4205	1.93	0.7091	3.85	1.01	-	-	-	-
Age 26-40	Work	0.4491	2.87	0.2273	1.42	-0.99	-	-	-	-
Age 40-60	In-home recreation	-0.7471	-2.91	-0.723	-2.88	0.07	-	-	-	-
1 underage child	Family	-1.0412	-2.8	-0.9904	-2.65	0.10	-	-	-	-
	Work	0.759	3.32	0.8092	3.68	0.16	-	-	-	-
2 underage children	Drop-off/Pick-up	1.1407	3.17	1.3097	3.85	0.34	-	-	-	-
	Family	1.7703	4.56	1.7248	4.45	-0.08	-	-	-	-
Low income	Drop-off/Pick-up	1.0297	3.83	0.6831	2.52	-0.91	-	-	-	-
	Family	0.4098	1.34	0.4197	1.37	0.02	-	-	-	-
	Household obligations	0.4264	3.35	0.4661	3.74	0.22	-	-	-	-
Agüita de la Perdiz	In-home recreation	0.8625	3.05	0.9479	3.35	0.21	-	-	-	-
	Social	0.2589	1.61	0.2467	1.53	-0.05	-	-	-	-
La Virgen	In-home recreation	1.0926	3.85	1.0763	3.75	-0.04	-	-	-	-
Driving Licence	Drop-off/Pick-up	0.7128	2.43	0.6433	2.35	-0.17	-	-	-	-
Internet Acess	Social	0.4019	1.92	0.3829	1.87	-0.06	-	-	-	-
	Study	1.0547	2.19	1.1192	2.34	0.10	-	-	-	-
Lives with partner	Household obligations	0.3694	2.81	0.3742	2.84	0.03	-	-	-	-
	Shopping	0.4715	2.43	0.6063	3.19	0.50	-	-	-	-
Partner works	Drop-off/Pick-up	0.6484	2.04	0.6864	2.18	0.08	-	-	-	-
Social network size	Social	0.3039	1.85	-	-	-	0.2943	1.7	-0.04	-
	Travel	1.4446	4.45	-	-	-	1.4437	4.64	0.00	-
Share of immediate family in the network	Household obligations	-1.04	-2.96	-	-	-	-1.0444	-2.96	-0.01	-
Share of friends in the network	Household obligations	-0.8087	-2.85	-	-	-	-1.0582	-3.57	-0.61	-
Share of friends in the network	Shopping	-0.8578	-2.48	-	-	-	-1.0733	-3.03	-0.44	-
Social capital children X female	Drop-off/Pick-up	0.774	2.83	-	-	-	0.9631	3.7	0.50	-
Social capital children X female	Study	0.3134	1.87	-	-	-	0.186	1.17	-0.55	-
Share of network in same age group (40-60)	Social	-0.6573	-2.31	-	-	-	-0.6767	-2.37	-0.05	-
Share of network with same work status (student)	Out-of-home recreation	1.2441	3.31	-	-	-	1.3752	3.62	0.25	-
Share of network with same work status (employed)	Work	1.4258	5.57	-	-	-	1.3274	5.05	-0.27	-
Share of network emplyed when ego is student	Study	4.2603	4.13	-	-	-	5.2369	6.6	0.75	-
Share of close network members living within 1 km	Drop-off/Pick-up	-1.8379	-2.99	-	-	-	-1.4174	-2.55	0.51	-
	Out-of-home recreation	-0.5204	-1.44	-	-	-	-0.5333	-1.44	-0.02	-
	In-home recreation	0.4135	1.47	-	-	-	0.3787	1.6	-0.09	-
	Shopping	-0.8606	-2.39	-	-	-	-0.9158	-2.5	-0.11	-
	Travel	-1.4028	-2.28	-	-	-	-1.3418	-2.2	0.07	-

Table 4.8: MDCNEV models with socio-demographics and social networks measures - Utility parameters

		Full Spec. MDCNEV (A)		Only Socio-demographics - MDCNEV (B)			Only Social Network - MDCNEV (C)			
	Activity	est	rob t-stat	est	rob t-stat	t-diff vs A	est	rob t-stat	t-diff vs A	t-diff vs B
Satiation parameters										
Baseline gamma	Drop-off/Pick-up	0.3443	1.7	0.3739	1.87	0.10	0.4007	2	0.20	0.09
	Family	2.173	10.16	2.1788	10.2	0.02	2.3898	12.31	0.75	0.73
	Household obligations	11.7755	53.86	12.6928	56.49	**2.93**	12.4104	54.86	**2.02**	-0.89
	Out-of-home recreation	2.6369	18.12	2.7457	18.72	0.53	2.5759	17.86	-0.30	-0.83
	In-home recreation	7.9366	29.29	8.0376	29.79	0.26	8.9861	32.62	**2.72**	**2.46**
	Services	1.6599	9.52	1.6289	9.37	-0.13	1.6152	9.36	-0.18	-0.06
	Social	2.6426	19.86	2.7614	21.7	0.65	2.6797	20.63	0.20	-0.45
	Shopping	0.8574	6.33	0.8269	6.43	-0.16	0.8564	6.29	-0.01	0.16
	Study	5.774	23.69	7.0771	25.79	3.55	6.512	25.57	**2.09**	-1.51
	Travel	0.1695	0.55	0.2969	1.14	0.32	0.1627	0.53	-0.02	-0.33
	Work	5.8414	46.02	6.7449	54.92	**5.12**	6.1281	50.85	1.64	**-3.58**
Shifts (log of baseline gamma)										
Age < 26	Social	0.0541	1.55	0.0784	2.17	0.48	-	-	-	-
Age 26-40	Household obligations	-0.1689	-2.04	-0.1996	-2.32	-0.26	-	-	-	-
1 underage child	Work	-0.1898	-2.92	-0.1832	-2.9	0.07	-	-	-	-
2 underage children	Study	-0.4857	-2.88	-0.4919	-2.43	-0.02	-	-	-	-
Agüita de la Perdiz	Household obligations	-0.2482	-4.06	-0.2872	-4.59	-0.45	-	-	-	-
Network size	Travel	-1.3054	-4.45	-	-	-	-1.2717	-4.78	0.085	-
Social capital travel	Travel	-0.1691	-1.94	-	-	-	-0.1472	-1.67	0.177	-
Share of close network members living within 1 km	Shopping	0.2167	1.89	-	-	-	0.2177	1.9	0.01	-
	Travel	0.2798	1.58	-	-	-	0.2642	1.5	-0.06	-
Nesting parameters										
In home		0.4356	-12.36	0.4416	-11.75	0.12	0.4561	-11.32	0.31	0.21
Out of home		0.7382	-6.48	0.7497	-6.18	0.07	0.7538	-6.07	0.27	0.07

Table 4.9: MDCNEV models with socio-demographics and social networks measures - Translation and nesting parameters

Scenario 1: everybody behaves as if they were women

			MDCEV			MDCNEV		
Nest	Activity	*Sample*	*Base scenario*	*Forecast*	*Change*	*Base scenario*	*Forecast*	*Change*
1	*Basic needs*	*28.6*	*26.58*	*26.26*	*-1.21%*	*26.15*	*25.82*	*-1.25%*
1	**Household obligations**	**2.6**	**2.65**	**3.29**	**24.00%**	**2.67**	**3.19**	**19.52%**
1	*In home recreation*	*0.8*	*0.78*	*0.76*	*-1.64%*	*0.77*	*0.74*	*-3.43%*
1	*Study*	*1.1*	*1.12*	*1.10*	*-1.54%*	*1.13*	*1.09*	*-3.52%*
2	Drop off/Pick up	0.1	0.17	0.17	-2.01%	0.16	0.16	-0.84%
2	Out-of-home recreation	0.8	0.99	0.97	-1.86%	1.07	1.07	-0.72%
2	Services	0.5	0.65	0.64	-1.82%	0.69	0.69	-0.71%
2	Social	4.0	4.16	4.09	-1.64%	4.37	4.34	-0.72%
2	Shopping	0.5	0.76	0.74	-2.05%	0.74	0.74	-0.86%
2	Travel	3.3	4.31	4.25	-1.49%	3.97	3.95	-0.69%
2	Work	4.9	5.06	4.98	-1.75%	5.45	5.40	-0.77%
3	Family	0.8	0.76	0.75	-1.70%	0.83	0.82	-0.82%

Scenario 2: everybody behaves as if no one had a partner who works

			MDCEV			nested MDCEV		
Nest	Activity	*Sample*	*Base scenario*	*Forecast*	*Change*	*Base scenario*	*Forecast*	*Change*
1	Basic needs	28.6	26.58	26.62	0.14%	26.15	26.17	0.09%
1	Household obligations	2.6	2.65	2.66	0.23%	2.67	2.67	0.14%
1	In home recreation	0.8	0.78	0.78	0.18%	0.77	0.77	0.09%
1	Study	1.1	1.12	1.12	0.11%	1.13	1.13	0.06%
2	**Drop off/Pick up**	**0.1**	**0.17**	**0.09**	**-46.66%**	**0.16**	**0.09**	**-43.34%**
2	*Out-of-home recreation*	*0.8*	*0.99*	*1.00*	*0.21%*	*1.07*	*1.08*	*0.32%*
2	*Services*	*0.5*	*0.65*	*0.65*	*0.19%*	*0.69*	*0.69*	*0.34%*
2	*Social*	*4.0*	*4.16*	*4.17*	*0.19%*	*4.37*	*4.39*	*0.24%*
2	*Shopping*	*0.5*	*0.76*	*0.76*	*0.25%*	*0.74*	*0.75*	*0.34%*
2	*Travel*	*3.3*	*4.31*	*4.32*	*0.17%*	*3.97*	*3.98*	*0.19%*
2	*Work*	*4.9*	*5.06*	*5.07*	*0.21%*	*5.45*	*5.46*	*0.27%*
3	Family	0.8	0.76	0.76	0.32%	0.83	0.83	0.20%

Scenario 3: everybody behaves as if income level was high (impact on Family only)

			MDCEV			nested MDCEV		
Nest	Activity	*Sample*	*Base scenario*	*Forecast*	*Change*	*Base scenario*	*Forecast*	*Change*
1	Basic needs	28.6	26.58	26.63	0.18%	26.15	26.20	0.19%
1	Household obligations	2.6	2.65	2.66	0.39%	2.67	2.68	0.45%
1	In home recreation	0.8	0.78	0.78	0.28%	0.77	0.77	0.30%
1	Study	1.1	1.12	1.12	0.17%	1.13	1.13	0.19%
2	Drop off/Pick up	0.1	0.17	0.17	0.46%	0.16	0.16	0.42%
2	Out-of-home recreation	0.8	0.99	1.00	0.28%	1.07	1.08	0.28%
2	Services	0.5	0.65	0.65	0.27%	0.69	0.69	0.27%
2	Social	4.0	4.16	4.17	0.26%	4.37	4.39	0.29%
2	Shopping	0.5	0.76	0.76	0.28%	0.74	0.74	0.26%
2	Travel	3.3	4.31	4.32	0.22%	3.97	3.98	0.22%
3	**Family**	**0.8**	**0.76**	**0.66**	**-13.74%**	**0.83**	**0.71**	**-13.56%**
2	Work	4.9	5.06	5.08	0.27%	5.45	5.46	0.30%

Table 4.10: Forecasting scenarios results- excluding social network variables

such as studying, travelling and household obligations, while past studies mostly focused on effects related to the spheres of social activity and leisure. While we cannot give definitive interpretations about the directionality of the causal effects between social network variables and time use, we can conclude that people's personal social environment is related to the choice of which activities to perform and for how long. This calls for more work to better understand this relationship, including causality. Crucially, our limited testing has revealed no major confounding between the variables associated with the social network and other socio-demographic measures.

From a policy perspective, the use of a dataset that includes information about personal and social contexts and of a method that jointly estimates activity type choice and duration provides rich contextual information about activity and travel patterns. As a consequence, disparate aspects such as income, the presence of children, personal network composition, communication technology use, lifecycle, and social support can be combined in an integrated framework to understand people's time and spatial patterns. In this way, the results highlight not only the trade-offs between mandatory and non-mandatory activities, but also how income and neighbourhood affect opportunities and constraints according to contextual personal characteristics. This is potentially useful information to understand the specificities of transport-related social exclusion aspects.

In spite of the interesting overall picture that this study provided, the present study presents some limitations that leave scope for future research, going beyond the already mentioned issue of directionality.

As explained, we estimated a model including both the weekday and weekend activities, but it is important to acknowledge that important differences in patterns between the two types of days exist. The size of the dataset did not allow the estimation of separate models for weekday and weekend activities, while separating time spent in an activity into weekday and weekend time could lead to violations of the separate 24 hour budgets.

In addition, social networks and social capital data imply a number of potential sources of measurement error: first of all, tools such as name generators rely on respondents' ability to recall all the relevant members of their network. Moreover, social capital is measured by asking respondents to name the people who are relevant for some specific form of help. Correct completion of this part of the survey relies on the ability to recall relevant contacts and on the homogeneous understanding of the question across the sample. These issues lead to the consideration of alternative model specification, e.g. treatment of social measures as latent constructs instead of direct incorporation in the utility function. This could be particularly interesting as the dataset contains a large numbers of personality and well-being questions, which could allow us to link network characteristics and activity choice to underlying personality traits of the decision maker.

Finally, an important direction for future research would be the consideration of whether activities have been performed by respondents on their own or together with other people (family, friends). In the present context, segmentation on the basis of the party involved would have led to an excessive number of possible choice alternatives for the sample size, but this is indeed an interesting exercise to perform with suitable data.

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Chapter 5

Accommodating correlation across days in multiple-discrete continuous models for activity scheduling: estimation and forecasting considerations

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Abstract

The MDCEV modelling framework has established itself as a preferred method for modelling time allocation, with data very often collected through travel or activity diaries. However, standard implementations fail to recognise the fact that many of these datasets contain information on multiple days for the same individual, with possible substitution between days. This paper discusses how the theoretical accommodation of these effects is not straightforward, especially with budget constraints at the day and multi-day level. We instead rely on additive utility functions where we accommodate correlation between activities at the within-day and between-day level using a mixed MDCEV model, with multi-variate random distributions. We put forward adaptations of the standard Pinjari and Bhat (2010) forecasting approach to allow us to make links across days also in model application. Finally, we illustrate the issue and the methods using two different time use datasets, confirming our theoretical points and highlighting the benefits of allowing for correlation across days in estimation and substitution in forecasting.

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1 Introduction

Understanding and modelling the way in which individuals allocate time across different activities is a key topic in travel behaviour research. The data for such research often come from travel or activity diaries, where increasingly, there has been a move away from paper based logbooks to smartphone (or other GPS logger) based digital surveys.

Over the course of a day, an individual allocates time to a set of different activities, with the amounts of time differing across those, where individuals can also decide to not engage in a particular activity on a given day. The choice process is thus one of choosing amongst different activities, that are no longer mutually exclusive (as they would be in a discrete choice context) and determining a continuous time allocation for each.

Starting from the late 1950s, econometric models accommodating both a discrete and a continuous dimension of choice were developed (e.g. De Jong, 1990; Dubin and McFadden, 1984; Heckman, 1977; Tobin, 1958; Train, 1986). Nowadays, the state-of-the-art model for accommodating both a discrete and a continuous element of choice is the Multiple Discrete-Continuous Extreme Value (MDCEV) model, especially with the work of Bhat (2008). This model is a generalisation of a multinomial logit model (MNL) for multiple discrete continuous choice contexts and has a simple closed-form probability which is practical even with a large number of alternatives. The model is based on the Kuhn Tucker (KT) first-order conditions for constrained random utility maximisation, previously employed by Hanemann (1978) and Wales and Woodland (1983), which are used to derive the optimal consumption for the given random utility specification subject to a linear budget constraint. The MDCEV model has become a popular tool for modelling time allocation (Kapur and Bhat, 2007; Wang and Li, 2011), where the specification of a time budget is conceptually easier than a money budget, albeit there is scope for doing both at the same time.

A key recognition in the time use survey and modelling literature is that the way an individual allocates time may be poorly understood by a single day snapshot, and numerous studies thus rely on multi-day surveys of varying length, for different research purposes, and using different methods (Arentze and Timmermans, 2009; Chow and Nurumbetova, 2015; Jara-Díaz et al., 2008; Kang and Scott, 2010). Some of these studies have accommodated interactions between different days, such as substitutions in time use between weekdays and weekend days (Bhat and Misra, 1999; Yamamoto and Kitamura, 1999). Minnen et al. (2015) argues that multi-day data allow to observe temporal regularities and habitual behaviour. Jara-Díaz and Rosales-Salas (2015), in their analysis of the duration of time diary data, recommend the collection of a week of data when the aim is to model time allocation, or at a minimum two or three days with appropriate weighting.

While multi-day data has the potential to lead to important insights into behaviour, it also creates further complexity in modelling. Modelling each individual day on its own by assuming separate 24 hour budgets remains behaviourally reasonable, as the decision about the activities to conduct (say during a week) is likely made day by day and not in one go, at the beginning of the week. Estimating day-specific model coefficients also allows an analyst to capture differences across days, but at the same time this approach ignores the fact that "links" between days may exist. While a number of previous applications of MDCEV have made use of such multi-day data (Chikaraishi et al., 2010; Habib et al., 2008; Spissu et al., 2009), it is not always clear what interactions, if any, between days have been accommodated. These "links" can represent correlations or complementarities across days. It is for example likely that, in a household, the person who performs certain household obligations on one day is more likely to perform them on the other days (an example of positive correlation caused by common unobserved heterogeneity), or maybe the parent who does the drop-off of the children on one day will not do it on the next (negative correlation), or that a person who performs out-of home social activities on one day also performs travel (complementarity).

On the other side, an overall model assuming (for example) a weekly budget of 168 hours, while creating a link between different days, would not allow us to understand differences in the utilities of activities across days (see Calastri et al., 2017, for an application using two days). This can be understood by noting that the estimation of day-specific coefficients would also require day-specific budgets. By not imposing the latter, the analyst would neglect an essential constraint which is present in the data on which the model is based. The issue becomes even clearer when thinking about forecasting. In the first case, i.e. with day specific budgets, a change in the utility of an activity on one day would have no effect on the time spent on any activities on other days, as there is no link between days. This is quite unlikely in reality, as, for example, if an individual is unable to work on a certain day, he/she will try to make up for it by working a little longer on the previous/following day. In the second case, i.e. using an overall budget, substitution between days becomes possible, but the model would not be constrained to allocating only 24 hours across all activities on a given day. Any forecasts would thus not allow us to understand what happens on individual days, but only at the aggregate level. These considerations highlight the fact that it is important to research solutions that allow the introduction of correlations as well as complementarities across different days in MDCEV models of time use, while avoiding violations of the 24 hour budget constraint so as to be able to obtain consistent forecasts.

In this paper, we start by recognising that some activities are more similar than others, i.e. that there is correlation between days as well as across days.

An analysis seeking to capture these "links" needs to recognise that these can include correlations due to common unobserved heterogeneity, substitution, or complementarity. When a model is estimated with only one such effect, for example correlations, then these could be due to common heterogeneity or substitution (if the correlation is negative) or complementarity (if the correlation is positive). It is usually not easy to disentangle the different sources of correlation, but the analyst can make an informed guess on the primary source of correlation. We investigate possible theoretical solutions, i.e. ways to develop a model framework that allows to incorporate correlations and complementarities in the MDCEV model across different days. We first show that this problem cannot be solved without making major changes to the model structure. To deal with these issues in a way that is computationally tractable, we put forward a mixed MDCEV model which directly accommodates correlations between activities within and across different days. We then discuss how the presence of inter-day correlations leads to a need for changes to the standard approach used for forecasting with MDCEV models, and we propose two different departures from that framework.

The remainder of this paper is organised as follows. Section 2 discusses the limitations of the *"standard"* implementation of MDCEV models for multi-day data, highlights the complexity of working with non-additive utility functions and puts forward a mixed MDCEV solution within an additive framework. Section 3 discusses the use of this models in forecasting and shows the required changes to the standard forecasting approach. We illustrate the modelling and forecasting approaches using two different datasets in Section 4. Finally, Section 5 summarises our findings and presents directions for future work.

2 Methodological considerations

In this section, we first discuss the limitations of the standard framework, before briefly looking at the use of a non-additive utility specification. We next put forward a mixed MDCEV model as a solution to the problem of working with multi-day data. Finally, we contrast these two solutions.

2.1 Base specification

The random utility specification of the MDCEV model, as introduced by Bhat (2008) is given by:

$$U(x) = \sum_{k} \frac{\gamma_k}{\alpha_k} [exp(\beta' z_k + \epsilon_k)] \left(\left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right) \tag{5.1}$$

so that $U(x)$ is quasi-concave, increasing and continuously differentiable with respect to the vector of consumptions x_k, and $\psi_k = [exp(\beta' z_k + \epsilon_k)]$. ψ_k is the baseline utility of good k, i.e. the marginal utility of the good at zero consumption. It is a function of observed characteristics of the decision maker and of good k, z_k, which also includes a constant representing the generic preference for good k. In this random specification, a multiplicative i.i.d. log-extreme value error term is introduced in the baseline utility.

The analyst can solve the optimal expenditure allocation (with respect to the money spent on goods 1...K):

$$Max\ U(e_1 \dots e_K) \quad s.t. \sum_{k=1}^{K} e_k^* = E \tag{5.2}$$

where e_k^* are the optimal amounts of expenditure on goods 1...K, that exhaust the budget E, and where $e_k = x_k p_k$. This problem is solved by forming the Lagrangian and applying the KT conditions, as detailed in Bhat (2008). The resulting model probability of the expenditure pattern where M goods are chosen, results in the closed-form expression below:

$$\begin{aligned} &P({e_1}^*, {e_2}^*, \dots, {e_M}^*, 0, \dots, 0) \\ =&\frac{1}{\sigma^{M-1}}\left(\prod_{i=1}^{M} c_i\right)\left(\sum_{i=1}^{M}\frac{1}{c_i}\right)\left(\frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma}\right)^M}\right)(M-1)! \end{aligned} \tag{5.3}$$

where σ is a scale parameter (not estimated in our case, as there is no price variation across products), $c_i = \frac{1-\alpha_i}{{e_i}^* + \gamma_i p_i}$ and $V_k = \beta' z_k + (\alpha_k - 1)\ln\left(\frac{{e_k}^*}{\gamma_k p_k} + 1\right) - \ln p_k$ $(k = 1, 2, 3, \dots, K)$. As explained in Bhat (2008), equation 5.3 can also be expressed in terms of consumption quantities. In our case, the two forms are interchangeable because there is no price variation, and in the remainder of our discussion we will refer to consumption quantities (x_i).

To model multi-day time-use choices, it is desirable to formulate a unified multiple discrete-continuous choice model that simultaneously recognises the day-level (24 hour) constraints individuals face, with as many constraints as the number of days modelled, and the interactions between activity time allocations across different days, such as substitution and complementarity across different days. This is because ignoring the day-level constraints while accommodating interactions across days can potentially lead to time allocations that either exceed or fall short of 24 hours on a day. On the other hand, a model without interactions across days does not allow for exogenous changes on a day to influence time allocations on another day.

2.2 Multi-day utility maximisation with day-level time constraints and non-additive utility functions

A first specification to model multi-day time use while accommodating day-level time constraints and interactions in time-use across different days is to use non-additive utility formulations that allow for explicit interactions between utility functions of different days while allowing for day-level constraints. One way to formulate non-additive utility functions is to begin with an additive utility form discussed in the previous section and add multiplicative utility terms that interact pairs of utility terms of activity participation on different days, as in Bhat et al. (2015). The parameters estimated on such multiplicative utility terms capture substitution and complementarity between the two choice alternatives being interacted. Specifically, $U = \sum_{l=1}^{L}\sum_{k=1}^{K} u_{kl} + \sum_{k=1}^{K}\sum_{q,m=2,q\neq m}^{L} \theta_{kqm}[u_{kq} \times u_{km}]$, where K refers to activities and L to days, θ_{kqm} are the parameters estimated on the multiplicative utility terms $[u_{kq} \times u_{km}]$, interacting utility derived from activity k on two different days q and m, to capture substitution and complementarity patterns between the two days.

2.3 Multi-day utility maximisation with day-level time constraints and correlated, additive utility functions

We will now look at our proposed use of a mixed MDCEV model to capture intra and inter-day correlations.

Let us consider the situation in which we have data from N separate individuals, where L_n days are observed for person n. On each day, individual n allocates time to K different activities $(k = 1, 2, \ldots, K)$, where $K = 1$ is an activity that is performed by every person on every day (i.e. an outside good). In this specification, it is assumed that an individual makes his/her time use choices across different days to maximise the total utility derived from time allocation choices on all days under consideration; subject to as many day-level constraints as the number of days, where the time allocation to all activities on each day sums up to 24 hours. Specifically, $U = \sum_{l=1}^{L} \sum_{k=1}^{K} u_{kl}$ is maximised subject to L day-level time budget constraints $\sum_{k=1}^{K} x_{kl} = 24, \forall l = 1, 2, \ldots, L$.

In this specification, U is the total multi-day utility derived by the person, $u_{1l} = \psi_{1l} x_{1l}^{\alpha}$ is the utility from time allocation x_{1l} to the outside good on day l $(l = 1, 2, \ldots, L)$, $u_{kl} = \frac{\psi_{kl}\gamma_{kl}}{\alpha}\left(\frac{x_{kl}}{\gamma_{kl}} + 1\right)^{\alpha}$ $\forall k = 2, \ldots, K$ is the utility from time allocation x_{kl} to activity k on day l, ψ_{kl} is the corresponding baseline utility parameter, γ_{kl} is the corresponding translation parameter, which allows for corner solutions as well as having a role in relation to satiation (with higher γ_{kl} implying lower satiation for activity k and day l). Finally,

α is the generic satiation parameter. Note that the subscript for person n is suppressed for ease in notation.

To introduce interactions across activities within a day and across different days, we introduce correlations through common mixing distributions in the utility functions, in both the baseline utility parameters as well as the translation parameters. As can be observed from the utility function, the utility derived from each activity on each day is assumed to be additively separable from that of other such utilities, and specified using a standard MDCEV utility function.

We remain with the example of L_n days for person n, with K different activities per day. We further assume that there are D different types of days, where a simple approach would use the same specification for a given activity on each day, while at the extreme end, we would have 7 different treatments. In our exposition below, we generally focus on the situation where weekdays (WD) are treated differently from Saturdays (SAT) and Sundays (SUN).

A number of different specifications are possible with the MDCEV model, where our empirical work uses a generic α parameter across activities, which we (after testing) set to 0, along with activity specific γ parameters for the $K-1$ activities that are not treated as outside goods. In our theoretical discussions, we ignore the possibility of including socio-demographic effects (though we do so in the empirical work), meaning that the baseline utility for activity k on day l for person n is simply given by $\psi_{n,k,l} = e^{\delta_{k,d_{l_n}} + \varepsilon_{n,k,l}}$ where $\varepsilon_{n,k,l}$ is an extreme value error term for person n, activity k and l, and where d_{l_n} is the day type for day l for person n . In addition to making the δ parameters activity and day specific, we do the same for the γ parameters. This would thus lead to the estimation of KD different δ parameters and KD different γ parameters.

A model of the form above would allow for different utilities for the same product across days and also different shapes for the indifference curves, but would fail to capture correlation across activities and across days. We now instead define $\theta_n = \langle \delta_n, \gamma_n \rangle$ to be a vector combining the individual δ and γ parameters for person n, making these parameters individual-specific. Within θ_n, we would have that e.g. $\delta_n = \langle \delta_{n,1}, \ldots, \delta_{n,D} \rangle$, i.e. comprising itself different vectors where for example $\delta_{n,d} = \langle \delta_{n,d,1}, \ldots, \delta_{n,d,K} \rangle$, i.e. containing the constants used in the baseline utilities for activities 1 to K on a day of type d by person n. The vector θ_n thus has $2KD$ elements, and we assume that it is distributed randomly across individuals, according to $\theta_n \sim f(\theta \mid \Omega)$.

Let $\theta_{n,d}$ be the subset of θ_n for days of type d. With $P_{n,l}(\theta_{n,d})$ giving the MDCEV probability (cf. Equation 5.3) for the consumption observed for individual n on day l (out of L_n), conditional on $\theta_{n,d}$. The unconditional probability for the observed sequence of day level consumptions for individual

n is then given by:

$$P_n(\Omega) = \int_{\theta_n} \prod_{l=1}^{L_n} P_{n,l}\left(\theta_{n,d_{l_n}}\right) f(\theta \mid \Omega)\, \mathrm{d}\theta_n, \tag{5.4}$$

where d_{l_n} is the day type for observation l for respondent n, where the above notation ensures that the right subset of θ_n is used in $P_{n,l}\left(\theta_{n,d_{l_n}}\right)$.

By carrying out the integration over the distribution of θ_n at the person level rather than at the day level, we already capture correlation across days for the same person and for the same activity if those days are of the same type. However, the key flexibility arises if we allow for correlation between the different δ and γ parameters. Different possibilities arise. Let us assume without loss of generality that the multivariate distribution[3] used for θ_n is characterised by a mean for each element (i.e. every δ and γ term) along with a covariance matrix. In the closed form MDCEV model, we would be estimating the $2KD$ mean values, while all elements of the covariance matrix would be fixed to zero. In a model allowing for simple independent heterogeneity for each element, we would in addition estimate $2KD$ variances.

As a first step, we may want to focus on correlations in the baseline utilities for activities conducted on days of the same type. For day type d, we would now estimate K means for $\delta_{n,d}$, along with $\frac{K\cdot(K+1)}{2}$ covariance elements. This would for example allow us to understand in which way the baseline utilities for day type d are correlated with each other, e.g. whether a respondent who is more likely to take part in activity k_1 on day type d is also more likely to take part in activity k_2 on day type d. We may also want to allow for correlations across different day types in the baseline utilities for a given activity. This will imply the estimation of $K\frac{D\cdot(D-1)}{2}$ additional off-diagonal elements in the covariance matrix and would for example tell us whether respondents who are more likely to conduct leisure activities on a weekday are less likely to do so on a Saturday. Allowing for correlations in baseline utilities within and across day types means the estimation of up to $\frac{KD\cdot(KD+1)}{2}$ elements of the covariance matrix. We can similarly allow for correlation between the individual elements of γ_n, which would give us some insights into how satiation is correlated across activities and day types.

The full level of flexibility of this mixed MDCEV model would involve the estimation of a full covariance matrix of $\frac{2KD\cdot(2KD+1)}{2}$ on top of the $2KD$ parameter means. This is substantial estimation issue which we address in our empirical work using Bayesian techniques.

Insights into substitution patterns can then be gained from the correlations. For example, negative correlation between the utilities of work activity on a weekday and that on Sunday implies a substitutive effect so that not

[3] Different distributions will likely apply for δ and γ, as discussed later on in our empirical work.

working (or allocating less time to work) on weekdays may lead to working and/or allocating more time to work on Sunday (or vice versa). Similarly, a positive correlation might imply complementarity, so that working (and allocation more time to work) on a weekday may lead to working more on Sunday as well.

Conceptually, the above formulation belongs to the class of MDCEV models with multiple budget constraints. An individual has multiple 24 hour budget constraints, such that on day l, we have that $\sum_{k=1}^{K} x_i = 24$ and an overall $L \cdot 24$ budget constraint, such that $\sum_{l=1}^{L} \sum_{k=1}^{K} x_{kl} = L \cdot 24$ (if the individual level budgets are all met, then the multi-day one will be too). However, there is a subtle difference between our formulation and existing formulations with multiple budget constraints, such as those in Castro et al. (2012) and Pinjari and Sivaraman (2013). In most previous formulations, multiple budget constraints arise due to the use of multiple resources, such as time and money, for consuming a same choice alternative. Each activity would draw from both budgets.

In our formulation, however, activity participation on a day can draw only from the time available (24 hours) on that day. In other words, one cannot use time available on Sunday to work on a weekday. Since the 24 hour time budgets are not *fungible* across different days, as long as the utility functions are additively separable, it can be shown that the maximum multi-day utility derived by a person subject to multiple day-level constraints is the same as the sum (across all days) of maximum single-day utilities derived by the person subject to a single day's 24 hour time constraint. That is, $[Max(U), \text{subject to} \sum_{k=1}^{K} x_{kl} = 24 \, \forall l] = \sum_{l=1}^{L} [Max(u_l), \text{subject to} \sum_{k=1}^{K} x_{kl} = 24]$.

Therefore, conditional on the mixing distributions used in the specification, the multi-day time-use MDC choice probability may be derived as a simple product of single-day MDC choice probabilities, with as many single-day probabilities in the product as the number of days being modelled. In short, conditional on the mixing distributions, the multi-day time-use probability may be derived as a product of independent single-day MDCEV probabilities. The unconditional probability is simply an integral of this product over the mixing distribution.

2.4 Discussion

We now provide some brief contrasts between the two approaches discussed above. In comparison with the correlated, additive utility functions, the non-additive approach from Section 2.2 provides a more structural way to allow interactions. A major disadvantage, however, is that such non-additive utility models are very difficult to estimate and apply in practice; because the desirable optimisation properties of additive utility functions do not hold anymore.

In addition, the additive utility specification easily allows correlations among baseline utility parameters as well as translation parameters, thereby differentiating substitution and/or complementarity effects in discrete choice from those in continuous choice dimensions. The non-additive utility approach, on the other hand, does not offer an easy way to disentangle interactions among the translation parameters from that of baseline utility parameters. This is because the interactions in the latter approach are between the utility terms, not between the parameters.

An advantage of the additive formulation in Section 2.3 is that it is simple, not very different from the standard mixed-MDCEV formulation, and therefore easy to implement for both estimation and application purposes. A drawback, however, as discussed in the next section, is that it is not easy to apply to predict substitution across different days. For example, if a person cannot work on a weekday due to some exogenous reasons, he/she will likely make up for the lost worktime by working more on a weekend day. Such substitution effects are not easy to accommodate when the model is applied for prediction despite the correlations retrieved during estimation, particularly when predictions are carried out separately for each day according to the estimated model. This is because the additively separable utility formulation does not incorporate explicit interactions between the utilities of time allocation across different days, except through correlations. Another disadvantage is that correlations between two utility functions may be either due to substitutive/complementarity relationships or simply due to common unobserved heterogeneity. The estimated correlation parameters typically capture a combined effect making it difficult to disentangle the source of correlation.

Given the difficulty of estimating and applying MDC models with non-additive utility functions, particularly those with multiple budget constraints, in this paper we employ the simpler model formulation discussed in Section 2.3 and explore various alternatives to apply such models for forecasting purposes, as discussed in Section 3. Of course, formulating, estimating, and applying non-additive, multi-day utility models while considering day-level constraints is an important avenue for future research.

3 Forecasting approach

We next turn our attention to forecasting from the above model, where our starting point is the efficient forecasting procedure of Pinjari and Bhat (2010), hereafter referred to as P&B, which we can rely on given the use of a generic α across all activities and a separate γ parameter for each inside good.

3.1 Base procedure adapted for random parameter case for a single day

We first illustrate the procedure for a specific individual n and a given day of type d, focussing on a time budget such that all *products* have unit prices (expressed in hours in most cases) and with a day level budget of 24 hours. The original approach uses sample enumeration (over R iterations) by relying on draws from the extreme value error terms of the model and we extend this to include the other random parameters in the model. The algorithm operates as follows.

Step 1 In iteration r, take a random vector of extreme value draws of length K ($\varepsilon_{n,d,r}$) and a realisation of the vector $\theta_{n,d}$ ($\theta_{n,d,r}$) taken from $f\left(\theta_{n,d} \mid \Omega_d\right)$ where Ω_d is the subset of Ω for day d.

Step 2 Assume that only the outside good is chosen by respondent n, setting the number of chosen goods M to 1.

Step 3 With the draws produced in Step 1, arrange the $K-1$ inside goods in descending order of $\psi_{n,d,k} = e^{\delta_{n,d,k}+\varepsilon_{n,d,k,r}}$, $\forall k$, and placing the outside good in first place, with $\psi_{n,d,1} = e^{\varepsilon_{n,d,1,r}}$.

Step 4 Using the ordering obtained in step 3, i.e. with $\psi_{n,d,m}$ being the m^{th} ranked activity[4], compute

$$\lambda = \left(\frac{24 + \sum_{m=2}^{M} \gamma_{n,d,m}}{\psi_{n,d,1}^{\frac{1}{1-\alpha}} + \sum_{m=2}^{M} \gamma_{n,d,m} \psi_{n,d,m}^{\frac{1}{1-\alpha}}} \right)^{\alpha-1}. \tag{5.5}$$

Step 5 If $\lambda > \psi_{n,d,M+1}$, again using the ordering from step 3, then conduct step 5a, else move to step 6.

Step 5a set the consumption of the outside good with draw r as

$$C_{n,d,1}^{(r)} = \frac{\psi_{n,d,1}^{\frac{1}{1-\alpha}} \left(24 + \sum_{m=2}^{M} \gamma_{n,d,m}\right)}{\psi_{n,d,1}^{\frac{1}{1-\alpha}} + \sum_{m=2}^{M} \gamma_{n,d,m} \psi_{n,d,m}^{\frac{1}{1-\alpha}}}. \tag{5.6}$$

Create a mapping index between the ordering of activities in the data (i.e. $k = 1, \ldots, K$) and the ordering of the activities from step 3. For example if the alternative ranked in position m in step 3 corresponds to the j^{th} activity in the data, then set $k_m = j$.

[4] Note that we only have correspondence between $k = 1$ and $m = 1$.

Next set the consumption of the remaining $M-1$ chosen activities as

$$C^{(r)}_{n,d,k_m} = \left(\frac{\psi_{n,d,m}^{\frac{1}{1-\alpha}} \left(24 + \sum_{l=2}^{M} \gamma_{n,d,l}\right)}{\psi_{n,d,1}^{\frac{1}{1-\alpha}} + \sum_{l=2}^{M} \gamma_{n,d,l} \psi_{n,d,l}^{\frac{1}{1-\alpha}}} - 1 \right) \gamma_{n,d,m},\ 1 < m \leq M. \tag{5.7}$$

If $M < K$, then set the consumption of alternatives above M, i.e. k_{M+1} and beyond in the mapping is set to zero.

Move to step 7.

Step 6 Set $M = M + 1$. If $M = K$, go to step 5a, else go to step 4.

Step 7 If $r = R$, stop the algorithm, else set $r = r + 1$ and go to step 1.

The application of the above algorithm produces a $R \cdot K$ dimensional matrix of consumption predictions for each individual n, and an average over the draws (i.e. rows of the $R \cdot K$ matrix) produces a vector of average predictions for this person.

3.2 Shortcomings of base algorithm when applied to multi-day data

Let us now consider a situation where we have estimated a model allowing for the types of heterogeneity and correlation discussed in Section 2.3 and wish to apply it to make a prediction not just for a single day but for a set of days for each person. In particular, and again without loss of generality, assume we want to make a prediction for a subset of L days for each person, where $L = D$, with one of each type $d = 1, \ldots, D$, for example a weekday, a Saturday and a Sunday.

The basic forecasting procedure in line with the estimated model would be very similar to that outlined in Section 3.1, with the only difference that it would be run L times for each individual respondent, i.e. once for each type of day in the above example. If multiple copies of the same day type were to be included, e.g. if making a prediction for two separate weekdays, then a further distinction would arise in that while the vector of extreme value draws in step 1 would differ across days, the same draws $\theta_{n,d,r}$ would be used for those days of the same type. This would lead to more similar predicted consumptions for those days of the same type, but with differences remaining due to the extreme value draws.

The forecasting process would account for the random heterogeneity across individuals as well as the correlations between the different parameters. For example, if the estimation reveals a positive correlation in the baseline utility for work on a weekday and on a Saturday, then this would be reflected in the forecasts, with those individuals who are predicted to work on a weekday also being more likely to have a prediction of working on a Saturday. However, a key aim of forecasting is to look at changes in behaviour. With the above approach, as the forecasts for each day are produced separately, then any changes in the scenario for say a weekday will not have any impact on the consumptions patterns observed for a Saturday. The forecasting approach is thus able to only account for the correlations between days in a base application but not for the effect this may have on redistribution across days in the case of a change from the base scenario.

3.3 Alternatives to base approach

It should be clear from the discussion in Section 3.2 that the application of the P&B routine at the day level makes it impossible for there to be any redistribution in activities across days, even if the model captures correlations that could reasonably be interpreted as grounds for such substitution to happen. Short of developing new model specifications (as discussed in Section 2.2) we now make initial attempts to adapt the approach from Section 3.1. Our discussions again focus on the case where we are making a prediction for a three day scenario covering a weekday (WD), Saturday (SAT) and Sunday (SUN), where the model estimation recovered separate parameters for these days, with correlations between them. We look at two possible approaches here, acknowledging that others are possible, and where for the second, we propose two versions.

3.3.1 Multi-day forecasting with separate outside goods

The forecasting routine in Section 3.1 works at the 24 hour level and needs to be applied separately for each day. With the three day example considered here, this approach would create, for person n, three separate $R \cdot K$ dimensional matrices of predicted consumptions. In our first departure from this approach, we now move away from the 24 hour budget and instead work with a budget of $L \cdot 24$ hours, where L is the number of days we make predictions for, in our case 3, such that the budget becomes 72. The algorithm will thus produce not three separate $R \cdot K$ matrices of predicted consumption, but a single $RxLK$ matrix, using $K' = LK$ activities, including L outside goods.

A number of changes are required to the base algorithm, as follows.

1. In step 1, we take a K' dimensional draw of extreme value errors, and similarly a $2K'$ dimensional vector of θ_n which now comprises δ and γ terms for different day types. If multiple days in the forecast are for the same day type, then the same draws from δ and γ would be used for those days. The subscript of day type is now dropped from γ and δ.

2. In step 2, we assume that all outside goods (i.e. one per day) are chosen and set $M = L$.

3. In step 3, the L outside goods are placed in first place, and the remaining $L \cdot (K-1)$ goods are put into descending order of utilities.

4. In step 4, Equation 5.5 is replaced by:

$$\lambda = \left(\frac{L \cdot 24 + \sum_{m=(L+1)}^{M} \gamma_{n,m}}{\sum_{m=1}^{L} \psi_{n,m}^{\frac{1}{1-\alpha}} + \sum_{m=(L+1)}^{M} \gamma_{n,m} \psi_{n,m}^{\frac{1}{1-\alpha}}} \right)^{\alpha-1} . \tag{5.8}$$

5. In step $5a$, we again start by creating a mapping index between the ordering of activities in our forecasting scenario (i.e. $k' = 1, \ldots, K'$) and the ordering of the activities from step 3

   Equations 5.6 and Equation 5.7 are then replaced by:

$$C_{n,l}^{(r)} = \left(\frac{\psi_{n,l}^{\frac{1}{1-\alpha}} \left(L \cdot 24 + \sum_{m=(L+1)}^{M} \gamma_{n,m} \right)}{\sum_{m=1}^{L} \psi_{n,m}^{\frac{1}{1-\alpha}} + \sum_{m=(L+1)}^{M} \gamma_{n,m} \psi_{n,m}^{\frac{1}{1-\alpha}}} \right), \forall l < (L+1), \tag{5.9}$$

   and

$$C_{n,k'_m}^{(r)} = \left(\frac{\psi_{n,m}^{\frac{1}{1-\alpha}} \left(L \cdot 24 + \sum_{l=(L+1)}^{M} \gamma_{n,l} \right)}{\sum_{l=1}^{L} \psi_{n,l}^{\frac{1}{1-\alpha}} + \sum_{l=(L+1)}^{l} \gamma_{n,l} \psi_{n,l}^{\frac{1}{1-\alpha}}} - 1 \right) \gamma_{n,m}, \; L < m \leq M \tag{5.10}$$

At this point, we are left with a $R \cdot K'$ matrix of predicted consumptions. However, these predictions do not enforce the day level 24 budget constraint, only the total $L \cdot 24$ hour constraint. In other words, we have that $\sum_l C_{n,l}^{(r)} = L \cdot 24, \forall n, r$, but not necessarily (or likely) that e.g. $\sum_{l=1}^{K} C_{n,l}^{(r)} = 24, \forall n, r$. The raw predictions thus need to be rescaled as follows:

$$\begin{aligned} \widehat{C_{n,l}^{(r)}} &= C_{n,l}^{(r)} \frac{24}{\sum_{k=1}^{K} C_{n,k}^{(r)}}, \; if \; 1 \leq l \leq K, \\ &\ldots \\ \widehat{C_{n,l}^{(r)}} &= C_{n,l}^{(r)} \frac{24}{\sum_{k=(L-1)*K+1}^{K'} C_{n,k}^{(r)}}, \; if \; (L-1)\,K < l \leq K' \end{aligned} \tag{5.11}$$

where this rescaling is performed prior to any averaging across draws.

3.3.2 Multi-day forecasting with single composite outside good

While the first proposed approach (Section 3.3.1) makes use of a $L \cdot 24$ hour budget with $K' = LK$ activities, including L outside goods, our second approach makes use of $K' = L(K-1)+1$ activities, using a single composite outside good. Behaviourally, this is consistent with a situation where an individual determines over the course of several days how much time to invest across the different inside activities, with all the remainder going into the outside good.

To arrive at such a single composite outside good, consider the consumer's problem of maximising $U = \sum_{l=1}^{L} \psi_{1l} \ln[x_l] + \sum_{l=1}^{L} \sum_{k=2}^{K} u_{kl}$, subject to L day-level time constraints $\sum_{k=1}^{K} x_{kl} = 24, \forall l = 1, 2, \ldots, L$. In this utility function, consider $\sum_{l=1}^{L} \psi_{1l} \ln[x_{1l}]$, which is the sum of utility accrued from outside goods on all L days. Now, define $\psi_1 \ln[x_1]$ as the utility accrued from a single composite outside good x_1, with ψ_1 as its baseline utility term. For x_1 to serve as the composite outside good, the following condition should be satisfied:

$$\left[Max \left(\sum_{l=1}^{L} \psi_{1l} \ln[x_{1l}] \right), \text{subject to} \left(x_1 = \sum_{l=1}^{L} x_{1l} \right) \right] = \psi_1 \ln[x_1]. \quad (5.12)$$

That is, the maximum utility accrued from all the outside goods subject to a constraint that $x_1 = \sum_{l=1}^{L} x_{1l}$ should be equal to the utility accrued from the single composite outside good. One can go through KKT conditions of optimality to derive the optimal time allocations to the original outside goods as $x_{1l}^{*} = x_1 \times \frac{\psi_{1l}}{\sum_{t=1}^{L} \psi_{1t}}$. Plugging this expression into $\sum_{l=1}^{L} \psi_{1l} \ln[x_{1l}^{*}]$, we get the following expression for maximum utility from all essential goods:

$$Max \left(\sum_{l=1}^{L} \psi_{1l} \ln[x_{1l}] \right) = \left(\sum_{l=1}^{L} \psi_{1l} \right) \ln(x_1) + \sum_{l=1}^{L} \psi_{1l} \ln \left(\frac{\psi_{1l}}{\sum_{t=1}^{L} \psi_{1t}} \right), \quad (5.13)$$

where the log formulation arises from $\alpha = 0$.

Next, the consumer's original utility maximisation problem mentioned at the beginning of this section may be expressed as:

$$Max \left[U = \left(\sum_{l=1}^{L} \psi_{1l} \right) \ln(x_1) + \sum_{l=1}^{L} \psi_{1l} \ln \left(\frac{\psi_{1l}}{\sum_{l=1}^{L} \psi_{1l}} \right) + \sum_{l=1}^{L} \sum_{k=2}^{K} u_{kl} \right], \quad (5.14)$$

subject to the following *single* time constraint: $x_1 + \sum_{l=1}^{L} \sum_{k=2}^{K} x_{kl} = L \cdot 24$.

This maximisation problem may further be rewritten as:

$$Max \left[U' = \left(\sum_{l=1}^{L} \psi_{1l} \right) \ln(x_1) + \sum_{l=1}^{L} \sum_{k=2}^{K} u_{kl} \right], \quad (5.15)$$

subject to $x_1+\sum_{l=1}^{L}\sum_{k=2}^{K}x_{kl}=L{\cdot}24$, because the term $\sum_{l=1}^{L}\psi_{1l}\ln\left(\frac{\psi_{1l}}{\sum_{l=1}^{L}\psi_{1l}}\right)$ is constant with respect to time allocations (which are the decision variables of the utility maximisation problem). Therefore, one can use the term $\left(\sum_{l=1}^{L}\psi_{1l}\right)\ln[x_1]$ to approximate the term $\left(\sum_{l=1}^{L}\psi_{1l}\ln[x_{1l}^{*}]\right)$ as a single composite good. To implement this for prediction purposes with a single composite outside good (representing multiple outside goods), we simulate a baseline utility that is equal to $\left(\sum_{l=1}^{L}\psi_{1l}\right)$ for the composite outside good.

In comparison with the approach with multiple outside goods, the changes required to the base algorithm are more limited, as follows.

- In step 1, we use the approach from the multi-day approach with separate outside goods when it comes to the $2K'$ dimensional vector of θ_n. For the extreme value terms, we also produce a vector of K' draws, however, the first three draws are then summed up to produce a composite error term for the composite outside good, leaving us with $L\,(K-1)+1$ error terms.
- This composite error term is then used in step 3 for the calculation of the baseline utility for the outside good.
- All other steps remain as in the P&B approach, with the difference that the budget is set to $L\cdot 24$ hours and that we work with $L\,(K-1)+1$ activities.

At this point, we are left with a $Rx\,(L\,(K-1)+1)$ matrix of predicted consumptions. Our first step consists of dividing the outside good up into L day-specific outside goods, again giving us a $R\cdot K'$ matrix of predicted consumptions. Two possibilities arise. In the first approach we evenly divide the prediction for the outside good across the L days. In the second approach, we recognise that some day types may see higher consumptions of the outside good and we make use of the sample level shares from the estimation data (i.e. what share of the outside good across L days is used on a given day) to guide the split across the L days[5]. Once this division has been performed, the same rescaling as described in Equation 5.11 is performed to ensure that the 24 hour level constraints are satisfied.

This approach thus allocates time to a single composite outside good and $L\,(K-1)$ inside goods, but where the utility of this outside good is greater than that of the single day outside goods in our other approach. A potential difference that arises between this approach and that using day-specific outside goods is that fewer corner solutions might arise for the inside goods with

[5]We acknowledge that other ways to split the outside good are possible, for example relative to the utilities of the individual outside goods, but in practice, we found little differences across these approaches in terms of overall results.

the composite outside good approach. This is the direct result of the way in which the P&B routine determines which activities to assign a non-zero consumption prior to determining the amount of continuous consumption, and the fact that the overall share (in terms of number of activities) for the inside goods is larger with the composite outside good approach ($L\left(K-1\right)$ out of $L\left(K-1\right)+1$ *vs* $L\left(K-1\right)$ out of $L \cdot K$).

3.4 Advantages and limitations

The discussions in this section have made clear the limitations of the standard P&B approach when used in the context of multi-day data where the model allows for correlations between days. With predictions produced separately for each day, no link is made between the consumptions for different days as a result of a change on a specific day. If for example the model retrieves positive correlation between the baseline utilities for working on a weekday and on a Saturday, then the forecasting approach will accommodate this correlation by predicting that someone who works more on a weekday will also work more on a Saturday (given that the random draws for δ are positively correlated). However, if an outside constraint were to affect working on a given weekday (leading to reduced consumption), this would have no impact on working on the Saturday, as that prediction comes from a separate 24 hour application of the model.

A different situation arises with our proposed alternatives. The consumption across all days and activities is predicted in a single step, prior to rescaling. The correlations in the baseline scenario would be dealt with in the same way as in the single day approach (e.g. someone who is likely to work more on a weekday will also work more on a Saturday). However, with these approaches, if an outside constraint were to affect working on a given weekday, then for someone who has a higher utility of weekday work, the utility of Saturday work will also be larger and this activity will thus get a greater time allocation in the joint forecast across days.

While the above points suggest greater realism of our forecasting approaches, it should also be acknowledged that the alternative approaches put forward in this paper are somewhat *ad hoc* and present departures from the estimated model in a different direction, namely moving away from the 24 hour budget, and then enforcing this through rescaling. Our empirical work in the remainder of the paper provides initial insights into both the issues with performing single day forecasting and any detrimental effects that the move to the $L \cdot 24$ hour budget in forecasting might entail.

4 Empirical application

4.1 Data

This paper makes use of two well-known surveys in the transport literature, the German travel survey *Mobidrive* and the Chilean study *Communities in Concepción*. The use of two different datasets, with a different number of observations (days) for each participant, is instrumental for interpreting and validating our results.

The *Mobidrive* project conducted a six-week travel diary in the two German cities of Karlsruhe and Halle, with data collection taking place in the autumn of 1999. The availability of trip purpose allowed us to transform the travel diary into a time use diary. We only exploited two weeks of data, in particular we selected the second and third week recorded by respondents, to avoid bias due to any learning effects that may have occurred at the very beginning of the survey. Further information about the data collection protocol and the sample can be found in Axhausen et al. (2002).

The *Communities in Concepción* project conducted a rich data collection effort in 2012 in the Chilean city of Concepción. The survey included a time use diary that participants had to fill in for two days, one weekday and one weekend day. Further information about the survey and the sample can be found in Moore et al. (2013).

We use a subset of the overall *Mobidrive* sample: we only included respondents who do not fail to report any activity for more than 4 days over the two weeks used for the analysis, ending up with a sample of 223 respondents. For *Concepción*, we removed respondents with extensive lack of data/activity type, which resulted in a sample of 234 people. Corrections were applied in a few cases where the overall number of hours within a day would exceed 24h, for example if a respondent recorded the start of his/her activity/trip before midnight and the end during the early hours of the next day.

Both studies relied on paper-and-pencil diaries, where participants were free to specify the purpose of their trip (in the case of *Mobidrive*) or the activities that they had conducted (in the case of Concepción). For modelling purposes, these activities were subsequently grouped into a number of macro categories, depending on what participants reported and what was considered to be most relevant for the specific geographical and cultural context. Table 5.1 reports the sample averages for the discrete choice (percentage of people performing a given activity) and continuous choice (time invested in the different activities when this is performed, in hours). We present the statistics separately for weekday and weekend day, and in the case of Mobidrive we have sufficient information to also separate Saturday from Sunday. Some of the activities are present in both samples, while other categories are specific to one of the datasets.

The first activity, *Basic Needs*, includes sleeping, eating meals at home and spending time at home for everyday essential tasks. Everybody in the

	Mobidrive						Concepción			
	Share participating			*Average time*			*Share participating*		*Average time*	
Activity	WD	SAT	SUN	WD	SAT	SUN	WD	WE	WD	WE
Basic Needs	100.00%	100.00%	100.00%	16.65	19.06	19.85	100.00%	100.00%	13.30	15.30
Work	41.75%	8.74%	3.59%	6.86	5.61	6.78	54.70%	13.68%	7.55	5.58
School	24.66%	2.02%	1.57%	5.30	3.01	5.85	-	-	-	-
Drop-off/Pick up	7.80%	7.85%	7.40%	0.71	0.42	0.54	14.10%	6.84%	0.43	0.72
Daily shopping	31.12%	36.10%	6.05%	0.60	0.69	0.29	-	-	-	-
Non daily shopping	14.53%	18.39%	2.47%	1.06	1.32	0.95	-	-	-	-
Social	24.08%	39.91%	42.15%	2.67	4.50	3.64	40.60%	55.56%	2.99	4.82
Leisure	19.46%	24.66%	29.15%	2.68	3.03	3.89	-	-	-	-
Private business	31.21%	16.82%	11.88%	1.15	1.42	0.98	-	-	-	-
Travel	97.26%	87.67%	79.82%	1.29	1.24	1.18	94.87%	81.62%	1.85	1.95
Family	-	-	-	-	-	-	11.97%	9.83%	3.57	3.41
Household obligations	-	-	-	-	-	-	26.50%	26.50%	4.48	5.39
Out-of-home recreation	-	-	-	-	-	-	12.82%	18.38%	2.46	2.74
In-home recreation	-	-	-	-	-	-	8.12%	11.97%	3.89	4.44
Services	-	-	-	-	-	-	16.24%	9.40%	1.66	2.51
Shopping	-	-	-	-	-	-	23.08%	26.50%	0.70	1.25
Study	-	-	-	-	-	-	20.51%	6.41%	4.24	4.02

Table 5.1: Average levels of continuous and discrete choice in the samples

sample performs this activity every day, and this allows us to treat it as the "outside good" in our models.

Most of the categories in Table 5.1 are self-explanatory. *Work* refers to all work and work related activities. *School* refers to schooling and education activities. We choose to keep this separate from *Study*, defined for the Chilean context, as the latter did not include children, so this category refers to higher education or individual study. *Private business* includes personal errands, such as going to the bank, dentist, hairdresser (these correspond to the category *Services* in the Chilean context) with the addition of other personal activities. *Shopping* is an aggregated category in the Chilean data, although it is mainly believed to be groceries shopping, while it is split into daily and non-daily in *Mobidrive*.

4.2 Model specification and estimation

In the specification of our MDCEV models, we used a generic α across all activities including the outside good, which was found empirically to be very close to zero, along with a separate γ parameter for every inside good. Day-specific parameters were estimated to allow for day-level differences, while random heterogeneity was also accommodated both in the baseline utility constants and in the translation parameters. A base model and one including basic socio-demographic characteristics are estimated. In the latter case, we simply allowed for a deterministic shift in the baseline utility constants (δ) of each activity for male respondents (identical across days). This is by no means a full specification and was included purely for illustration purposes.

For the random parameters in *Mobidrive*, we use Normal distributions for the δ parameters and positive Lognormal distributions for the γ parameters (to ensure consistency with the modelling framework). For *Concepción*, we use negative Lognormals for δ and positive Lognormals for γ. The distributional assumptions for δ were arrived at by empirical testing of different possibilities. With both datasets, a full covariance matrix was estimated, to allow for correlation between all the model parameters.

As mentioned earlier, we make use of Bayesian estimation techniques to deal with the high number of parameters to be estimated, where we specifically make use of the *RSGHB* package (Dumont et al., 2015) from the R libraries (R Core Team, 2016). We use noninformative (diffuse) priors and make use of $300,000$ burn-in iterations to guarantee stable chains prior to averaging across iterations of the posteriors.

4.2.1 Mobidrive estimation results

The *Mobidrive* estimation results are presented in Table 5.2. As expected, we obtain a better log-likelihood (LL) for the model with the gender effect, where the improvement in fit is significant, as shown by a likelihood ratio test ($p \sim 1.6^{-5}$).

We first report the means and standard deviations across iterations for the Bayesian posteriors of both the mean and variances of the underlying Normal distribution (i.e. for the logarithm of γ). As mentioned earlier, the full covariance matrix between all random parameters was estimated, and this was used in the computation of correlations discussed below, where, because of space constraints, the full covariance matrix for each model is reported in Appendix B. As discussed in Train (2001), these means and standard deviations of the posteriors have similar properties to maximum likelihood estimates and standard errors, respectively. Next to these, we provide the actual means (μ) and standard deviations (σ) for δ and γ, as used in the model. For *Mobidrive*, the δ parameters are normally distributed, and no transformation is needed, while the means and standard deviations for the lognormally distributed γ terms are calculated analytically from the means and standard deviations of the underlying Normals.

Looking at the resulting parameters for the base model, we observe that most of the baseline utility parameters are negative, mainly reflecting the discrete choice and indicating that the outside good (used as a base) is always "preferred", with respect to the inside goods, as everybody in the sample always chooses it. The value of the δ coefficients can also be affected by the continuous choice, so that it is possible to obtain positive δ coefficients for popular inside goods such as $Travel_{WD}$. This also motivates the use of a Normal distribution (instead of negative Lognormals, like in the *Concepción* case) for the δ parameters in this model. The γ parameters mainly describe the continuous choice, indicating that people spend most time in, i.e. they get less satiated by, *Work* on weekdays and on Sunday (this is reflected in the data on average time spent in different activities presented in Table 5.1), although the high standard deviations suggest large variation across people.

The results clearly show substantially different sensitivities during weekday and weekend days. In addition, they reveal substantial random heterogeneity (the σ parameters), highlighting that different people have different sensitivities, both in terms of the participation and in the time invested in different activities. Turning to deterministic heterogeneity, a comparison with the model including gender effects shows no substantial differences in the δ parameters on average. Larger changes are present in the γ parameters, for example in the case of *Drop-off/Pick-up* on Saturday, where we observe lower satiation in the model with the gender effect. The fixed shifts suggest that men are less likely to perform both daily and non daily shopping and more likely to perform leisure activities.

We next turn our attention to the correlations between the different model parameters, which we report in Table 5.3. For each of the 9 activities (inside goods), we present correlations between the δ and γ parameters across each

			Base model						Model with gender effect					
		Final LL	-24,707.60						-24,673.78					
		Parameters	1,539						1,548					
			Bayesian posteriors				**Resulting parameters**		**Bayesian posteriors**				**Resulting parameters**	
			μ_N		σ_N^2				μ_N		σ_N^2			
	Activity	**parameter**	mean	sd	mean	sd	μ	σ	mean	sd	mean	sd	μ	σ
parameters for baseline utilities	*Work*	δ_{WD}	-4.18	0.24	10.39	1.56	-4.18	3.22	-4.25	0.25	10.05	1.25	-4.25	3.17
		δ_{SAT}	-5.33	0.12	1.09	0.36	-5.33	1.04	-6.14	0.15	1.82	0.27	-6.14	1.35
		δ_{SUN}	-6.64	0.14	1.68	0.30	-6.64	1.29	-5.99	0.09	0.28	0.19	-5.99	0.53
		Δ_{male}	-	-	-	-	-	-	0.23	0.16	-	-	0.23	-
	School	δ_{WD}	-5.86	0.25	11.18	1.27	-5.86	3.34	-6.28	0.34	16.03	1.96	-6.28	4.00
		δ_{SAT}	-7.01	0.10	1.47	0.22	-7.01	1.21	-7.30	0.12	1.34	0.29	-7.30	1.16
		δ_{SUN}	-7.40	0.12	1.35	0.22	-7.40	1.16	-7.05	0.13	1.29	0.30	-7.05	1.13
		Δ_{male}	-	-	-	-	-	-	-0.33	0.28	-	-	-0.33	-
	Drop-off/ Pick-up	δ_{WD}	-5.99	0.14	2.08	0.33	-5.99	1.44	-6.12	0.16	2.40	0.40	-6.12	1.55
		δ_{SAT}	-5.93	0.13	1.11	0.36	-5.93	1.05	-5.66	0.11	0.40	0.14	-5.66	0.64
		δ_{SUN}	-5.92	0.15	1.14	0.19	-5.92	1.07	-5.63	0.11	0.95	0.20	-5.63	0.97
		Δ_{male}	-	-	-	-	-	-	-0.02	0.17	-	-	-0.02	-
	Daily shopping	δ_{WD}	-4.00	0.10	1.28	0.18	-4.00	1.13	-3.76	0.09	0.94	0.14	-3.76	0.97
		δ_{SAT}	-3.35	0.06	0.23	0.07	-3.35	0.48	-3.54	0.12	0.48	0.19	-3.54	0.69
		δ_{SUN}	-5.84	0.08	0.44	0.09	-5.84	0.66	-5.48	0.07	0.27	0.09	-5.48	0.52
		Δ_{male}	-	-	-	-	-	-	-0.32	0.11	-	-	-0.32	-
	Non daily shopping	δ_{WD}	-4.68	0.05	0.24	0.05	-4.68	0.49	-4.41	0.06	0.12	0.04	-4.41	0.35
		δ_{SAT}	-4.48	0.05	0.17	0.05	-4.48	0.42	-4.29	0.08	0.34	0.07	-4.29	0.58
		δ_{SUN}	-6.64	0.08	0.14	0.04	-6.64	0.38	-6.60	0.08	0.34	0.10	-6.60	0.58
		Δ_{male}	-	-	-	-	-	-	-0.44	0.10	-	-	-0.44	-
	Social	δ_{WD}	-4.21	0.08	0.78	0.13	-4.21	0.88	-4.24	0.11	0.83	0.13	-4.24	0.91
		δ_{SAT}	-3.47	0.09	0.46	0.11	-3.47	0.68	-3.64	0.08	0.46	0.10	-3.64	0.68
		δ_{SUN}	-3.45	0.08	0.51	0.11	-3.45	0.71	-3.38	0.10	0.22	0.06	-3.38	0.47
		Δ_{male}	-	-	-	-	-	-	0.11	0.11	-	-	0.11	-
	Leisure	δ_{WD}	-4.76	0.12	1.74	0.28	-4.76	1.32	-4.82	0.14	1.54	0.23	-4.82	1.24
		δ_{SAT}	-4.20	0.09	0.81	0.16	-4.20	0.90	-4.51	0.10	0.64	0.18	-4.51	0.80
		δ_{SUN}	-4.09	0.11	0.96	0.18	-4.09	0.98	-4.10	0.13	0.84	0.15	-4.10	0.92
		Δ_{male}	-	-	-	-	-	-	0.28	0.15	-	-	0.28	-
	Private business	δ_{WD}	-3.79	0.07	0.55	0.09	-3.79	0.74	-3.80	0.08	0.57	0.11	-3.80	0.76
		δ_{SAT}	-4.60	0.10	0.31	0.11	-4.60	0.56	-4.51	0.09	0.18	0.07	-4.51	0.43
		δ_{SUN}	-5.05	0.11	0.55	0.10	-5.05	0.74	-5.05	0.16	0.24	0.08	-5.05	0.49
		Δ_{male}	-	-	-	-	-	-	-0.01	0.10	-	-	-0.01	-
	Travel	δ_{WD}	0.87	0.09	0.25	0.06	0.87	0.50	0.78	0.08	0.22	0.05	0.78	0.47
		δ_{SAT}	-0.80	0.08	0.11	0.04	-0.80	0.33	-0.67	0.09	0.49	0.16	-0.67	0.70
		δ_{SUN}	-1.35	0.11	0.45	0.11	-1.35	0.67	-1.36	0.09	0.30	0.08	-1.36	0.55
		Δ_{male}	-	-	-	-	-	-	0.08	0.06	-	-	0.08	-
translation parameters	*Work*	γ_{WD}	1.63	0.14	3.03	0.51	23.28	103.15	1.73	0.14	3.09	0.49	26.42	121.13
		γ_{SAT}	1.23	0.09	0.33	0.09	4.03	2.53	0.87	0.09	1.11	0.24	4.18	5.98
		γ_{SUN}	1.93	0.14	0.62	0.17	9.41	8.71	1.92	0.09	0.46	0.12	8.62	6.57
	School	γ_{WD}	0.75	0.12	0.72	0.18	3.04	3.11	1.15	0.14	1.65	0.34	7.18	14.73
		γ_{SAT}	0.16	0.12	0.52	0.12	1.53	1.26	-0.01	0.10	0.68	0.14	1.39	1.37
		γ_{SUN}	1.67	0.09	0.35	0.08	6.34	4.08	1.88	0.16	0.85	0.20	9.97	11.50
	Drop-off/ Pick-up	γ_{WD}	-0.99	0.08	0.35	0.06	0.44	0.28	-1.09	0.11	0.58	0.13	0.45	0.40
		γ_{SAT}	-1.86	0.11	1.13	0.21	0.27	0.40	-0.55	0.11	0.44	0.12	0.72	0.53
		γ_{SUN}	-0.22	0.16	1.82	0.33	1.99	4.53	-0.94	0.13	1.04	0.23	0.65	0.89
	Daily shopping	γ_{WD}	-1.03	0.06	0.32	0.06	0.42	0.26	-1.17	0.09	0.20	0.09	0.34	0.16
		γ_{SAT}	-1.17	0.06	0.10	0.04	0.33	0.10	-1.07	0.06	0.13	0.06	0.36	0.13
		γ_{SUN}	-1.16	0.13	0.34	0.12	0.37	0.24	-1.96	0.16	0.38	0.11	0.17	0.12
	Non daily shopping	γ_{WD}	-0.46	0.09	0.07	0.03	0.66	0.18	-0.50	0.08	0.07	0.02	0.63	0.17
		γ_{SAT}	-0.34	0.08	0.56	0.10	0.94	0.81	-0.36	0.07	0.25	0.05	0.79	0.42
		γ_{SUN}	0.53	0.10	0.43	0.09	2.12	1.56	-0.09	0.10	0.62	0.14	1.24	1.14
	Social	γ_{WD}	0.55	0.06	0.18	0.08	1.90	0.86	0.72	0.13	0.23	0.05	2.31	1.17
		γ_{SAT}	1.19	0.07	0.11	0.05	3.48	1.21	1.09	0.10	0.21	0.06	3.31	1.61
		γ_{SUN}	0.64	0.12	0.08	0.03	1.98	0.59	0.52	0.07	0.07	0.03	1.73	0.46
	Leisure	γ_{WD}	0.37	0.14	0.12	0.05	1.53	0.54	0.56	0.07	0.13	0.04	1.87	0.69
		γ_{SAT}	0.88	0.08	0.11	0.06	2.54	0.87	0.72	0.07	0.23	0.10	2.30	1.16
		γ_{SUN}	1.04	0.10	0.20	0.07	3.13	1.49	0.84	0.09	0.12	0.04	2.47	0.88
	Private business	γ_{WD}	-0.74	0.06	0.14	0.07	0.51	0.20	-0.81	0.07	0.16	0.03	0.48	0.20
		γ_{SAT}	-0.16	0.12	0.61	0.10	1.16	1.06	-0.71	0.06	0.26	0.07	0.56	0.31
		γ_{SUN}	-0.93	0.15	1.15	0.19	0.70	1.03	-1.34	0.10	0.46	0.12	0.33	0.25
	Travel	γ_{WD}	-3.63	0.09	0.09	0.03	0.03	0.01	-3.56	0.09	0.09	0.04	0.03	0.01
		γ_{SAT}	-2.29	0.09	0.07	0.04	0.11	0.03	-2.52	0.07	0.29	0.08	0.09	0.05
		γ_{SUN}	-2.00	0.07	0.24	0.08	0.15	0.08	-1.95	0.05	0.13	0.04	0.15	0.06

Table 5.2: Mobidrive - Estimation results

pair of days j and k, both for the model with and without a gender effect. Interestingly, there are significant changes in the correlations between the two models, and it is not necessarily the case that the introduction of gender effects reduces the correlation in the unobserved heterogeneity, as might have been expected. Focussing on a few examples, we can see that the baseline utility constant for *Work* shows high levels of correlation across different days, with lower correlations between weekday and Sunday as well as Saturday and Sunday when the male effect is included in the model, as expected. Using the same activity as an example in the base model, we observe a negative correlation between the time invested in *Work* during weekdays and Saturdays, as well as weekdays and Sundays, while the correlation is positive between the two weekend days. Therefore, while people who work on weekdays are more likely to also work on weekends, the amount of time they spend working is likely to be negatively correlated.

Of course, we could not report all the possible correlations between all the model coefficients due to space constraints. In the lower part of the table we include some additional correlations that we considered of interest. Here, we specify the two activities and the respective days (in the order in which the activities are listed). As an example, we observe that there is a positive correlation between performing *Drop-off/Pick-up* and *Travel* on a Sunday, an effect which is stable in both the model with and without the gender effect. The correlation, although rather low, is positive also in terms of amount of time invested in these activities.

4.2.2 Concepción estimation results

The *Concepción* estimation results are presented in Table 5.4. As in the case of *Mobidrive*, we first present the statistics on the Bayesian posteriors before turning to the transformed parameters, where this time, as mentioned above, we use a negative Lognormal for the baseline utility constants and a positive Lognormal for the translation parameters.

The base model shows that the means of δ_{WD} and δ_{WE} for *Travel* are the least negative, reflecting the fact that this is the most popular activity after the outside good. For some activities, such as *Work*, the coefficients differ between weekday and weekend, showing that people are less likely to perform work activities during the weekend, while in the case of other activities, such as *Household Obligations* or *In-home recreation*, the difference is not as strong. A similar reasoning can be applied to the γ parameters to interpret the time investment in the different activities.

The model with gender effects shows reduced utility for men for *Household Obligations*, with increased utility for *In-home recreation* and *Shopping*. As in the *Mobidrive* case, we can see that there is substantial variation not only across days but also across people in sensitivities. This is particularly

		Base model		With gender	
Activity	Day	$corr(\delta_j, \delta_k)$	$corr(\gamma_j, \gamma_k)$	$corr(\delta_j, \delta_k)$	$corr(\gamma_j, \gamma_k)$
	WD-SAT	0.71	-0.13	0.93	-0.13
Work	WD-SUN	0.61	-0.10	0.17	0.16
	SAT-SUN	0.77	0.54	0.19	-0.19
	WD-SAT	0.67	0.64	0.62	-0.05
School	WD-SUN	0.85	0.46	0.67	0.37
	SAT-SUN	0.88	-0.03	0.64	-0.37
	WD-SAT	0.81	-0.14	0.73	0.13
Drop-off/ Pick-up	WD-SUN	0.68	0.40	0.74	0.45
	SAT-SUN	0.38	-0.12	0.57	0.67
	WD-SAT	0.67	0.47	0.80	0.74
Daily shopping	WD-SUN	0.60	0.61	0.69	0.48
	SAT-SUN	0.48	0.16	0.49	0.23
	WD-SAT	0.09	0.05	0.48	-0.37
Non daily shopping	WD-SUN	0.17	-0.07	0.39	0.34
	SAT-SUN	0.32	-0.08	0.03	-0.19
	WD-SAT	0.85	0.36	0.77	0.37
Social	WD-SUN	0.84	0.20	0.77	-0.37
	SAT-SUN	0.79	0.18	0.66	-0.11
	WD-SAT	0.90	0.29	0.91	0.05
Leisure	WD-SUN	0.87	0.36	0.88	0.47
	SAT-SUN	0.85	0.42	0.92	0.26
	WD-SAT	0.76	0.58	0.76	0.61
Private business	WD-SUN	0.66	0.56	0.46	0.31
	SAT-SUN	0.34	0.67	0.28	0.50
	WD-SAT	0.58	0.26	-0.01	-0.43
Travel	WD-SUN	0.52	0.47	-0.08	-0.19
	SAT-SUN	0.62	0.23	0.75	0.35
Daily shopping & Non daily shopping	SUN-SUN	0.39	-0.25	0.69	0.64
Drop-off/ Pick-up & Travel	SUN-SUN	0.79	0.13	0.75	0.15
Leisure & Travel	SUN-SUN	0.58	0.33	0.60	0.08
School & Daily shopping	WD-WD	-0.64	-0.39	-0.70	-0.35
	WD-SAT	-0.42	-0.37	-0.66	-0.26
School & Non daily shopping	WD-WD	-0.60	0.11	-0.70	0.09
Social & Private business	SAT-SUN	0.25	-0.13	0.61	-0.41
Social & Travel	SAT-SUN	0.61	0.24	0.69	0.39
Work & School	WD-WD	-0.55	-0.04	-0.52	-0.04
Work & Social	SUN-SUN	-0.28	0.32	-0.53	0.45

Table 5.3: Mobidrive - Key correlations

pronounced in the case of *Household Obligations* and *Work*.

Selected correlations between the model parameters are reported in Table 5.5. We observe high positive correlations in the δ parameters for *Household Obligations*, *Study* and *In-home recreation*, with the first two being stable across the two models. The correlation for *Work* is positive but not as high as in the *Mobidrive* data, while the negative correlation in the γ between the weekday and the weekend day is relatively weak.

As in the *Mobidrive* case, we present some additional correlations between the coefficients related to different activities, both for the same day and across different days. For example, we find a positive correlation in the baseline utility constant of *Drop-off/ Pick-up* and *Work* on a weekday, possibly suggesting that the same people perform both activities on that day, although the time spent is negatively correlated. While the signs are maintained, the magnitude of the effects is again slightly stronger in the model with the gender effect. On the contrary, a negative correlation in the δ parameter on the same day (weekday) is observed for *Out-of-home recreation* and *Work*; this could be due to the fact that these are both activities that are quite time-intensive and so, if performed, require a relatively high time investment.

4.3 Forecasting examples

We next turn to the results of model application using the different forecasting approaches presented in Section 3. In what follows, for ease of presentation, we use the following labelling for the different approaches:

Approach A The base approach using predictions at the day level, with a separate 24 hour budget for each day (see Section 3.1)

Approach B Our approach using multi-day forecasting with separate outside goods for each day, followed by rescaling to satisfy the 24 constraint for each day (see Section 3.3.1)

Approach C1 Our approach using multi-day forecasting with a single composite outside good, followed by rescaling to satisfy the 24 constraint for each day, where the outside good is split evenly into L parts before rescaling (see Section 3.3.2)

Approach C2 Like approach C1, but where the split of the composite outside good before rescaling takes into account the split from the data used in estimation (see Section 3.3.2)

As discussed in detail below, we look at forecasts for 3 or 4 days with *Mobidrive*, and 2 days with *Concepción*. We apply the different forecasting approaches using 250 MLHS draws (Hess et al., 2006) per individual.

4.3.1 Preliminary appraisal

As discussed in Section 3, our proposed alternatives to the base approach are not theoretically in line with the estimated model. From that perspective, it becomes important to test the reasonableness of the forecasts not just in terms of the implied substitution patterns (which will almost surely be better for our proposed approaches given that they allow for cross-day substitution) but also in terms of the *quality* of the base forecasts, i.e. predictions under a *do nothing* scenario. We do this by looking both at how likely the predictions are according to the estimated model (i.e. calculating the log-likelihood for the prediction) and what the total utility of the predicted consumptions is across

			Base model						***Model with gender effect***					
		Final LL	***-5,051.03***						***-5,030.01***					
		Parameters	***1,034***						***1,045***					
			Bayesian posteriors				**Resulting parameters**		**Bayesian posteriors**				**Resulting parameters**	
			μ_N		σ^2_N				μ_N		σ^2_N			
	Activity	**parameter**	mean	sd	mean	sd	μ	σ	mean	sd	mean	sd	μ	σ
parameters for baseline utilities	*Work*	δ_{WD}	0.97	0.05	0.06	0.03	-2.72	0.66	1.00	0.05	0.08	0.04	-2.84	0.29
		δ_{WE}	1.55	0.04	0.03	0.02	-4.80	0.87	1.58	0.05	0.04	0.02	-4.93	0.19
		Δ_{male}	-	-	-	-	-	-	0.29	0.20	-	-	-	-
	Drop-off/ Pick-up	δ_{WD}	1.51	0.04	0.03	0.02	-4.60	0.85	1.51	0.05	0.04	0.03	-4.63	0.21
		δ_{SAT}	1.72	0.05	0.03	0.02	-5.70	1.07	1.73	0.05	0.04	0.02	-5.74	0.20
		Δ_{male}	-	-	-	-	-	-	0.07	0.32	-	-	-	-
	Social	δ_{WD}	1.12	0.04	0.03	0.01	-3.12	0.55	1.16	0.04	0.02	0.01	-3.22	0.15
		δ_{WE}	0.97	0.04	0.03	0.01	-2.68	0.46	1.03	0.04	0.03	0.02	-2.85	0.19
		Δ_{male}	-	-	-	-	-	-	0.31	0.16	-	-	-	-
	Travel	δ_{WD}	-1.29	0.15	0.03	0.02	-0.28	0.05	-1.82	0.15	0.03	0.03	-0.16	0.18
		δ_{WE}	0.52	0.09	0.04	0.03	-1.72	0.37	0.40	0.08	0.13	0.07	-1.59	0.36
		Δ_{male}	-	-	-	-	-	-	0.20	0.14	-	-	-	-
	Family	δ_{WD}	1.53	0.05	0.03	0.02	-4.70	0.83	1.56	0.06	0.04	0.03	-4.84	0.20
		δ_{WE}	1.64	0.06	0.03	0.02	-5.20	0.84	1.61	0.06	0.03	0.01	-5.08	0.16
		Δ_{male}	-	-	-	-	-	-	-0.14	0.33	-	-	-	-
	Household obligations	δ_{WD}	1.40	0.07	0.23	0.10	-4.55	2.30	1.27	0.07	0.14	0.05	-3.82	0.38
		δ_{WE}	1.42	0.05	0.13	0.05	-4.39	1.63	1.33	0.05	0.09	0.05	-3.95	0.30
		Δ_{male}	-	-	-	-	-	-	-0.81	0.28	-	-	-	-
	Out-of-home recreation	δ_{WD}	1.53	0.05	0.05	0.03	-4.77	1.13	1.60	0.05	0.06	0.03	-5.11	0.25
		δ_{WE}	1.49	0.06	0.05	0.03	-4.54	1.02	1.49	0.04	0.04	0.02	-4.54	0.20
		Δ_{male}	-	-	-	-	-	-	0.31	0.26	-	-	-	-
	In-home recreation	δ_{WD}	1.64	0.06	0.04	0.03	-5.27	1.11	1.81	0.10	0.08	0.04	-6.35	0.28
		δ_{WE}	1.61	0.08	0.05	0.04	-5.16	1.18	1.73	0.08	0.08	0.04	-5.84	0.28
		Δ_{male}	-	-	-	-	-	-	0.91	0.37	-	-	-	-
	Services	δ_{WD}	1.43	0.04	0.02	0.01	-4.24	0.55	1.46	0.05	0.02	0.01	-4.33	0.13
		δ_{WE}	1.62	0.04	0.02	0.01	-5.11	0.78	1.65	0.06	0.04	0.03	-5.33	0.20
		Δ_{male}	-	-	-	-	-	-	0.20	0.28	-	-	-	-
	Shopping	δ_{WD}	1.34	0.04	0.02	0.01	-3.87	0.60	1.41	0.04	0.03	0.02	-4.16	0.17
		δ_{WE}	1.34	0.05	0.03	0.02	-3.87	0.64	1.38	0.04	0.04	0.02	-4.03	0.19
		Δ_{male}	-	-	-	-	-	-	0.40	0.21	-	-	-	-
	Study	δ_{WD}	1.41	0.06	0.05	0.02	-4.21	0.93	1.44	0.05	0.05	0.03	-4.32	0.22
		δ_{WE}	1.79	0.09	0.06	0.04	-6.16	1.58	1.74	0.08	0.05	0.02	-5.85	0.22
		Δ_{male}	-	-	-	-	-	-	0.05	0.30	-	-	-	-
translation parameters	*Work*	γ_{WD}	1.74	0.16	0.07	0.08	5.91	1.64	1.64	0.13	0.07	0.05	5.34	1.47
		γ_{WE}	1.56	0.15	0.03	0.02	4.83	0.89	2.05	0.23	0.06	0.03	7.98	1.91
	Drop-off/ Pick-up	γ_{WD}	-1.76	0.10	0.04	0.02	0.18	0.03	-1.54	0.13	0.04	0.02	0.22	0.04
		γ_{SAT}	-0.76	0.18	0.03	0.02	0.47	0.09	-1.07	0.14	0.06	0.04	0.35	0.09
	Social	γ_{WD}	0.62	0.11	0.03	0.03	1.89	0.34	0.40	0.14	0.03	0.02	1.52	0.26
		γ_{WE}	0.49	0.09	0.04	0.03	1.65	0.32	0.75	0.06	0.03	0.02	2.14	0.38
	Travel	γ_{WD}	-2.08	0.11	0.02	0.01	0.13	0.02	-2.26	0.10	0.03	0.02	0.11	0.02
		γ_{WE}	-0.92	0.18	0.04	0.03	0.41	0.09	-1.24	0.08	0.04	0.03	0.29	0.06
	Family	γ_{WD}	0.55	0.15	0.03	0.02	1.76	0.30	0.92	0.10	0.04	0.03	2.56	0.51
		γ_{WE}	1.45	0.15	0.07	0.04	4.42	1.16	0.74	0.16	0.03	0.02	2.12	0.37
	Household obligations	γ_{WD}	0.90	0.10	0.03	0.02	2.49	0.41	1.08	0.07	0.04	0.03	3.01	0.61
		γ_{WE}	1.38	0.25	0.05	0.04	4.08	0.92	1.79	0.16	0.05	0.03	6.11	1.32
	Out-of-home recreation	γ_{WD}	0.48	0.11	0.04	0.03	1.65	0.32	-0.34	0.09	0.05	0.03	0.73	0.16
		γ_{WE}	0.69	0.08	0.03	0.02	2.02	0.36	0.68	0.12	0.05	0.04	2.02	0.46
	In-home recreation	γ_{WD}	0.91	0.10	0.04	0.03	2.52	0.52	1.44	0.16	0.05	0.03	4.31	0.94
		γ_{WE}	1.58	0.10	0.03	0.02	4.92	0.92	1.18	0.14	0.04	0.03	3.30	0.64
	Services	γ_{WD}	0.13	0.12	0.04	0.03	1.16	0.23	-0.02	0.16	0.04	0.03	1.00	0.20
		γ_{WE}	1.08	0.16	0.07	0.05	3.05	0.80	0.77	0.08	0.03	0.02	2.19	0.37
	Shopping	γ_{WD}	-0.88	0.16	0.03	0.02	0.42	0.08	-0.77	0.14	0.04	0.03	0.47	0.10
		γ_{WE}	-0.37	0.19	0.04	0.02	0.70	0.13	-0.16	0.14	0.04	0.03	0.87	0.18
	Study	γ_{WD}	1.08	0.12	0.03	0.02	2.98	0.53	0.93	0.14	0.06	0.03	2.61	0.64
		γ_{WE}	1.34	0.09	0.04	0.04	3.90	0.83	0.39	0.13	0.09	0.08	1.55	0.49

Table 5.4: Concepción - Estimation results

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		Base model		With gender	
Activity	**Day**	$corr(\delta_j, \delta_k)$	$corr(\gamma_j, \gamma_k)$	$corr(\delta_j, \delta_k)$	$corr(\gamma_j, \gamma_k)$
Work	WD-WE	0.46	-0.16	0.48	-0.14
Drop-off/ Pick-up	WD-WE	0.12	0.10	0.43	-0.36
Social	WD-WE	0.11	0.25	0.11	-0.01
Travel	WD-WE	-0.10	-0.17	0.28	-0.16
Family	WD-WE	0.02	0.30	0.02	0.02
Household obligations	WD-WE	0.85	-0.10	0.84	-0.21
Out-of-home recreation	WD-WE	0.60	0.06	0.56	-0.28
In-home recreation	WD-WE	0.57	-0.04	0.73	-0.12
Services	WD-WE	0.01	0.22	-0.22	-0.29
Shopping	WD-WE	0.01	-0.11	0.30	0.31
Study	WD-WE	0.67	-0.07	0.65	0.24
Drop-off/ Pick-up & Work	WD-WD	0.44	-0.43	0.59	-0.26
Work & Household obligations	WD-WE	0.55	-0.31	0.58	0.34
Shopping & Travel	WE-WE	0.13	0.27	0.52	0.30
Drop-off/ Pick-up & Family	WD-WD	0.44	-0.30	0.51	0.20
Work & Shopping	WD-WE	0.39	-0.31	0.36	0.13
Household obligations & Out-of-home recreation	WE-WE	-0.62	-0.06	-0.62	-0.25
Out-of-home recreation & Work	WD-WD	-0.59	-0.13	-0.64	0.34
Household obligations & Out-of-home recreation	WD-WD	-0.49	-0.14	-0.65	-0.09
Study & Work	WD-WD	-0.56	0.03	-0.66	0.34
In-home recreation & Travel	WE-WE	-0.50	-0.25	-0.72	0.41

Table 5.5: Concepción - Key correlations

all individuals. The use of the log-likelihood could be affected by a greater share of corner solutions in some forecasts, which is likely to inflate it (as they are easy to explain) and this is the reason for looking at other measures too. For the utility calculations, a key reason is to see which approach provides the maximum utility. One would expect Approach A to yield forecasts with maximum utility according to the estimated model. The second reason is to assess how suboptimal the utility of time allocations from the alternative approaches is (since they are not based on the estimated model). We are able to perform this calculation on the raw forecasts which do not enforce the day-level constraints as well as on the rescaled ones. In addition, we compare the predicted discrete and continuous consumptions to those from the estimation data by means of a root mean square error (RMSE).

An overview of the findings is given in Table 5.6. In terms of LL, we observe that approaches C1 and C2 give very similar fit, where C1 is always better than C2. More importantly, both C1 and C2 outperform approaches A and B, where B is always better than A, though it is closer to A than C1 and C2 in the case of *Mobidrive*. While these differences in LL provide some reassurance about the use of our approaches, they raise the question of why they perform better than the approach which is consistent with the estimated model (A). The answer would seem to lie in the fact that while approach A explicitly recognises the 24 hour constraint, it fails to accommodate the correlation across different days. This *disadvantage* seems to outweigh the *advantage* approach A has over B and C in terms of theoretical consistency. The advantage of approach C1 and C2 seems to be down the use of a composite outside good which leads to fewer corner solutions for the inside goods than the use of separate outside goods for each day in approach B. The latter predicts more corner solutions than those actually present in the data, while approaches C1 and C2 produce a prediction which is closer to what is observed in reality. In the *Mobidrive* data, we can compute the average of the discrete choice (which for each person and each activity on a given day takes value 0 or 1) across all people and all inside goods at the 3 day level, which gives 0.27. This is equivalent to stating that on average across all people and all inside activities, the probability of conducting an inside activity is 27% (or conversely a probability of 73% of a corner solution). Looking at this share as predicted by the different forecasting approaches, we see that approach A predicts this to be 0.24, while it is 0.19 with approaches C1 and C2. However, with approach B, it is only 0.12, with similar patterns in the other application runs. This implies that approach B predicts on average a share of corner solutions of 0.88, which is higher than in the case of the other approaches. This is in line with the earlier hypothesis in Section 3.3.2.

These differences in the predicted shares of respondents participating in different activities leads us directly to the RMSE measures, where we look at the differences between the predicted values and the ones actually observed in the data, for both discrete and continuous. For *Mobidrive*, we see that the C approaches perform best for the continuous consumption, and A performs worst. B is not too different from C1 and C2 in the continuous, but worse for discrete. For *Concepción*, approaches C1, C2 and B however perform badly for the continuous choice as they in fact overestimate the consumption of the outside good across the two days.

We finally turn our attention to the total utilities for the forecast. We see that these are similar for the different approaches, but are slightly better for approach A in all cases, which reflects the fact that this approach is in line with the estimated model. However, the loss in utility for approaches B and C is small. It is interesting to see that the utility of the different approaches before the rescaling to meet the 24 hour constraint is applied is much higher. Approach B is greatly penalised by the rescaling. An important area for future work is to look at ways for the forecasting to benefit from the $L \cdot 24$ allocation while respecting day level constraints and thus not requiring rescaling.

4.3.2 Mobidrive - Forecasting results

In this section, we present detailed results for the different forecasting approaches applied to the *Mobidrive* dataset. Table 5.7 presents the detailed results for the application with 3 days, including a Friday, a Saturday and a Sunday, while in Table 5.8 we add an additional weekday. In addition to the *do nothing* scenario, we look at a forecast scenario in which a change is made. In the absence of detailed explanatory variables, we look at a situation where

				LL for forecast using estimated model	*Utility of consumption*	*Utility of consumption before rescaling*	*RMSE vs data for continuous consumption*	*RMSE vs data for discrete consumption*
Mobidrive	3 days	Base model	Approach A	-2,043.40	155,510.88	-	0.57	0.03
			Approach B	-1,921.85	154,999.52	205,900.88	0.32	0.16
			Approach C1	-1,559.39	155,297.61	158,614.68	0.29	0.09
			Approach C2	-1,564.38	155,296.55	159,850.18	0.28	0.09
		With gender	Approach A	-1,987.85	154,963.08	n/a	0.52	0.04
			Approach B	-1,905.62	154,362.57	204,904.84	0.36	0.17
			Approach C1	-1,521.64	154,759.63	157,715.96	0.32	0.09
			Approach C2	-1,525.80	154,758.41	158,951.47	0.32	0.09
	4 days	Base model	Approach A	-2,792.49	167,178.24	n/a	0.56	0.03
			Approach B	-2,614.20	165,969.48	233,066.88	0.43	0.19
			Approach C1	-1,893.44	166,798.58	170,831.69	0.41	0.10
			Approach C2	-1,900.85	166,796.52	170,473.57	0.42	0.10
		With gender	Approach A	-2,736.61	168,744.14	n/a	0.52	0.04
			Approach B	-2,612.34	167,235.39	234,685.64	0.47	0.19
			Approach C1	-1,871.73	168,366.19	172,794.46	0.45	0.10
			Approach C2	-1,877.33	168,364.04	172,436.34	0.45	0.10
Concepcion	2 days	Base model	Approach A	-2,080.13	39,172.62	n/a	0.24	0.05
			Approach B	-1,724.88	38,760.58	45,373.11	0.50	0.14
			Approach C1	-1,710.35	38,999.36	42,524.61	0.55	0.10
			Approach C2	-1,714.65	38,998.62	42,475.57	0.55	0.10
		With gender	Approach A	-2,050.42	43,266.13	n/a	0.25	0.05
			Approach B	-1,750.78	42,957.59	50,298.50	0.47	0.14
			Approach C1	-1,694.62	43,091.81	47,341.17	0.52	0.09
			Approach C2	-1,698.92	43,091.15	47,292.13	0.52	0.09

Table 5.6: Overview of the forecasting approaches

working on a Friday becomes less attractive for some reason, and where we subtract half the absolute mean of the randomly distributed δ for *Work*. This implies that people will not gain as much utility from *Work* on that day. In practical terms, this could be associated to a situation when someone has some errands to perform on a Friday, so he/she could decide to work less or not work at all (i.e. have a corner solution). The Tables show percentage changes (averages across the sample) in the discrete consumption, i.e. in the number of people who perform the activity, and changes in the continuous consumption, i.e. in time invested in the different activities (average time across all people, not only those who perform the activity).

Approach A is the base forecasting procedure, which forecasts according to the model, i.e. at the 24 hour level. There is a 51.17% reduction in the share of people who go to work on Friday (base model), while we see an increase in the share of people performing other activities. It is worth remembering that there is no change in the outside good as it is always consumed by everyone in the sample, by definition. When it comes to the continuous choice, we observe redistribution within the day: in the base model, there is, on average, a 73.31% decrease in the time allocated to *Work* and an increase in time allocated to other activities; the vast majority of this decrease comes from those people who move to corner solutions, and there are far smaller changes in the time use for those who do not change their discrete choice. This increase is not equal across activities and is driven in part by the estimated correlations. Given that the forecasting is performed at the day level, we do not observe any substitution across days.

Moving on to the other approaches, we see similar percentage reductions in the share of people performing the activity as well as in the time allocation to *Work* on the Friday, but also a redistribution to *Work* on Saturday and Sunday, implying that if unable to work on Friday, people will compensate on the weekend days. Approaches B, C1 and C2 all show a similar reallocation to Saturday and Sunday in the base model, while in the model with gender effects, the reallocation is much higher to Saturday than to Sunday. These results are in line with the correlations across the different days for *Work* presented in Table 5.3.

As explained in Section 3.2, we can include more than one day of the same type, in our case weekdays. We perform the forecasting exercise with four days, assuming we include a Thursday, a Friday, a Satuday and a Sunday. In this case, we apply the change to the baseline utility of *Work* on the Thursday. The average percentage reduction in time spent at work on the Thursday, similarly to the case of the Friday in the 3-day example, is higher than 70% (cf. Table 5.8). We observe here that the substitution to Saturday and Sunday is much higher than the one to Friday. This is due to the fact that Thursday and Friday are two identical days prior to the change in the baseline utility (and notwithstanding the use of different extreme value draws), and the base consumption for *Work* is high on the Friday already. If a person cannot work on a Thursday, he/she will only be able to allocate a small extra amount of work on a Friday, while he/she might be able to allocate more hours to make up for the time lost during the weekend. This is also true for the discrete part of the model.

As in the 3-day case, we observe that the base model redistributes time more evenly from Thursday to Saturday and Sunday (reflecting correlations, respectively, of 0.71 and 0.61), while in the model with the gender effect, the difference is larger (reflecting correlations, respectively, of 0.93 and 0.17).

4.3.3 Concepción - Forecasting results

The detailed results for the forecasting application to the *Concepción* data are reported in Table 5.9. We will only comment briefly on those as most of the considerations reported for the *Mobidrive* data also apply in this case. We again subtract $0.5 * \mu$ from δ_{WD} for the *Work* activity. We see that the percentage reduction in the share of people performing *Work* during the weekday is similar for all approaches across the model with and without the gender effect, although it is slightly higher in the case of approach B. A higher reduction in the average continuous time allocation to *Work* on the weekday is observed for approach A. The approaches also differ in the pattern of time

			Base model				With gender			
			Approach A	Approach B	Approach C1	Approach C2	Approach A	Approach B	Approach C1	Approach C2
Change in share participating	Friday	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**-51.17%**	**-57.51%**	**-54.82%**	**-54.82%**	**-52.45%**	**-58.63%**	**-56.09%**	**-56.09%**
		School	2.72%	0.69%	0.90%	0.90%	2.61%	0.56%	1.03%	1.03%
		Drop-off/ Pick-up	13.46%	6.96%	4.81%	4.81%	14.10%	5.49%	6.05%	6.05%
		Daily shopping	9.73%	4.09%	3.87%	3.87%	10.35%	3.66%	4.21%	4.21%
		Non daily shopping	12.43%	6.06%	4.96%	4.96%	14.26%	6.50%	5.43%	5.43%
		Social	11.46%	4.75%	4.75%	4.75%	12.01%	4.38%	4.63%	4.63%
		Leisure	9.71%	3.22%	3.45%	3.45%	10.14%	4.08%	4.03%	4.03%
		Private business	10.84%	4.51%	4.39%	4.39%	10.35%	3.99%	4.48%	4.48%
		Travel	0.41%	0.24%	0.16%	0.16%	0.41%	0.21%	0.15%	0.15%
	Saturday	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**0.00%**	**14.20%**	**11.33%**	**11.33%**	**0.00%**	**21.79%**	**15.42%**	**15.42%**
		School	0.00%	0.51%	2.50%	2.50%	0.00%	1.62%	2.40%	2.40%
		Drop-off/ Pick-up	0.00%	5.43%	5.51%	5.51%	0.00%	5.35%	5.43%	5.43%
		Daily shopping	0.00%	5.26%	4.67%	4.67%	0.00%	4.91%	4.36%	4.36%
		Non daily shopping	0.00%	4.16%	4.31%	4.31%	0.00%	8.27%	5.99%	5.99%
		Social	0.00%	4.20%	4.02%	4.02%	0.00%	4.40%	4.01%	4.01%
		Leisure	0.00%	4.94%	4.35%	4.35%	0.00%	4.68%	4.76%	4.76%
		Private business	0.00%	4.32%	5.10%	5.10%	0.00%	5.45%	4.29%	4.29%
		Travel	0.00%	1.88%	1.27%	1.27%	0.00%	1.40%	1.10%	1.10%
	Sunday	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**0.00%**	**15.13%**	**11.84%**	**11.84%**	**0.00%**	**6.44%**	**6.75%**	**6.75%**
		School	0.00%	2.05%	1.41%	1.41%	0.00%	1.33%	1.71%	1.71%
		Drop-off/ Pick-up	0.00%	6.33%	5.55%	5.55%	0.00%	3.33%	3.81%	3.81%
		Daily shopping	0.00%	4.70%	4.95%	4.95%	0.00%	4.79%	4.07%	4.07%
		Non daily shopping	0.00%	4.26%	4.82%	4.82%	0.00%	2.38%	2.90%	2.90%
		Social	0.00%	5.85%	5.10%	5.10%	0.00%	5.25%	4.71%	4.71%
		Leisure	0.00%	3.32%	3.59%	3.59%	0.00%	3.73%	3.83%	3.83%
		Private business	0.00%	4.29%	5.04%	5.04%	0.00%	5.12%	5.08%	5.08%
		Travel	0.00%	2.23%	2.04%	2.04%	0.00%	2.12%	2.04%	2.04%
Change in average consumption in sample population	Friday	Outside good	9.48%	7.65%	7.73%	8.01%	9.66%	7.77%	7.92%	8.20%
		Work	**-73.31%**	**-74.12%**	**-75.37%**	**-75.16%**	**-74.70%**	**-75.50%**	**-76.63%**	**-76.43%**
		School	2.11%	0.90%	1.26%	1.31%	2.12%	1.11%	1.44%	1.49%
		Drop-off/ Pick-up	11.06%	8.40%	7.65%	7.89%	11.75%	9.24%	8.40%	8.65%
		Daily shopping	12.72%	9.06%	8.44%	8.72%	13.54%	9.05%	8.95%	9.24%
		Non daily shopping	13.83%	9.88%	9.38%	9.62%	14.27%	9.34%	9.90%	10.16%
		Social	11.22%	6.14%	7.32%	7.52%	12.49%	6.90%	8.13%	8.36%
		Leisure	9.57%	5.58%	6.19%	6.36%	10.24%	6.20%	6.73%	6.91%
		Private business	10.65%	7.96%	7.49%	7.70%	10.48%	7.23%	7.27%	7.47%
		Travel	12.56%	9.75%	10.02%	10.34%	13.20%	10.18%	10.58%	10.92%
	Saturday	Outside good	0.00%	-0.56%	-0.48%	-0.47%	0.00%	-0.56%	-0.51%	-0.51%
		Work	**0.00%**	**12.31%**	**8.88%**	**8.86%**	**0.00%**	**22.81%**	**16.44%**	**16.44%**
		School	0.00%	1.09%	0.82%	0.82%	0.00%	0.84%	0.88%	0.88%
		Drop-off/ Pick-up	0.00%	2.50%	1.72%	1.72%	0.00%	2.57%	1.72%	1.72%
		Daily shopping	0.00%	2.13%	1.64%	1.64%	0.00%	2.28%	1.52%	1.52%
		Non daily shopping	0.00%	2.74%	1.87%	1.87%	0.00%	3.84%	2.68%	2.68%
		Social	0.00%	2.66%	2.43%	2.43%	0.00%	2.31%	2.25%	2.24%
		Leisure	0.00%	2.52%	2.25%	2.24%	0.00%	2.35%	2.04%	2.04%
		Private business	0.00%	1.04%	1.39%	1.39%	0.00%	2.04%	1.60%	1.60%
		Travel	0.00%	0.55%	0.24%	0.25%	0.00%	0.25%	0.16%	0.16%
	Sunday	Outside good	0.00%	-0.50%	-0.40%	-0.38%	0.00%	-0.43%	-0.34%	-0.32%
		Work	**0.00%**	**13.99%**	**9.98%**	**9.94%**	**0.00%**	**3.69%**	**3.60%**	**3.57%**
		School	0.00%	1.21%	1.05%	1.05%	0.00%	2.11%	1.87%	1.86%
		Drop-off/ Pick-up	0.00%	1.92%	1.28%	1.28%	0.00%	1.98%	1.49%	1.49%
		Daily shopping	0.00%	1.60%	1.48%	1.47%	0.00%	0.39%	0.80%	0.80%
		Non daily shopping	0.00%	2.84%	3.05%	3.03%	0.00%	1.45%	0.87%	0.87%
		Social	0.00%	3.88%	3.04%	3.02%	0.00%	3.46%	2.62%	2.60%
		Leisure	0.00%	2.17%	2.01%	2.00%	0.00%	2.72%	2.15%	2.14%
		Private business	0.00%	1.97%	1.36%	1.36%	0.00%	3.55%	2.21%	2.19%
		Travel	0.00%	1.32%	0.72%	0.72%	0.00%	1.22%	0.83%	0.82%

Table 5.7: Mobidrive - 3 day forecasting approaches

redistribution across different activities during the weekday. This is again largely a result of the differences in the rates of conducting activities.

As explained above, we see no redistribution to the weekend day for approach A, while the other approaches redistribute time especially to *Work* on the weekend day (in line with the correlations), although there are differences between the model with and without gender. These differences are again a result of different correlation patterns in the two models, this time not in terms of work on a WD and WE, but between WD work and other activities, both on a weekday and weekend.

5 Conclusions

The MDCEV modelling framework has established itself as a preferred method for modelling time allocation, with data very often coming from travel or activity diaries. However, while many of these datasets contain information on multiple days for the same individual, the standard modelling approach has treated each day in isolation. This paper has made the case that not only does this miss out on important links between days, but it potentially leads to issues also in forecasting.

We started by discussing possible ways of accommodating links across days within an MDCEV framework. While the implementation of a non-additive utility function would be the theoretically correct way to accommodate the complementarities and substitutions across days, such an approach is very difficult to estimate and apply in practice, especially with budget constraints at the day and multi-day level. We instead rely on additive utility functions where we accommodate correlation between activities at the within-day and between-day level. This can be accommodated through a mixed MDCEV model, with multi-variate random distributions.

While the use of a mixed MDCEV model in this manner allows us to capture correlations across days without the use of non-additive utility functions and by relying on a simple day-level budget, it raises the issue of how to allow for substitution across days in model application, i.e. forecasting. We discuss how the standard Pinjari and Bhat (2010) approach will fail to make this link and instead propose two different adaptations of this algorithm that relax the 24 hour constraint in forecasting and then reinstate it through rescaling.

We illustrate the issue and the methods using two different datasets, a 2-day activity diary from *Concepción* (Chile) and two weeks of the six weeks *Mobidrive* study (Germany). Our estimation work confirms the presence of deterministic and random heterogeneity, and crucially in the context of the present paper, correlations both at the within-day and between-day level. We then test the proposed forecasting approaches, showing that they lead to more behaviourally meaningful results than the simple day-level forecasts.

			Base model				With gender			
			Approach A	Approach B	Approach C1	Approach C2	Approach A	Approach B	Approach C1	Approach C2
Change in share participating	Thursday	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**-51.13%**	**-63.66%**	**-56.47%**	**-56.47%**	**-52.10%**	**-65.36%**	**-57.90%**	**-57.90%**
		School	2.59%	0.37%	0.68%	0.68%	2.45%	0.33%	0.64%	0.64%
		Drop-off/ Pick-up	13.11%	2.80%	3.33%	3.33%	13.80%	3.81%	3.97%	3.97%
		Daily shopping	9.98%	2.14%	2.62%	2.62%	10.38%	2.45%	2.72%	2.72%
		Non daily shopping	13.58%	3.18%	2.99%	2.99%	14.40%	4.11%	3.77%	3.77%
		Social	11.49%	2.84%	2.79%	2.79%	12.15%	3.16%	3.51%	3.51%
		Leisure	9.19%	1.56%	2.20%	2.20%	10.18%	3.90%	2.09%	2.09%
		Private business	10.78%	1.44%	2.75%	2.75%	10.61%	2.17%	2.74%	2.74%
		Travel	0.37%	0.39%	0.15%	0.15%	0.30%	0.17%	0.13%	0.13%
	Friday	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**0.00%**	**3.01%**	**1.78%**	**1.78%**	**0.00%**	**2.96%**	**1.74%**	**1.74%**
		School	0.00%	0.12%	0.74%	0.74%	0.00%	-0.06%	0.66%	0.66%
		Drop-off/ Pick-up	0.00%	2.39%	2.80%	2.80%	0.00%	1.80%	2.61%	2.61%
		Daily shopping	0.00%	1.67%	2.57%	2.57%	0.00%	1.89%	2.68%	2.68%
		Non daily shopping	0.00%	2.12%	3.72%	3.72%	0.00%	2.05%	3.85%	3.85%
		Social	0.00%	2.58%	2.52%	2.52%	0.00%	3.21%	2.92%	2.92%
		Leisure	0.00%	1.85%	2.61%	2.61%	0.00%	2.28%	2.48%	2.48%
		Private business	0.00%	2.72%	2.80%	2.80%	0.00%	2.40%	2.56%	2.56%
		Travel	0.00%	0.45%	0.11%	0.11%	0.00%	0.27%	0.10%	0.10%
	Saturday	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**0.00%**	**7.48%**	**6.42%**	**6.42%**	**0.00%**	**13.94%**	**9.24%**	**9.24%**
		School	0.00%	0.00%	1.17%	1.17%	0.00%	1.88%	2.11%	2.11%
		Drop-off/ Pick-up	0.00%	2.72%	3.17%	3.17%	0.00%	2.34%	3.00%	3.00%
		Daily shopping	0.00%	2.74%	2.91%	2.91%	0.00%	3.28%	3.02%	3.02%
		Non daily shopping	0.00%	1.91%	2.85%	2.85%	0.00%	4.46%	4.65%	4.65%
		Social	0.00%	2.22%	2.72%	2.72%	0.00%	2.04%	2.82%	2.82%
		Leisure	0.00%	2.01%	3.02%	3.02%	0.00%	1.63%	2.91%	2.91%
		Private business	0.00%	0.89%	2.92%	2.92%	0.00%	2.86%	2.97%	2.97%
		Travel	0.00%	1.27%	0.97%	0.97%	0.00%	0.93%	0.78%	0.78%
	Sunday	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**0.00%**	**10.64%**	**7.52%**	**7.52%**	**0.00%**	**4.49%**	**3.74%**	**3.74%**
		School	0.00%	0.58%	2.01%	2.01%	0.00%	-0.47%	1.39%	1.39%
		Drop-off/ Pick-up	0.00%	3.29%	3.82%	3.82%	0.00%	3.36%	2.28%	2.28%
		Daily shopping	0.00%	2.41%	3.11%	3.11%	0.00%	2.62%	2.98%	2.98%
		Non daily shopping	0.00%	1.24%	2.61%	2.61%	0.00%	0.00%	1.90%	1.90%
		Social	0.00%	3.40%	3.38%	3.38%	0.00%	2.48%	2.96%	2.96%
		Leisure	0.00%	2.46%	2.09%	2.09%	0.00%	2.61%	2.32%	2.32%
		Private business	0.00%	1.70%	2.63%	2.63%	0.00%	2.26%	3.38%	3.38%
		Travel	0.00%	1.47%	1.34%	1.34%	0.00%	1.40%	1.55%	1.55%
Change in average consumption in sample population	Thursday	Outside good	9.61%	7.19%	7.40%	7.67%	9.80%	7.36%	7.57%	7.85%
		Work	**-73.73%**	**-77.02%**	**-76.76%**	**-76.55%**	**-75.03%**	**-78.34%**	**-77.98%**	**-77.77%**
		School	2.17%	0.80%	1.09%	1.13%	2.17%	0.86%	1.18%	1.22%
		Drop-off/ Pick-up	11.68%	7.34%	7.01%	7.26%	12.66%	7.63%	7.74%	8.01%
		Daily shopping	12.32%	7.43%	7.10%	7.34%	13.14%	7.39%	7.52%	7.77%
		Non daily shopping	14.04%	6.85%	8.09%	8.35%	14.92%	8.03%	8.63%	8.91%
		Social	11.40%	5.80%	6.28%	6.47%	12.51%	6.55%	7.05%	7.25%
		Leisure	9.77%	4.19%	5.22%	5.37%	10.37%	5.63%	5.59%	5.74%
		Private business	10.64%	5.20%	6.10%	6.29%	10.30%	5.25%	5.93%	6.13%
		Travel	12.62%	9.29%	9.20%	9.52%	13.19%	9.54%	9.69%	10.02%
	Friday	Outside good	0.00%	-0.27%	-0.19%	-0.20%	0.00%	-0.22%	-0.20%	-0.21%
		Work	**0.00%**	**2.32%**	**1.00%**	**1.00%**	**0.00%**	**1.96%**	**1.04%**	**1.04%**
		School	0.00%	-0.03%	0.20%	0.20%	0.00%	0.01%	0.17%	0.17%
		Drop-off/ Pick-up	0.00%	-0.16%	0.58%	0.58%	0.00%	-0.01%	0.48%	0.48%
		Daily shopping	0.00%	0.15%	0.64%	0.64%	0.00%	0.13%	0.67%	0.67%
		Non daily shopping	0.00%	0.41%	1.10%	1.10%	0.00%	0.46%	1.11%	1.11%
		Social	0.00%	0.97%	0.98%	0.99%	0.00%	1.43%	1.06%	1.06%
		Leisure	0.00%	0.88%	0.90%	0.91%	0.00%	1.07%	1.02%	1.02%
		Private business	0.00%	0.80%	0.70%	0.70%	0.00%	0.22%	0.58%	0.58%
		Travel	0.00%	-0.50%	-0.06%	-0.06%	0.00%	-0.64%	-0.07%	-0.08%
	Saturday	Outside good	0.00%	-0.29%	-0.28%	-0.27%	0.00%	-0.30%	-0.28%	-0.27%
		Work	**0.00%**	**8.41%**	**5.18%**	**5.15%**	**0.00%**	**14.83%**	**9.06%**	**9.05%**
		School	0.00%	0.17%	0.34%	0.33%	0.00%	1.23%	0.85%	0.85%
		Drop-off/ Pick-up	0.00%	2.04%	1.08%	1.07%	0.00%	0.68%	0.91%	0.90%
		Daily shopping	0.00%	0.63%	1.14%	1.13%	0.00%	0.98%	1.26%	1.26%
		Non daily shopping	0.00%	1.32%	1.32%	1.31%	0.00%	3.19%	1.90%	1.89%
		Social	0.00%	1.56%	1.70%	1.69%	0.00%	1.41%	1.53%	1.52%
		Leisure	0.00%	1.47%	1.45%	1.44%	0.00%	1.12%	1.24%	1.23%
		Private business	0.00%	0.00%	0.95%	0.94%	0.00%	0.82%	0.85%	0.84%
		Travel	0.00%	0.52%	0.24%	0.25%	0.00%	0.51%	0.19%	0.19%
	Sunday	Outside good	0.00%	-0.25%	-0.23%	-0.22%	0.00%	-0.21%	-0.20%	-0.19%
		Work	**0.00%**	**11.57%**	**6.84%**	**6.80%**	**0.00%**	**4.55%**	**2.48%**	**2.45%**
		School	0.00%	0.40%	0.88%	0.87%	0.00%	0.02%	1.81%	1.81%
		Drop-off/ Pick-up	0.00%	1.51%	0.83%	0.82%	0.00%	1.27%	0.80%	0.79%
		Daily shopping	0.00%	-0.61%	1.19%	1.18%	0.00%	0.53%	0.66%	0.65%
		Non daily shopping	0.00%	1.89%	1.82%	1.80%	0.00%	-1.81%	0.63%	0.62%
		Social	0.00%	2.43%	2.02%	2.00%	0.00%	1.86%	1.75%	1.73%
		Leisure	0.00%	1.55%	1.32%	1.31%	0.00%	1.65%	1.39%	1.37%
		Private business	0.00%	0.35%	0.77%	0.77%	0.00%	0.51%	1.43%	1.43%
		Travel	0.00%	0.54%	0.53%	0.53%	0.00%	0.74%	0.59%	0.59%

Table 5.8: Mobidrive - 4 day forecasting approaches

			Base model				With gender			
			Approach A	Approach B	Approach C1	Approach C2	Approach A	Approach B	Approach C1	Approach C2
Change in share participating	Weekday	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**-60.58%**	**-65.97%**	**-64.36%**	**-64.36%**	**-60.86%**	**-66.92%**	**-65.32%**	**-65.32%**
		Drop-off/ Pick-up	18.19%	8.04%	10.27%	10.27%	18.62%	10.12%	10.01%	10.01%
		Social	12.74%	5.83%	6.69%	6.69%	12.20%	5.72%	6.42%	6.42%
		Travel	1.80%	1.12%	1.18%	1.18%	1.47%	0.85%	0.90%	0.90%
		Family	19.91%	9.77%	10.77%	10.77%	18.82%	8.92%	10.12%	10.12%
		Household obligations	14.20%	7.29%	7.47%	7.47%	15.26%	8.07%	8.21%	8.21%
		Out-of-home recreation	12.99%	6.11%	6.92%	6.92%	12.18%	5.29%	5.80%	5.80%
		In-home recreation	14.53%	6.74%	7.13%	7.13%	14.85%	5.57%	7.73%	7.73%
		Services	16.17%	7.54%	8.38%	8.38%	16.25%	7.30%	8.32%	8.32%
		Shopping	13.47%	6.75%	7.72%	7.72%	14.09%	6.63%	7.35%	7.35%
		Study	12.64%	6.54%	6.69%	6.69%	12.05%	5.37%	6.32%	6.32%
	Weekend	Outside good	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		Work	**0.00%**	**9.19%**	**9.82%**	**9.82%**	**0.00%**	**9.41%**	**9.93%**	**9.93%**
		Drop-off/ Pick-up	0.00%	9.91%	9.66%	9.66%	0.00%	8.81%	10.98%	10.98%
		Social	0.00%	5.99%	6.18%	6.18%	0.00%	5.36%	6.11%	6.11%
		Travel	0.00%	3.78%	3.80%	3.80%	0.00%	3.03%	3.29%	3.29%
		Family	0.00%	8.24%	7.87%	7.87%	0.00%	7.00%	6.98%	6.98%
		Household obligations	0.00%	6.92%	8.36%	8.36%	0.00%	7.98%	8.28%	8.28%
		Out-of-home recreation	0.00%	6.95%	7.27%	7.27%	0.00%	6.61%	7.27%	7.27%
		In-home recreation	0.00%	6.54%	7.45%	7.45%	0.00%	4.42%	5.62%	5.62%
		Services	0.00%	6.65%	8.33%	8.33%	0.00%	6.65%	9.25%	9.25%
		Shopping	0.00%	8.12%	8.79%	8.79%	0.00%	7.56%	8.40%	8.40%
		Study	0.00%	5.76%	5.96%	5.96%	0.00%	4.44%	6.08%	6.08%
Change in average consumption in sample population	Weekday	Outside good	10.96%	4.40%	0.34%	-5.10%	11.10%	3.29%	-0.96%	-6.35%
		Work	**-67.88%**	**-60.19%**	**-59.15%**	**-60.03%**	**-68.65%**	**-61.98%**	**-60.92%**	**-61.77%**
		Drop-off/ Pick-up	20.01%	14.54%	30.70%	26.48%	21.46%	14.75%	29.90%	25.76%
		Social	14.25%	31.37%	38.68%	35.12%	14.56%	27.65%	34.80%	31.18%
		Travel	13.51%	7.52%	22.90%	18.88%	13.84%	5.26%	21.02%	17.04%
		Family	19.70%	32.52%	42.92%	39.31%	20.45%	38.87%	46.02%	42.56%
		Household obligations	17.06%	37.18%	43.45%	40.03%	18.07%	41.15%	46.53%	43.14%
		Out-of-home recreation	13.16%	26.54%	34.73%	31.03%	12.02%	13.74%	24.27%	20.40%
		In-home recreation	13.53%	33.84%	41.19%	37.66%	14.48%	41.89%	45.92%	42.56%
		Services	17.40%	27.17%	37.92%	34.12%	16.74%	23.02%	34.94%	31.12%
		Shopping	15.77%	15.40%	27.29%	23.37%	15.87%	13.96%	25.91%	21.98%
		Study	13.42%	36.03%	41.76%	38.31%	11.72%	32.78%	38.29%	34.86%
	Weekend	Outside good	0.00%	-9.87%	-12.62%	-7.56%	0.00%	-9.10%	-11.88%	-6.80%
		Work	**0.00%**	**35.60%**	**38.90%**	**42.17%**	**0.00%**	**45.14%**	**46.18%**	**49.19%**
		Drop-off/ Pick-up	0.00%	2.00%	15.29%	19.21%	0.00%	-2.38%	12.61%	16.53%
		Social	0.00%	17.38%	24.34%	27.92%	0.00%	21.43%	28.28%	31.77%
		Travel	0.00%	0.01%	12.17%	15.98%	0.00%	-1.05%	12.03%	15.86%
		Family	0.00%	32.56%	36.30%	39.60%	0.00%	19.97%	26.40%	29.95%
		Household obligations	0.00%	31.58%	34.73%	37.89%	0.00%	35.72%	37.58%	40.69%
		Out-of-home recreation	0.00%	21.14%	28.04%	31.53%	0.00%	21.95%	28.99%	32.49%
		In-home recreation	0.00%	30.36%	34.33%	37.51%	0.00%	27.40%	31.13%	34.39%
		Services	0.00%	26.96%	31.74%	35.21%	0.00%	22.61%	30.54%	34.04%
		Shopping	0.00%	6.72%	16.55%	20.29%	0.00%	10.58%	19.61%	23.29%
		Study	0.00%	25.91%	31.05%	34.35%	0.00%	16.19%	24.84%	28.39%

Table 5.9: Concepción - forecasting approaches

We also show that the loss in terms of utility of these "alternative" approaches is relatively small when compared to the theoretically correct model. The fact that we obtain consistent insights from two different datasets adds further empirical weight to our paper.

As always, there is substantial scope for further work, both in terms of refined model specification at the empirical end (e.g. other distributions and more covariates) and in terms of further theoretical work, be it with other forecasting approaches or the incorporation of substitution between days at the model level. We believe that the work conducted here is a first step in this direction and further empirical testing of our approaches on other data is thus welcome too.

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Chapter 6

Mode choice with latent availability and consideration: theory and a case study

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Abstract

Over the last two decades, passively collected data sources, like Global Positioning System (GPS) traces from data loggers and smartphones, have emerged as a very promising source for understanding travel behaviour. Most choice model applications in this context have made use of data collected specifically for choice modelling, which often has high costs associated with it. On the other hand, many other data sources exist in which respondents' movements are tracked. These data sources have thus far been underexploited for choice modelling. Indeed, although some information on the chosen mode and basic socio-demographic data is collected in such surveys, they (as well as in fact also some purpose collected surveys) lack information on mode availability and consideration. This paper addresses the data challenges by estimating a mode choice model with probabilistic availability and consideration, using a secondary dataset consisting of "annotated" GPS traces. Exploiting stated mode availability by part of the sample allowed the specification of an availability component, while the panel nature of the data and explicit incorporation of spatial and environmental factors enabled estimation of latent trip specific consideration sets. The research thus addresses an important behavioural issue (explicit modelling of availability and choice set) in addition to enriching the data for choice modelling purposes. The model produces reasonable results, including meaningful value of travel time (VTT) measures.

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Our findings further suggest that a better understanding of modes choices can be obtained by looking jointly at availability, consideration and choice.

1 Introduction

In recent years, there has been increasing interest in using ubiquitous data sources for behavioural modelling in different fields of research.

The concept of *ubiquitous data* has been defined as "such data that emerges in an asynchronous, decentralized way from many different, loosely coupled, partially overlapping, possibly contradicting sources" (Hoto et al., 2010). In most of the literature, it is used to convey the idea of "being everywhere". Practitioners thus use the term ubiquitous to refer to the continuous stream of data automatically generated from distributed mobile and/or embedded devices. They are usually very large in volume and/or very detailed (e.g. GPS and mobile phone trajectories, smart card and credit card transactions, etc.), though there are exceptions (e.g. automatic passenger counts, aggregate ticket sales data) and their collection is not intrusive or particularly demanding for respondents. Often, all they are asked to do is to authorise data collection from a device that they would carry with them at all times in any case, while in some cases, there is no *user* involvement at all. Semi-ubiquitous data refers to the variant of the data, where the data collection is semi-automatic: that is, it requires some (usually minimal) input from the users, like correcting their passively collected trajectories or adding details about their trips.

In the context of transport and mobility, GPS data (collected via different devices, such as black boxes in cars, portable loggers or smartphones) have been used since the mid-90s.

Most of the existing research has focussed on improving GPS data quality using smoothing and map matching techniques (Quddus et al., 2007) and identifying trip details like departure time, trip purpose (e.g. Chen et al., 2010; Schuessler and Axhausen, 2009; Shen and Stopher, 2013; Stopher et al., 2008) and travel mode (e.g. Bohte and Maat, 2009; Chen et al., 2010; Feng and Timmermans, 2014; Schuessler and Axhausen, 2009; Sheung and Shalaby, 2006). Some research efforts also focused on the assessment of public transport infrastructures (Bullock and Jiang, 2003); traffic flows and similar phenomena (Quiroga et al., 2002), analysis of individual travel behaviour patterns (Broach et al., 2012) and evaluation of policies (Stopher et al., 2009). Several studies have compared the quality of GPS data with phone and paper recall surveys and traditional travel diaries to find under-reporting in the latter (Casas and Arce, 1999; Kelly et al., 2013; Murakami and Wagner, 1999).

However, despite the better accuracy, lower costs, lower respondent burden and availability of multiple observations for the same traveller, the use of the GPS data in econometric models of travel behaviour has been primarily limited to models for route (e.g. Bierlaire et al., 2010; Bierlaire and Frejinger, 2008; Broach et al., 2012; Dhakar and Srinivasan, 2014; Hess et al., 2015; Prato, 2009), destination (e.g. Huang and Levinson, 2015; Miyashita et al., 2008) and tour pattern (Iqbal et al., 2013) choice. The lack of attention paid to mode choice is believed to be mainly due to the lack of information about the attributes of the unchosen (and in some cases the chosen) alternative(s) and absence of information regarding the characteristics of the decision makers and their choice sets – this is quite different in a mode choice context from, for example, a route choice context.

A first research issue that this paper aims to address at least in part is thus how analysts can better accommodate mode availability and consideration when working with GPS data. Existing studies have suggested a number of different approaches to deal with consideration in choice models (Cantillo and de Dios Ortúzar, 2005; Cascetta and Papola, 2001; Manski, 1977; Swait and Ben-Akiva, 1987). We address this by proposing a latent class approach which treats mode availability and consideration in a probabilistic manner, with the former being at the person level and the latter at the trip level.

Applications using GPS data in travel behaviour modelling also generally rely on data collected specifically for that purpose. However, because of the relative ease of collecting these data, more and more businesses, research centres and public institutions have started to set up projects for diverse purposes that are different from travel behaviour modelling, such as detecting congestion flows or simply providing an accessible overview of mobility in a city or limited area by different visualisation techniques.

Our second research aim thus concerns the specific nature and source of the GPS data. A rapidly growing source of data for choice modelling has been smartphone application-based surveys, where users are provided with automatically inferred trip details (e.g. time-stamped origin-destinations, routes, etc.) and asked to input additional information and/or correct the details on their smartphone or in a web-portal (e.g. Cottrill et al., 2013; Jariyasunant et al., 2011). When such data are collected with the specific purpose of travel behaviour modelling, those in charge of the surveys will ensure the collection of the required information for their survey aims. However, as mentioned above, a wealth of GPS data is collected for purposes other than travel behaviour modelling, and the investigation of whether and how these sources can be used for our analyses is our second research question. In the context of such *non-customised data*, dealing with mode availability and consideration is even more complex. The development of methodologies and techniques able to overcome some of the challenges related to these data could be the key to accessing a valuable resource and gaining new insights into travel behaviour.

This paper attempts to address both of the above questions (use of data collected for non-modelling reasons, and accommodating unobserved mode availability and consideration) using a dataset from Italy consisting of "tagged" GPS traces where the trips, passively recorded by a smartphone GPS application, were subsequently annotated by respondents with trip modes and purposes.

The remainder of this paper is organised as follows. The next section presents the data used in our study. This is followed in the third section by a presentation of the modelling approach adopted, while the fourth section details the empirical application and reports the estimation results. The last section concludes the paper with discussion of the insights gained through this modelling experiment and outlines potential future research directions.

2 Data

2.1 Data collection

The data used for the present research were collected by the Italian National Research Council in the context of the Tag My Day project, with the generic scope of gaining a better understanding of urban mobility and providing suggestions to policy makers to improve traffic problems, but without the explicit aim of travel behaviour modelling. The data collection took place in the city of Pisa (Italy) and surrounding areas between May and October 2014. Pisa is a medium sized city (approx. 91,000 permanent inhabitants, but also hosting approx. 51,000 students, most of whom are not residents) in the Tuscany region. The city is served by buses (there is no metro or light-rail service), and trains are only used for inter-city trips. There are 17 urban bus lines, of which 15 operate during the day (approximately 6 AM until 9 PM) and 2 during the night. At the time of the survey, a bike sharing system had recently been introduced, with 10 pick-up and drop-off stations. The city centre, as in most Italian cities, is very compact and walking and cycling are widely used modes especially among students, although car remains the main mode of transport for most residents.

Participants were recruited through social media and flyers distributed around the University and on the streets. They could join the project at any time by registering on the project website and by completing a short socio-demographic questionnaire. Once registered, they were asked to install a GPS logger on their smartphones. This could be installed like a normal smartphone application and deleted after the end of the study. Users were instructed to turn the tracker on at the beginning of each trip and turn it off at the end (the tracker would, in any case, turn off automatically if no movement was detected for 2 minutes), leading to a collection of panel data, with multiple trips per respondent. While the specific approach of turning the tracker on and off was used to prevent excessive impact on the phone battery, as the app recorded the users' position every second, it probably resulted in missing or partially recording trips if users forgot to turn the logger on at trip origins. GPS data collection relies on a positioning signal received by a ground-level device from at least 4 GPS satellites. The precision of the system is believed to be around 5 metres (GPS.gov, 2016), although accuracy varies with devices and locations. The time interval between each two measurements of the user's position is set by the programmer/researcher, who generally aims for a compromise between spatial precision and battery consumption. The time gap between successive readings also depends on the ability of the logger to connect to receive a signal from the satellites; in our data, the median gap between readings was 6 seconds, and the median spatial gap was 11 metres. This represents a high level of accuracy, going beyond the level of precision required for a mode choice application such as presented here.

Recorded trajectories were displayed in users' personal area of the Tag My Day website. Here, they could visualise each trip on a map, together with start and end time and average speed. Respondents were then asked to add information for each displayed trip in relation to travel mode and purpose. The "mode" dropdown menu listed 8 possible options: car, bicycle, walking, bus, train, taxi, boat, other. The "purpose" field included 12 categories: going to work, eating out, social activities (pub, visits to friends and family, gatherings), pick up-drop off, getting fuel, errands (bank, doctor, hairdresser), grocery shopping, other shopping, stop/mode change (stopping at the red lights and changing travel mode), study, leisure (sport, day trips, museums), going home. Two additional categories were provided to indicate problems with the recorded trip, one for incomplete trips due to app crash or low battery and one for wrong trajectory due to GPS errors.

Figure 6.1 represents a screenshot of the user interface: all the days for which trips have been recorded are displayed on the left hand side, while the selected day's trips are each presented in detail, alongside a map.

Participants were asked to use the app to record and annotate all their trips for at least one week, but they could keep using the system until the end of the survey period, if they wanted. This resulted in high variability in the number of trips recorded across people. As an incentive to take part in the project, people could accumulate "points" through greater engagement with the app/online portal, and these points entitled them to lottery tickets to win a number of prizes in the form of bicycles and iPads.

A total of 160 people voluntarily signed up to take part in the project and 129 of them annotated all their trips, with a final total of $8,500$ trips. As the purpose of the study was limited to graphical and descriptive analysis of mobility patterns, no additional information was collected from the majority of the sample. A small additional survey was sent to participants afterwards,

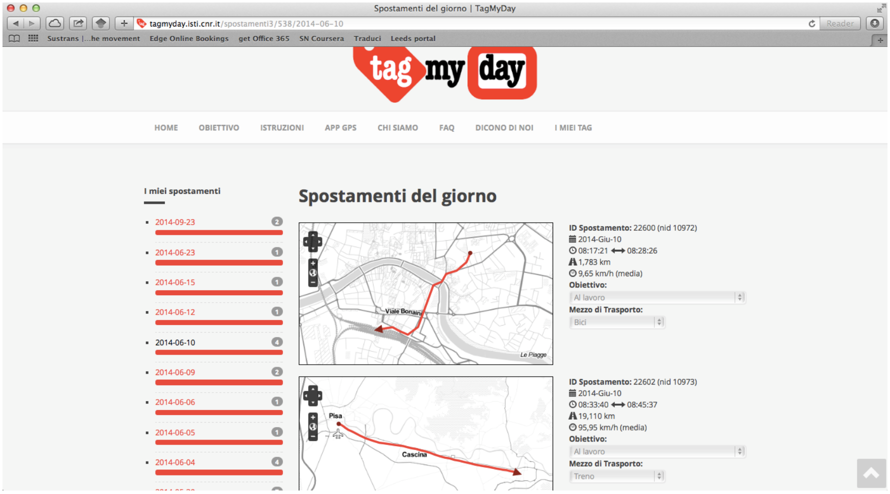

Fig. 6.1: The user intreface

collecting information on mode availabilities, job type and attitudes, and this was completed by 54 of the respondents.

2.2 Data cleaning and censoring

A number of distinct criteria were used in cleaning the data in preparation for the modelling work:

- A small number of taxi trips and inter-city trips by train were removed in order to focus on intra-urban mobility and limit the number of choice alternatives. Train trips were excluded because of their exclusively inter-urban nature, while taxi trips, although urban, were negligible in number. This implied that all the trips included in the dataset were by foot, bicycle, scooter, car or bus.

- The focus of our study is not on inferring mode choice but to understand actual observed mode choices. We therefore focus only on respondents who tag all their trips.

- In a few cases, participants reported trips by modes that they stated as unavailable to them and these trips were excluded.

- We also excluded trips that were annotated as having the purpose of getting fuel, technical stop (e.g. traffic lights, congestion) and those flagged by users as errors or incomplete trips. No mode choice would have taken place for those trips.

- Finally, in order to avoid an excessive impact by a few outliers on the coefficients, we only included trips shorter than 50km; this approach is also in line with the focus on urban mobility.

A further issue arises as a result of the data collection protocol, given the open-ended participation. In order to avoid people with an extremely high number of repetitive trips having excessive impact on our results, we decided to limit the heterogeneity in the number of trips. We excluded from our sample the people who reported fewer than 5 trips, and we limited the maximum number of trips per person to 200. Only a few reported a number of trips higher than this upper limit, and in these cases, the 200 trips to be used in the modelling were randomly selected. The final sample thus contained $5,149$ trips, recorded by 102 participants, which included the 54 respondents who also completed the follow-up questionnaire. Males (70%), people with a highly level of education (50%) and young people (90% of the sample is younger than 45 years) are over-represented, probably because the survey was mainly advertised at the University and through social media.

Although the data contained recorded times (and inferred speeds) for each trip on the chosen mode, this was unsuitable for use in the choice models. Firstly, it contained errors leading to excessively long or short travel times in some cases. Secondly, and more importantly, it would have led to a disconnect between chosen and unchosen modes to use observed times (and network costs) for the former and network times (and costs) for the latter. For this reason, travel times were recomputed for each trip and for each mode, using the navigation tool of Google Maps (Google, 2016). This tool accounts for the actual travel times depending on the likely congestion at specific times of the day. The query from Google Maps was performed for the same time and day of the trip, but two weeks in the future, so to avoid the consideration of temporary disruption or changes to the road network, and in order to reproduce the expected times that people are likely to consider when making their travel choices. Of course, our approach is not optimal, as we would have ideally needed to retrieve the travel times for each mode at the precise time and day when the trip was performed. But given the tools available to us, we believe this is the best solution amongst the viable ones.

Tables 6.1 and 6.2 report some characteristics of the trips recorded by people in the selected sample. While most people reported a low number of trips, with approximately 40% of the sample reporting fewer than 20 trips, Table 6.1 shows that the high number for some leads to a median of 28.5. Some of this variation is of course a result of using the app over a shorter or longer period. On average, people reported 2.36 trips per day, a figure slightly lower than those achieved by some other GPS-based studies (Bohte and Maat, 2009; Safi et al., 2015; Stopher and Wargelin, 2010). Given the specific app usage protocol, a comparison is difficult, as most studies rely on devices which automatically detect when the user starts moving.

	Min	Max	Mean	Median
Number of overall trips per person	5	200	50.48	28.5
Number of trips per person per day	1	13	2.36	2
Trip length (km) by mode				
Walk	0.2	4.9	0.9	0.7
Bicycle	0.2	16.6	1.8	1.5
Scooter	0.3	40.9	6.2	4.1
Car	0.2	49.8	10	6.2
Bus	0.5	22.9	4.8	3.6

Table 6.1: Number of trips per person and trip length by mode

		Travel mode					*Summary by purpose*	
		Walk	*Bicycle*	*Scooter*	*Car*	*Bus*	***Total***	*%*
Trip purpose	*Going to work*	62	136	74	390	14	*676*	*13%*
	Eating out	71	70	10	105	0	*256*	*5%*
	Social activities	144	115	30	377	9	*675*	*13%*
	Pick up-drop off	18	47	11	230	0	*306*	*6%*
	Services	29	64	29	157	4	*283*	*5%*
	Shopping	18	24	12	113	5	*172*	*3%*
	Grocery Shopping	17	75	14	200	5	*311*	*6%*
	Study/Training	92	161	20	86	4	*363*	*7%*
	Leisure	78	79	52	180	1	*390*	*8%*
	Going home	199	370	137	985	26	*1717*	*33%*
Summary by mode	***Total***	*728*	*1141*	*389*	*2823*	*68*	***5149***	*100%*
	%	*14%*	*22%*	*8%*	*55%*	*1%*	*100%*	

Table 6.2: Number of trips by purpose and mode

As expected, the longest trips were by car (just under 10 km on average), followed by scooter, bus, bicycle and walk, as shown in Table 6.1. Table 6.2 reports the number of trips by mode and purpose. The largest number of the trips (33%) are towards home and a vast majority of them are by car. Car is also observed to be the most frequent choice for other purposes, especially work and social. The sample contains a very low number of trips by bus, only 1% of the total.

2.3 Data enrichment

As mentioned above, basic socio-demographic information such as gender, age and level of education were collected upon registration to the Tag My Day project. Key characteristics such as time, cost and elevation data were computed using various Google services (Google, 2016). Travel cost information was computed differently for different modes. Cars and scooters consume more fuel at very low and very high speeds, and the shares of different road types for each specific trip were used alongside road type specific speed data to compute the associated fuel consumption as accurately as possible (cf. Department for Transport (2015) for cars and COPERT (2010) for scooters).

The value used for fuel price is the average of the prices in the months when the data collection took place (Ministero dello sviluppo economico, 2014). A fixed kilometre cost for the average scooter and car was added to the fuel consumption according to the data provided by the Automobile Club d'Italia (ACI, 2014). The cost for bus trips was inferred from price lists made available by the local public transportation providers. Urban tickets have a fixed price, independent of the line and distance travelled. Inter-urban fares depend on distance and vary across provinces. Similar information about bus headways was gathered and included in the dataset.

Finally, online archives (Archivio Meteo Pisa, 2016) were used to retrieve the weather conditions for the survey area on a daily basis. The temperature records were used to compute the heat index (Winterling, 2009), a function of temperature and humidity, which gives an indication of the perceived temperature, which is expected to have higher influence on decisions than the nominal temperature.

3 Modelling approach

While in the case of stated preference data, the choice set (i.e. the set of feasible alternatives) is observed by the analyst, this is not the case in many revealed preference datasets, and in particular not in the case of passive data sources like GPS. Both types of data are also generally affected by a lack of information on choice context specific consideration sets. We will now look at these two issues in turn.

As mentioned in the introduction, our modelling approach is aimed at overcoming some limitations of the present data to correctly represent mode choice behaviour. Dealing with missing data for mode availability as well as incorporating consideration sets in the model are the central themes of our approach. We will first look at the treatment of choice in the absence of the mode availability and consideration dimensions, before adding these in one by one.

3.1 Choice model component

We assume that conditional on a given set of alternatives (which will be affected by availability and consideration as discussed below), the choice probability for mode m out of a set of M available and considered alternatives (described by set $G_{n,t}$ for person n and trip t) is given by a Multinomial

Logit Model (MNL) model (see e.g. McFadden et al. (1973), with:

$$P_{m,n,t}\left(G_{n,t}\right)=\frac{e^{V_{m,n,t}}}{\sum_{j=1}^{M} e^{V_{j,n,t}}} j \in G_{n,t} \tag{6.1}$$

where $V_{m,n,t}$ is the utility that person n derives from mode m in choice task t.

3.2 Availability component

We first start by looking at mode availability at the respondent level. Among the five alternative modes, it is safe to assume that "walking" is an available option for everyone in the sample and that the availability of bus depends on the network, i.e. on the presence of an active bus line along a specific route at the time and day when the trip was made.

The situation is, however, different for car, scooter and bicycle. As already mentioned earlier, our dataset did not include mode availability for the majority of respondents, in line with many other similar datasets. As we expect variations across individuals in the availability of these three modes, we define eight possible "classes" of availability to which each individual can belong, corresponding to all possible combinations of availability of bicycle, scooter and car. On the basis that we do not observe mode availability at the person level, each individual belongs to each one of these classes with a probability, where each class makes use of a different choice set, but with a choice model using the same model parameters. This means that the resulting model structure can be formalised as a Latent Class Model (Hess, 2014; Kamakura and Russell, 1989), where the probability of the sequence of choices observed for person n is given by:

$$L_n=\sum_{s=1}^{S} \pi_{n,s}\left(\prod_{t=1}^{T_n} P_{s,m_{n,t}}\left(G_{n_s}\right)\right) \tag{6.2}$$

where S is the total number of classes (in our case 8) and $\pi_{n,s}$ is the probability that individual n belongs to class s (i.e. has choice set G_{n_s}), with $0<\pi_{n,s}<1$ and $\sum_{s=1}^{S} \pi_{n,s}=1$, while $m_{n,t}$ is the alternative that respondent n was observed to have chosen in choice task t. The $P_{s,m_{n,t}}$ in this formula now corresponds to the MNL probability in Equation 6.1, with the choice set determined on the basis of which class s we are looking at, in particular G_{n_s} for class s, where the subscript t on the choice set from Equation 6.1 is dropped for now as availability is constant across all trips for the same respondent. In the following discussion we will identify class $s=1$ to be the one with all modes (bicycle, scooter, car) available.

We test four specific versions of the model, as follows:

- *Specification a* assumes that all modes are available to everyone, meaning that $\pi_{n,1} = 1$ for all n respondents, and $\pi_{n,s} = 0$ for $s > 1$ (i.e. nobody belongs to a class where some or all the modes are not available).

- *Specification b* uses stated availability from respondents who provided the information, meaning that $\pi_{n,s} = 1$ for the specific class s corresponding to the stated availability for respondent n, and zero for all other classes. For all other respondents, we assume that $\pi_{n,1} = 1$ and $\pi_{n,s} = 0$ for $s > 1$, i.e. that if the availability information is not given, all modes are available for that person.

- *Specification c* uses stated availability for respondents who provided the information, and inferred availability for others; we return to inferred availability below.

- *Specification d* uses inferred availability for all respondents.

In specifications c and d, we now have a situation where we do not have a deterministic class allocation for some (specification c) or all (specification d) of the respondents. Instead, we now have a non-zero probability for each class for these respondents, where these are given by the product of the probabilities of having each of the three modes available. Therefore, if $s = 1$ is the class where all modes are available, and $s = 2$ is the class where bicycle and scooter are available and car is not, we will have:

$$\begin{aligned} \pi_{n,s=1} &= \omega_{n,bike} \cdot \omega_{n,scooter} \cdot \omega_{n,car} \\ \pi_{n,s=2} &= \omega_{n,bike} \cdot \omega_{n,scooter} \cdot (1 - \omega_{n,car}) \end{aligned} \tag{6.3}$$

where $\omega_{n,m}$ represents the probability of mode m being available to respondent n. The $\omega_{n,m}$ terms are estimated separately from the choice model using logistic regression on those respondents who provided stated mode availability. The probabilistic inference is given by:

$$\omega_{n,m} = \frac{1}{1 + e^{-q}} \tag{6.4}$$

with $q = a_o + \sum_l a_l x_l$ where the independent variables x_l are represented by sex, age and level of education. With the estimates for a_0 and a_l, we can then compute a value for $\omega_{n,s}$ for every respondent n and use it to derive the probability of belonging to every class s, where $\omega_{n,s}$ is now no longer simply 0 or 1. In specification c, we use these predicted $\pi_{n,s}$ only for those respondents who did not provide stated availabilities, while, in specification d, we use them for all respondents (i.e. we do not make direct use of the stated availabilities).

3.3 Consideration component

A further level of complexity is needed to accommodate the possibility that decision makers may consider only a subset of the available alternatives for a particular trip, and that this subset varies across trips (an issue discussed in the stated choice context by e.g. Cantillo and de Dios Ortúzar (2005); Swait (2001). In the presence of repeated choice data for the same decision maker, the choice set can thus have a decision maker-specific component (available set) and a context specific consideration component (consideration set). Detailed investigation of these choice sets is a central theme in our work, as we aim to show that the explicit modelling of inclusion of availability and consideration sets constitutes a successful strategy to overcome the issue of missing values and substantially improves the model.

It is important to appreciate the difference between mode availability and consideration. The first one refers to the fact that a person or someone in their household might or might not own a bicycle/scooter/car. In our regression approach in equation 6.4, we indeed assume that this depends on socio-demographic characteristics, as availability is a person-level condition. Differently, consideration is trip-specific: even if a person owns a bicycle, he/she might not consider it in his/her choice set if it is raining or for a very steep route.

In the present work, we include mode consideration only for two modes: walk and bicycle. This approach is motivated by the belief that, in general, if car, scooter and bus are available, they will always be considered. In the case of car, for example, a warmer/colder day or a steeper/flatter route will not in general affect the consideration of car itself, but it might affect the consideration of walk as if it is cold or if the particular route is very steep. In our empirical analysis, we approach the incorporation of the mode consideration through an additional layer of latent classes in equation 6.2:

$$L_n = \sum_{s=1}^{S} \pi_{n,s} \left(\prod_{t=1}^{T_n} \sum_{c=1}^{C} \theta_{c,n,t} P_{s,c,m_{n,t}} \left(G_{n_s,t_c} \right) \right) \tag{6.5}$$

where, in addition to the S availability classes defined in equation 6.2, we have, within each choice situation (i.e. trip), C consideration classes, with $\theta_{c,n,t}$ being the probability of individual n belonging to consideration class c for trip t. In any given combination of availability (s) and consideration (c) class, the choice set is defined by G_{n_s,t_c}, where only those modes available and considered are included in the choice set, and where $P_{s,c,m_{n,t}}$ again corresponds to the MNL probability in Equation 6.1. This of course means that the choice of a mode which is not considered or not available in a given class has a probability of zero in that class.

The structure that results is thus a latent class model, with two layers of classes, one at the traveller level (mode availability) and one at the trip level (mode consideration). We have 8 classes at the upper level (concerning availability) and 4 classes at the lower level, given by the combinations of consideration for cycling and walking. This gives a total of 32 classes in the combined model. Some of these classes are of course redundant; e.g. if for class s, bicycle is not available, then any of the consideration sub-classes involving bicycle are not required either. In particular, only 16 of the 32 classes will include bicycle as an available option. Therefore, the remaining 16 are not feasible independently of the consideration aspect. This leaves us with 24 feasible classes.

We use a similar structure as the one used in the case of the specification of availability classes. For example, the probabilities of belonging to consideration class 1, in which both bicycle and walk are considered, or class 2, where only bicycle is, can be formally stated as:

$$\begin{aligned} \omega_{c,n,t} &= \kappa_{bike,n,t} \cdot \kappa_{walk,n,t} \\ \omega_{c,n,t} &= \kappa_{bike,n,t} \cdot (1 - \kappa_{walk,n,t}) \end{aligned} \tag{6.6}$$

where $\kappa_{m,n,t}$ represents the probability of mode m being considered by each respondent for trip t.

We test three specifications of this component of the model:

- *Specification 1* only takes availability into account, i.e. implicitly assuming that, subject to availability, all the modes are considered, thus setting $\kappa_{bike,n,t} = 1$ and $\kappa_{walk,n,t} = 1$. This means that the model collapses to that from Equation 6.2.

- *Specification 2* assumes that, subject to availability, bicycle and walk are considered only if the distance of the trip is less than the maximum distance at which anyone in the sample chose that mode. This is a deterministic way to define consideration, i.e. $\kappa_{bike,n,t} = 1$ if and only if $dist_{n,t} \leq maxdist_{bike}$ where $maxdist_{bike}$ is the maximum distance for which bicycle is chosen in the data. The same principle applies to walking.

- *Specification 3* makes the consideration probabilistic, where the probability of a mode being considered is a function of trip characteristics, and hence varies across trips for the same person. Probabilistic inference of consideration of each mode by each respondent in each choice scenario is given by:

  $$\kappa_{m,n,t} = \frac{1}{1 + e^{-r_{m,n,t}}} \tag{6.7}$$

  with $r_{m,n,t} = b_m z_{n,t}$, where $z_{n,t}$ is a vector of trip-specific attributes for respondent n on trip t and b_m is a vector of estimated coefficients measuring the effect of each attribute on the probability to consider mode m. The b_m coefficients are estimated simultaneously with the remainder of the model.

It may be noted that the use of 32 classes does not involve the estimation of different sets of parameters for each class. Rather, the marginal utility coefficients can be generic across classes.

Before moving on to the empirical work, it is important to again stress that the coefficients used in the model do not vary across classes, i.e. the structure is used to test for availability and consideration, not taste heterogeneity, and there is no proliferation of parameters.

4 Empirical Analysis

The modelling framework developed above is used to test whether accommodating the availability and consideration structures will result in a better model and more reasonable results.

All models were coded in R (R Core Team, 2016) and estimated using maximum likelihood estimation. Two important points need to be addressed in this context. Firstly, the model structure in Equation 6.5 is a two-layer latent class structure, which leads to a log-likelihood function that clearly does not have a concave shape as with a simple MNL model. To deal with this issue and reduce the risk of the model converging to a poor local optimum, models were estimated multiple times, using different sets of random starting values. Secondly, the model now has three components, namely a mode availability component, a consideration component and a choice component. The specification of the mode availability component is given exogenously and there is thus no risk of empirical confounding, also as it is person specific while the latter two components are trip specific. The same does not apply for the consideration and mode choice component as both make use of trip specific information. This raises the possibility of using the same attribute in both components, namely in $r_{m,n,t}$ and in $V_{m,n,t}$. However, the partial derivatives of the log-likelihood function (i.e. the sum across people of the logarithm of Equation 6.5) of the same attribute entered into $r_{m,n,t}$ and in $V_{m,n,t}$ are different across $r_{m,n,t}$ and in $V_{m,n,t}$, and there is thus no theoretical identification issue. Empirically of course, it is reasonable to expect that the same attribute may matter more in one component than the other, and even drop out in one, but the analyst needs to test this on a case by case basis. In our analysis, we tested the effects of a number of such attributes (e.g. weather) jointly in both components, and made decisions on which parameters to retain where (not precluding the possibility of retaining in both) on the basis of statistical significance, improvements in fit, and behavioural reasonableness. It is difficult for us to contrast our results with other studies – for example, if a previous study finds an impact of weather on mode choice while our study points towards an impact only on consideration, then it is not clear whether the previous findings were affected by the absence of a consideration component.

In order to test the effect of the 4 availability specifications and the 3 consideration specifications, we estimated 12 models which share the utility specification but vary in terms of the underlying availability and consideration assumptions:

- Models 1a to 1d: The four assumptions on availability are separately tested. Heterogeneous consideration across trips is not included at this stage, i.e. we are using specification 1 from the consideration discussions.
- Models 2a to 2d: Each model corresponds to one of the four assumptions on mode availability, as in models 1a to 1d; but consideration is now accounted for: walk and bicycle are considered available only if the trip distance does not exceed the maximum distance walked/cycled in the sample, i.e. using specification 2 from the consideration discussions.
- Models 3a to 3d: As for the previous models, each of these four models has a separate assumption on availability, but we now include mode consideration probabilistically, as in specification 3 from the consideration discussions.

For improved clarity, the empirical estimation procedure is summarised in Table 6.3.

		Consideration assumptions		
		1.All modes always considered	2.Max distance rule	3.Probabilistic
Availability assumptions	a. All modes available for everyone	Model 1a	Model 2a	Model 3a
	b. Stated availability for those who gave it, all modes available for everyone else	Model 1b	Model 2b	Model 3b
	c. Stated availability for those who gave it, availabilities from regression for everyone else	Model 1c	Model 2c	Model 3c
	d. Availabilities from regression for everyone	Model 1d	Model 2d	Model 3d

Table 6.3: The empirical approach

A comparison of the fit of the different models is provided in Table 6.4. This table reports, for each model, the number of parameters (PAR) and the final Log-Likelihood (LL), the Bayesian information criterion (BIC) (Schwarz

MODEL	LL	PAR	BIC	AIC	VTT scooter (s.e.)	VTT car (s.e.)	VTT bus (s.e.)
Model 1a	-4207.91	27	8646.6	8469.8	20.5(8.1)	21.37(8.5)	11.33(4.9)
Model 1b	-3548.70	27	7328.2	7151.4	14.96(4.9)	15.41(5.1)	7.65(2.8)
Model 1c	-3125.74	27	6482.2	6305.5	14.02(4.8)	14.73(4.9)	7.24(2.7)
Model 1d	-3079.77	27	6390.3	6213.6	14.27(5)	15.09(5.2)	7.54(2.8)
Model 2a	-4206.49	27	8643.7	8467.0	20.5(8.1)	21.38(8.5)	11.33(4.9)
Model 2b	-3546.96	27	7324.7	7147.9	14.95(4.9)	15.41(5.1)	7.64(2.8)
Model 2c	-3123.55	27	6477.9	6301.1	14.03(4.8)	14.74(4.9)	7.22(2.7)
Model 2d	-3077.56	27	6385.9	6209.1	14.26 (5)	15.08 (5.2)	7.52 (2.8)
Model 3a	-4205.73	32	8685.0	8475.5	20.8(8.3)	21.68(8.8)	11.5(5.1)
Model 3b	-3541.33	32	7356.2	7146.7	15.22 (5)	15.68 (5.2)	7.75 (2.8)
Model 3c	-3113.54	32	6500.6	6291.1	14.54 (5)	15.29 (5.2)	7.46 (2.8)
Model 3d	-3060.36	32	6394.2	6184.7	14.90 (5.3)	15.78 (5.5)	7.77 (2.9)

Table 6.4: Model Fit Comparison

et al., 1978) and the Akaike information criterion (AIC) (Akaike, 1974) measures to assess model fit.

The number of parameters in models 3a-3d is higher than in the other models due to the estimation of the parameters for the consideration probabilities. Both the Log-Likelihood and the AIC statistics suggest that model 3d fits the data best. The BIC penalises the additional parameters in the model more strongly and gives preference to model 2d, but this yields reduced insights into behaviour, and on balance, we therefore proceed with model 3d.

The improvements in log-likelihood show a reasonable and clear trend across models, highlighting the better performance of more flexible models. While we acknowledge that statistical significance is not the only criterion to evaluate the goodness of a model (also because of its relation with the number of estimated parameters), we believe that in our case the best fit coincides with an intuitively plausible behavioural mechanism underlying the present choice context. Nevertheless, the benefits of more flexible availability specifications are clearer than those from a similar treatment of consideration, which is again not surprising given that availability is dealt with at the respondent rather than observation level, and that the mixing in Equation 6.4 then captures correlation across choices for the same person. In the treatment of availability, specification d always performs the best in each group, while, for consideration, we also as expected see that specification 3 always gives the better log-likelihood. Overall, any treatment of availability or consideration leads to improvements, but these differ across specifications.

The final three columns of Table 6.4 display value of travel time (VTT) measures obtained by computing the ratio between the mode-specific travel time coefficients and the cost coefficient. All the VTT measures are significantly different from zero and the standard errors are calculated using the delta method for this ratio. Within each model, the difference between car and scooter is not statistically significant (t-ratio of 1.14 in model 3d), while the difference with bus is (t-ratio of 5.45 for bus and scooter, and 5.70 for bus and car).

It is easy to notice how the models which do not include any availability nor consideration treatment (Models 1a, 2a and 3a) do not only provide a worse fit, but also excessively high VTT, while the other models provide more reasonable values, only slightly higher with respect to values computed in other studies with Italian data (Wardman et al., 2016) although comparison is difficult as a national value of travel time study has never been performed in Italy and therefore official data are unavailable.

As mentioned above, the 12 models described were estimated with the same utility specification, to control for the effect of the assumptions on availability and consideration. The final specification was obtained by starting off with a base model and systematically adding socio-demographic and trip-level variables to the utilities of the different choice alternatives on the basis of intuition and statistical significance. Due to space constraints, we cannot show the results of all the models (although these are available from the authors on request), so we only present the results for model 3d in Table 6.5. In order to correctly account for the panel nature of the data, robust t-ratios are reported alongside the estimates, where the log-likelihood entered the sandwich matrix calculations at the individual person level, i.e. grouping together choices and thus recognising the repeated choice nature of the data. Although the signs and magnitudes of the estimated parameters did not vary considerably across the different models, there are minor differences in the significance of the different coefficients, which results in some of them not being significant in the model presented.

4.1 Utility parameters

The first four coefficients in Table 6.5 are the alternative-specific constants for the modes, where walk is used a base. The travel time coefficients for motorised modes, as well as the cost coefficient, which enters the utility of motorised modes only, are negative and robustly significant. For walking and cycling, we work with distance rather than travel time, as time is a function of speed which is determined by physical ability and desire for exercise. We allow for non-linearity in the impact of distance on utility through a Box-Cox transform. The value of the Box-Cox parameters is below 1 for both modes, implying decreasing marginal sensitivity with increasing distance, where for walk, the value is not significantly different from 0, hence pointing towards a log shape. With these values for the β parameter and the Box-Cox parameter, the marginal disutility per kilometre is larger for walk than bicycle for the first 10 kilometres, while the marginal disutility caused by distance "crosses over" (bicycle becoming more negative than walk) at a distance of about 44 kilometres, well outside the range where walking is likely to be considered in our model.

As mentioned in Section 2, participants annotated their trips with the

Utility coefficients			
	Mode	*Estimate*	*Robust t-rat*
Alternative-specific constants	Bicycle	-1.931	-0.68
	Scooter	-4.930	-1.37
	Car	1.244	0.43
	Bus	-2.552	-0.90
Distance	Walk	-3.453	-11.67
	Bicycle	-1.052	-4.40
Distance transformation coeff.	Walk	0.198	0.94
	Bicycle	0.695	4.60
Travel time	Scooter	-0.263	-6.67
	Car	-0.278	-6.43
	Bus	-0.137	-5.30
Travel cost	Scooter, car, bus	-1.058	-3.41
Purpose = social	Walk	0.707	2.40
Purpose=leisure	Walk	2.131	4.12
	Bicycle	1.126	2.91
Purpose=groceries	Bicycle	1.076	2.37
	Car	0.997	2.39
Weekday	Car	-0.585	-2.08
Rain	Walk	-0.357	-2.09
	Bicycle	-0.232	-1.14
Heavy rain	Bus	0.698	1.71
Heat index	Walk	-0.044	-1.16
	Scooter	0.059	1.74
Ascent ratio	Bicycle	-0.029	-0.95
Age 20-30 (base=older)	Walk	0.997	1.66
	Bicycle	1.301	2.43
Sex = male	Scooter	0.445	1.38
Consideration probability coefficients			
Distance	Walk	5.874	3.08
Square of distance	Walk	-1.098	-3.18
Purpose=groceries	Walk	5.064	1.35
Distance	Bicycle	-0.060	-0.32
Heat index	Bicycle	0.027	2.09

Table 6.5: Parameter estimates for model 3d

purpose, which is found to have an impact on mode choice. We find that people are more likely to walk to social activities, which is not surprising, as the middle-sized city of Pisa and the small urban centres in its surrounding areas are easily walkable for most people. Probably for similar reasons, we find that walk and bicycle are more likely to be used for leisure activities, which include sports, going to the city centre, or visiting attractions. The utility of choosing car and bicycle, both modes that make it easy to transport goods, is higher for grocery shopping trips.

Further significant effects were found at the level of characteristics of the day of observation. During weekdays, probably because of higher levels of congestion, the utility of car decreases. We also observe that rain, irrespective of the amount of precipitation, negatively affects the utility of walk and bicycle, although the latter coefficient is not significant in this model. Heavy rain is associated with a preference for bus, a mode which provides shelter from the rain but also implies being able to avoid driving in difficult weather conditions. The area of analysis is characterised by mild winters and hot summers. High levels of the heat index discourage people from walking, as this is the slowest and most onerous mode in this context (although this coefficient is not significant in this model), but can make scooter very appealing, as this mode allows people to benefit from the wind without any physical effort. Although past literature has found evidence that weather conditions impact several aspects of travel behaviour, including mode choice (Akar and Clifton, 2009; Cools and Creemers, 2013), we believe that these results are strongly related to the climate of the region, and should be interpreted using knowledge of the specific context. For example, Guo et al. (2007) find a strong weather effect in the case of Chicago, IL, but the ease of finding such an effect is also a factor of the variability in weather across days and seasons, which is much reduced in Pisa.

Another interesting coefficient, albeit not significant in the present model, is the fraction of the trip that implies going uphill. Prior studies showed how this variable negatively impacts the utility from non-motorised modes such as walking and cycling as this would increase the effort required (Cervero and Duncan, 2003; Rodríguez and Joo, 2004). The reason for the lack of a stronger level of significance can be related to the fact that the city of Pisa and surrounding areas are rather flat, while of course an uphill outbound journey would imply a downhill return journey, cancelling the effect out and with a mode needing to be chosen for both.

Finally, we consider the effect of some socio-demographic characteristics. In line with expectations, younger people are found to be more likely to walk and cycle than older ones. In addition, a positive (although not strongly significant) correlation between being male and choosing scooter is found, in line with previous evidence from Italy (Bernetti et al., 2008).

4.2 Consideration parameters

Models 3a-3d, differently from the preceding ones, imply the estimation of additional parameters due to the probabilistic approach to mode consideration discussed in the previous section. Table 6.5 displays the variables found to have an effect on the probability of consideration for model 3d. Trip distance was included in the expression of both modes. In the case of walk, we include both linear and squared distance. The signs and values of these coefficients imply that walk is considered with a probability of nearly 1 for short distances (cf. equation 6.7), but this decreases rapidly just below 5 kilometres, and the probability of considering walk goes to near 0 over 6 kilometres, a value that is close to the maximum distance where walk was chosen in the data. For grocery trips, this cut-off point is shifted slightly to the right, where this needs to be interpreted alongside the increases in utility for car and bicycle for grocery trips. For bicycle, the consideration model works less well, with only a small and statistically insignificant negative impact for distance, while consideration increases in warmer weather. As the data were collected starting in spring, this result could be interpreted by noting that, in a very flat context like Pisa, cycling might be a good option on warmer days.

5 Conclusions

In line with the diffusion of cheaper technology and improved functionalities of smartphones and tablets, an increasing amount of mobility data is now being collected for a variety of reasons by researchers as well as institutional and commercial bodies, often relying on users' personal devices. These data are generally not aimed at developing choice models of travel behaviour, but at more general spatial or descriptive analyses.

The first research question that was proposed in the Introduction of this paper concerned the investigation of whether these passively collected data sources such as GPS can be used for travel behaviour modelling beyond route choice, in particular for mode choice modelling. We showed that this type of data, at least in our case, can indeed be used for this purpose, although special care needs to be taken in understanding, cleaning, enriching and handling the data.

Our second question revolved around finding ways to deal with the issue of mode availability and consideration. In our case, as in many similar datasets, the lack of information about person-level mode availability requires them to be inferred, which can be done by using other socio-demographic information if available. This method proved not only effective, but superior to the use of stated availabilities, suggesting that inferred information can be more reliable than what is stated by respondents, as it allows for some uncertainty compared to simple 0/1 availability. In addition, the inclusion of a consideration set seems to provide an improvement in model fit, showing that real-life behaviour is better represented if this additional layer is added to the choice set formation process. Our findings thus suggest that a better understanding of mode choices can be obtained by looking jointly at availability, consideration and choice.

Despite the challenges faced when trying to model this type of data, the gains in terms of understanding of behaviour can be considerable. Not only can capturing the complexity of real-world behaviour provide better measures of sensitivities to different influencing factors, but it also allows us to address the biases of SP data by comparing the outcomes of models estimated with different data sources. Notwithstanding the challenges discussed, the present paper serves as a proof of concept that the use of data collected by passive data sources for various purposes could be a valuable resource for travel behaviour modelling. This is confirmed by reasonable model results, including a realistic estimate of the monetary value of travel time. The current research needs to be followed by confirmatory analyses with different datasets, including comparison with SP data (which has its own limitations) for value of time research.

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Chapter 7

We want it all: experiences from a survey seeking to capture social network structures, lifetime events and short-term travel and activity planning

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Abstract

Recent work in transport research has increasingly tried to broaden out beyond traditional areas such as mode choice or car ownership and has tried to position travel decisions within the broader life context. However, while important progress has been made in terms of how to capture these additional dimensions, both in terms of detailed tracking of movements and in-depth data collection of long term decisions or social network influences, surveys have tended to look at only a handful (or often one) of these issues in isolation, especially at the data collection end. Making these links is the key aim of the data collection described in this paper. We conducted a comprehensive survey capturing respondents' travel, energy and residential choices, their social environment, life history and short-term travel patterns. The survey is composed of a detailed background questionnaire, a life-course calendar and a name generator and name interpreter. Participants were also required to use a smartphone tracking app for two-weeks. We believe that this is an unprecedented effort that joins complexity of the survey design, amount of information collected and sample size. The present paper gives a detailed overview of the different survey components and provides initial insights into the resulting data. We share lessons that we have learned and explain how

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our decisions in terms of specification were shaped by experiences from other data collections.

1 Introduction

Alongside major theoretical innovations, the field of travel behaviour research has over the last two decades been characterised by a fundamental re-evaluation of what is driving people's travel decisions. This has been accompanied by work into how to capture information on factors going beyond traditional level-of-service characteristics and socio-demographic information, with an increasing embrace of new data collection techniques, in particular based on mobile technologies.

A number of distinct strands can be identified. Perhaps the most prominent area has been the research into the role of attitudes, perceptions and plans (Choudhury et al., 2010; Daly et al., 2012; Molin et al., 2016). Notwithstanding the criticisms leveled at this area of research over the last two years (Chorus and Kroesen, 2014; Vij and Walker, 2016), capturing information on such *soft* factors remains a very active area of research.

A different area of research has encouraged analysts to look at the role of other people, both in terms of joint decision making (Arentze and Timmermans, 2009) and the influence that someone's social and professional network may have on that person's decisions, even if travelling alone (Dugundji and Walker, 2005; Maness and Cirillo, 2016). This has again motivated extensive research into how to capture data on the interactions between people in their travel behaviour (Lin and Wang, 2014; Silvis and D'Souza, 2006), where a particular focus has also been on the formation and maintenance of social networks and the way in which people interact with those in their network (Calastri et al., 2017c,d; Kowald et al., 2010).

While much of the above work has looked at the role of such non-traditional (from a travel behaviour research perspective) influences on choices, other research has questioned the wisdom of treating individual decisions in isolation. Much has been made of research looking at the inter-dependencies of travel and activity choices at the day-level (in activity based as well as time use modelling) (Arentze and Timmermans, 2005; Bhat and Singh, 2000), but it is clearly conceivable that interactions and influences cover a much broader time horizon. Paleti et al. (2013) have simultaneously analysed different short, medium and long term choice dimensions such as residential location choice, car ownership, work location choice as well as commuting mode and distance and find strong interdependencies in the choice continuum. They conclude that ignoring these correlations is not reflective of the true relationships that exist across these choice dimensions. Not only are there likely to be influences by past decisions, often in a seemingly unrelated context (e.g.

residential location during childhood may drive mode choice decisions as an adult), but there is also scope for forward looking, e.g. making a commuting mode choice decision now with a view to changing car ownership next year.

The final piece of the puzzle has been a very rapid uptake of mobile data collection approaches as well as a growing interest in longitudinal data sources that can help to understand some of the longer term influences. For the former, especially GPS surveys have grown in popularity, and they are rapidly replacing traditional travel diary surveys. The latter, while appealing from the point of view of following the same person over many years, is often beset by poor retention rates as well as a lack of data on short term decisions.

The various developments above are reasons for great excitement in the field. However, as is all too often the case in research, these are individual research efforts by separate communities within the field, with often little or no interaction amongst them, especially at the data collection end. If we accept the notion of a role for social networks impacts as well as attitudes and perceptions, then there is clearly scope for some interaction between the two. The same goes for the interplay between different choice dimensions, both within and across different time horizons. Capturing detailed data of a person's travel decisions using GPS tracking has reduced appeal if we do not at the same time understand the influence of past choices and life events for the same person.

Making these links was the key aim of the survey described in this paper, driven by our own experience of working with datasets from surveys focussing on just one aspect. We conducted a comprehensive survey capturing respondents' travel, energy and residential choices, their social environment and life history and a two-week smartphone app travel survey. Guided by recent efforts in the literature, we try to capture multiple aspects that jointly play a role in shaping travel behaviour, and consider the possibility of interaction with other decisions, such as energy use. At the same time, we also make refinements to the individual components of this overall survey, again driven by our recent insights gained in work using GPS data (Calastri et al., 2017a), name generators (Calastri et al., 2017c,d) and time use data (Calastri et al., 2017b,e).

While individual research contributions making use of this data will follow, this paper serves as a resource for other researchers who wish to break away from more one-dimensional surveys. We share lessons we have learned and also explain how our decisions in terms of specification were shaped by experiences with other datasets.

The remainder of this paper is organised as follows. The next section describes the different survey components in details. We then discuss the survey protocol and conduct, including the channels used for recruitment, the incentives used and the timing of the data collection. We will also discuss some of the challenges we faced and acknowledge the potential biases implied by the survey tools adopted. In the fourth section, we will describe the sample by providing some descriptive statistics related to the different survey parts. Finally, we will conclude by giving some recommendations to scholars interested in carrying out similar data collections and outline the next steps for the present project.

2 Survey structure

Our survey was made up of a number of separate components, which we will now look at in turn. The first three components of the survey were completed using an online portal while the final part relied on a smartphone app.

2.1 Online survey components

In the first three components of the survey, respondents answered basic background questions, gave an overview of life events and provided a snapshot of their social network. The average time respondents took for completing this part of the survey was 37 minutes (s.d. 42.4).

2.1.1 The background questionnaire

The background questionnaire (BQ) first collected essential socio-demographic information such as sex, age, education history, personal and household income, country of origin, occupation and marital status.

We next focussed on travel, residential location and energy, as well as susceptibility to influence by other people.

Respondents first provided data on transport mode ownership and usage (including frequency and mode split for commuting), as well as the availability of parking at home, work and other locations. This information is not only later used to prepopulate available options in the smartphone travel app (see Section 2.2.1), but is also crucial in understanding the trip patterns observed there without a need to infer information on mode availability and consideration as was the case in Calastri et al. (2017a).

They then gave detailed information on residential location and dwelling type, with extensive questions about energy sources (e.g. heating) used, as well as energy saving interventions such as double-glazing and insulated walls. People were also asked about what temperature they set their heating too (if under their control), how frequently they used different home appliances and what waste they recycled. Going beyond simple income questions, we also collected detailed information on monthly expenditure, with categories covering rent/mortgage, grocery, childcare, transport, communication, as well as money spent on utility bills.

The final component of the BQ included questions related to respondents' susceptibility to interpersonal influence, probing for agreement with a number of carefully worded statements. They covered the level of importance that respondents attribute to other people's behaviour, especially in the domain of active travel and environmental friendliness, as well as the importance they attach to how others perceive their behaviour.

2.1.2 The life-course calendar

One important aspect of our survey concerns collecting information about respondents' past choices and behaviour. While such information is often collected in longitudinal surveys, these are affected by poor response rates and fail to make the link with short-term activities. We instead rely on a life-course or life-history calendar to retrospectively obtain data about events and activities occurred during the life of respondents (Caspi et al., 1996). Life-course calendars have been used to collect data on many different life events, such as education, employment, family events. Examples of research questions pursued using this type of data are timing of employment, receipt of welfare, marriage, cohabitation and children's schooling (Furstenberg et al., 1987) and timing of work and migration (Anderson and Silver, 1986).

Figure 7.1 shows the LCC used in the present study. The list of events shown on the left-hand side is pre-populated on the basis of BQ information provided by participants about their education and employment history, their past home location, important relationships, children as well as cars currently and previously owned. We implemented an easy-to-use tool in which respondents simply need to click on any point on the timeline and then drag and drop the blue line to indicate start and end points. Respondents could change the occurrence and duration of events even after creating them in the tool.

While all education *events* were presented, only up to and including the three most recent employments were shown, while, for residential location, only those after moving out of the parents' home were presented in the calendar grid (with others covered in the BQ). The number of years shown in the grid depends on the age bracket of the respondent.

As explained by Freedman et al. (1988), there are two main advantages of this tool. First of all, the visual and mental relation of different kinds of events provided by the LCC improves the quality of the data by providing reference points and preventing time inconsistencies. Secondly, the visual aid of the calendar tool eases the task of listing a potentially high number of different short events, a task that would be more difficult in traditional surveys. Especially the first point is apparent from Figure 7.1. In our example, the year 2007 marked a change in employment, address and relationship. Remembering that these changes occurred at the same time will aid the com-

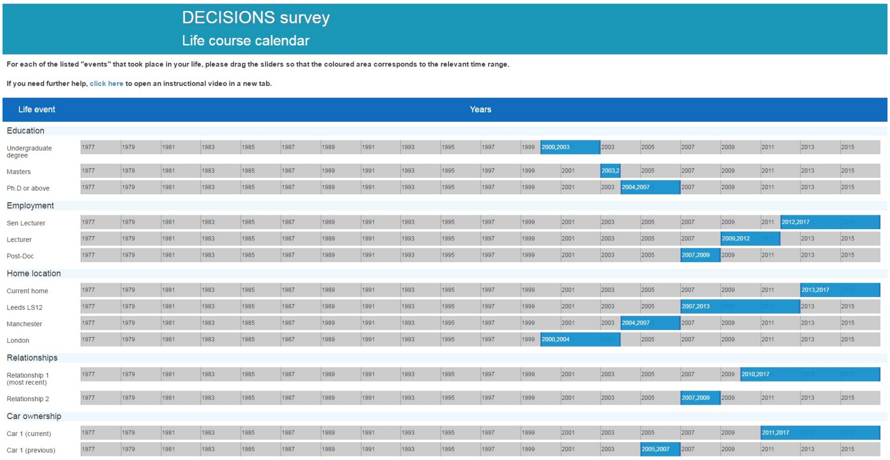

Fig. 7.1: Life course calendar - example

pletion of the survey.

A number of past studies have linked changes in life events to mobility decisions making use of data collected via life-course calendars. Beige and Axhausen (2012) use of a 20-years longitudinal retrospective survey, showing how turning points in life such as relocation or marriage are connected to one another as well as to long term mobility decisions. Similarly, Schoenduwe et al. (2015) observe that half of the changes in the travel mode for work trips coincide with a key life event (in the same year), while this is true for only around 30% of changes in the numbers of cars per household. Our survey allows us to capture such links too.

2.1.3 The name generator and name interpreter

A key area of research activity has looked at the role of social networks in shaping travel decisions (Calastri et al., 2017b; Dugundji and Walker, 2005; Lin and Wang, 2014; Maness and Cirillo, 2016). This requires a snapshot of the composition and influence of a respondent's network of acquaintances.

A name generator (NG) is a tool originating from the sociology literature used to collect information about egocentric social networks. It takes the form of a table that participants are asked to fill in with the names, nicknames or initials of the members of their social network. A specific survey question is presented, and the specific formulation is instrumental to the scope of the study. Studies making use of NGs to subsequently estimate the number of acquaintances have suggested an overall network size of around 1,500 (Freeman and Thompson, 1989; Killworth et al., 1990). In order to have a manageable list of social contacts, most studies do not ask the generic question "Who do you know?" but more specific questions depending on the research objectives, such as "Who are your three closest friends?" or "Who would watch your home if you were out of town?" (Campbell and Lee, 1991).

The approaches to define the boundaries of the network differ depending on the part of social network that researchers aim to capture. For example, some studies ask respondents to report the names of those with whom they interact during a certain period of time (e.g. Pike, 2014), while others capture those who are emotionally close to the ego, i.e. an affective approach (e.g. Carrasco et al., 2008b). Some studies also focused on contacts providing/receiving a specific form of support (e.g. Burt, 1984).

NGs are generally followed by *name interpreters*, which gather additional information about the named contacts and their relationship with the respondent, such as socio-demographic characteristics, time they have known the respondent and circumstances where they met him/her, frequency of interaction. A known challenge is represented by finding a balance for the amount of information asked for each social contact, especially as in most surveys the number of social contacts that can be reported is not limited (Marsden, 1990).

Travel studies have recognised that social networks are likely to be more relevant for travel for social and leisure purposes and have consequently prompted respondent to report the members of their social network who could most likely have an influence on decisions regarding this type of travel, i.e. emotionally closer contacts (Carrasco et al., 2008b) and people with whom respondent spend their free time with (Kowald et al., 2010). Our recent work (Calastri et al., 2017c,d) has used data capturing using either of these approaches. We see value in combining the two approaches to more fully capture people's network in our survey.

We first adopt the Kowald et al. (2010) approach and ask respondents to report those people with whom they interact outside of work. The exact wording of the name generator question is "Please list the people with whom you choose to regularly interact outside of work, either in person or via phone or digital media." Respondents were also told to report just the name and the first letter of the surname (for privacy reasons). In the next line, they could also read "We provide you with 30 spaces below, but please feel free to use just as many as you need, and focus on who you normally stay in contact with". An example is shown in Figure 7.2. In this first screen, respondents were also asked to specify the type of relationship with each of their social contacts from a drop-down menu. The possible options were *Partner/spouse*, *Parent*, *Sibling*, *Friend*, *Other relative*, *Colleague*, *Other acquaintance*. Thirty lines were available in this screen for respondents to list their social contacts, but if needed, they could add ten additional spaces by clicking on a "I want to add more people" button at the end of the page.

Upon selecting the "All relevant people entered" option, an additional

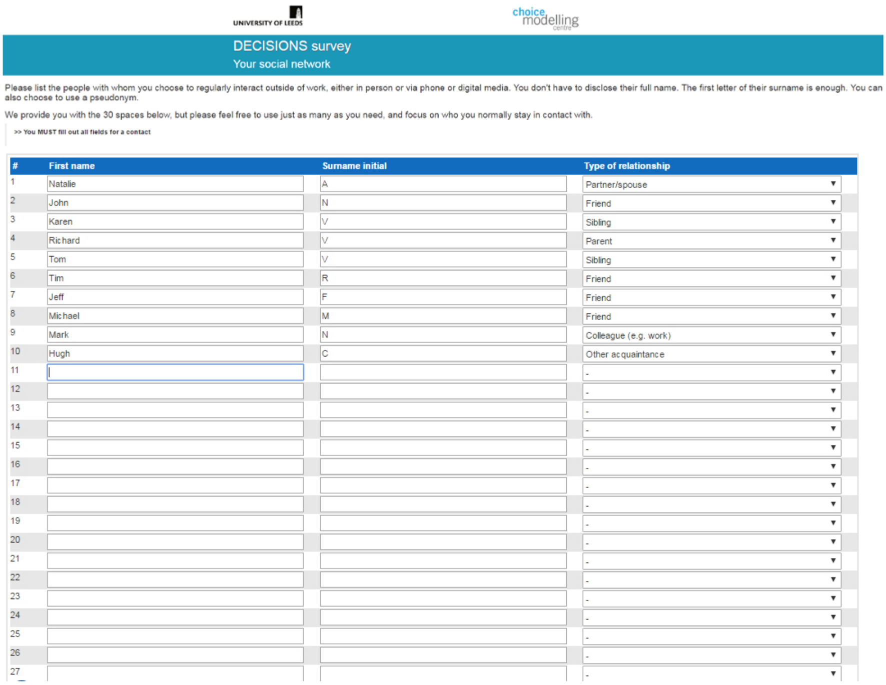

Fig. 7.2: Name generator - example

prompt was used to ensure respondents had not omitted anyone by asking "Is there any person with whom you spend time or you have an affective relationship that you did not include in the list?", thus seeking to also capture the angle covered by Carrasco et al. (2008b).

After completing the NG part, the survey moved to the name interpreter questions. For each social contact, the respondent was required to select the sex, age range, city in the United Kingdom (or state whether the person lived abroad) and frequency of interaction in person, by phone (separately by call and text), by email and by online social networks. Seven different categories were possible for the frequency of interaction, ranging from "Multiple times per day" to "Never".

2.2 Smartphone travel and activity app

After completing the three online survey components, respondents were invited to download and install a smartphone app which would collect data on their travel and activities for a period of two weeks.

2.2.1 rMove

The use of mobility apps allows a less burdensome data collection (as opposed to traditional travel diaries) and relaxes the constraint of collecting a single day of travel data that characterises many studies. The collection of multi-day data has great advantages in that it allows to observe habits and patterns in time use and travel that give a complete picture of real-life behaviour (Calastri et al., 2017e). A growing number of smartphone based GPS apps are available, where our work made use of a heavily customised version of rMove (Resource Systems Group, 2017), an app previously used in several US-based household surveys (e.g. Greene et al., 2016). The app was adapted for the specific needs of this survey, both in terms of suitability for the UK context, and to meet our specific requirements, in particular the links with other survey components.

Participants were invited to download the app from GooglePlay™ or iTunes™ immediately after completing the online survey. They then received a personal activation code by email approximately 24 hours after completing the survey, which ensured that the app interface was customised for each specific respondent. This made use of BQ and NG data on vehicle availability and social network members, helping survey engagement by making the app relevant to each person while also improving the accuracy of the data we collected.

rMove passively records travel data such as position, speed and route using multiple sensors, including GPS. For each completed trip, participants are asked to fill in short surveys, asking them questions about their travel mode, trip cost (if the trip was by taxi or public transport) and trip purpose. Over time, the app starts *learning* about regular trips and prepopulates the answers and only asks the respondent to confirm. Maps are used to help recall but also to allow users to add stops or correct a trip, if not displayed correctly. Figure 7.3 shows screenshots from the iOs version of the app where a trip is first displayed, then the respondent is asked to confirm whether the trip is correct and then to answer questions about the trip mode and purpose.

Respondents were asked to indicate who was with them during the trip, and, in the case of a leisure or social activity, whether someone joined them at destination. They could select contacts that they had listed in the NG as well as indicate that other people were present. The time burden required by the app varied depending on individual levels of travel activity, but decreased over time, both as users became more familiar with the app and as the app started learning about frequent trips and destinations.

The app also contained a specific feature to collect information about in-home activities. Each day, respondents were asked to indicate which activities they performed while at home during the previous day. The list included cooking, cleaning, do-it-yourself (DIY), eating, exercising, playing games,

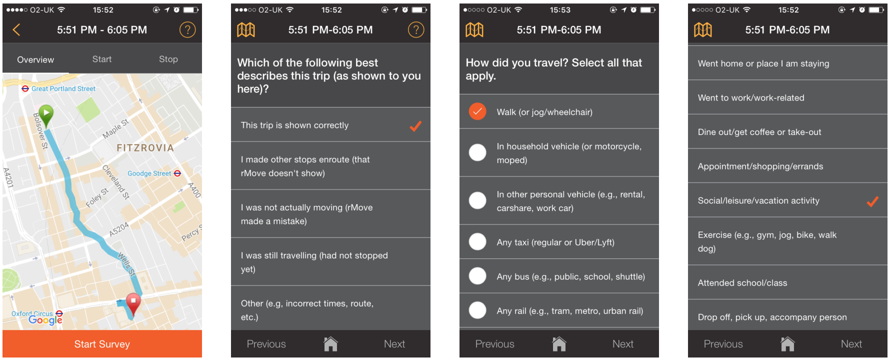

Fig. 7.3: rMove smartphone app screenshots

listening to music, online activities, talking on the phone, reading, socialising, watching TV, working. Twice a week, on a weekday and on a weekend day, respondents were also asked to indicate the time intervals during which such activities were performed, as well as the home appliances used.

2.2.2 The feedback system

As mentioned above, one of the rising trends in travel behaviour research looks at understanding social influences on travel and activity behaviour. We specifically looked at the role of feedback in this context, with a view to understand how respondents could be *nudged* to change their behaviour.

The sample of respondents was split into three different groups (or treatments). The first (control) group used the app for two weeks without receiving any feedback information. The second (treatment 1) group used the app for one week and then received a digital feedback sheet on their activities. This contained a breakdown of the time spent travelling per day by each mode, and the resulting CO_2 emissions as well as calories burnt by active travel. An example of the feedback received by this group is shown in the left panel of Figure 7.4.

The third group (treatment 2) received a similar feedback sheet (see right panel of Figure 7.4), with the difference that the respondents in this group could compare their performance with other respondents taking part in the study. In particular, the comparison was made with people who were "similar" to the respondent in term of socio-economic status. This approach was inspired by studies such as the Quantified Traveller (QT) experiment (Jariyasunant et al., 2014), which combined the use of a tracking app and the online social feedback system. The QT study was focused on testing the *Theory of Planned Behaviour* and therefore largely focused on attitudinal questions, while we aimed at investigating changes in behaviour occurring during the

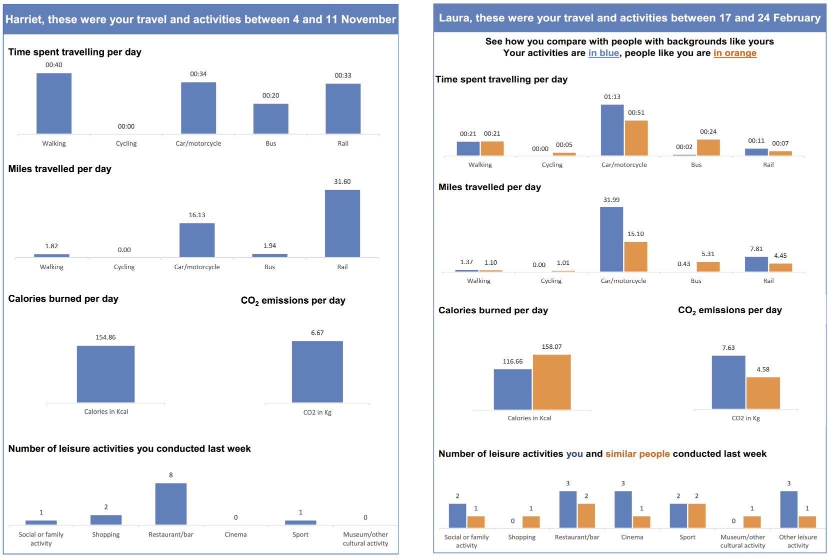

Fig. 7.4: Treatment 1 (left) and Treatment 2 (right) user feedback examples

second week. Moreover, we included a control group and work with a larger sample, overcoming some of the limitations of that study.

3 Data collection and post-pilot changes

The data collection for the present survey started in November 2016 and ended in April 2017, after two smaller pilot studies aimed at testing the different survey components, one in January 2016, mainly involving University staff and students, and one in April-May 2016, for which a sample of 70 people in the city of Leeds were recruited. A detailed description of the recruitment strategy for the main survey is given below, after we cover some of the changes made after the pilot survey.

3.1 Insights from pilot survey and subsequent changes

Our survey represents a very rich and complex data collection effort, where a vast amount of information relating to different choice domains are gathered from respondents, and important trade-offs between the amount and quality of information needed to be considered. As expected, changes and modifications had to be implemented with respect to the initial survey design, and several parts of the BQ and LCC were cut or shortened to minimise respondents' burden and focus on aspects deemed more important for our research objectives. The initial survey design differed from the final implementation, and we wish to share some of the challenges we faced, hoping that this might help researchers overcome certain obstacles in future efforts. In addition, the survey tools adopted in the present data collections imply potential sources of bias that we wish to acknowledge, explain how we addressed these and make suggestions about areas where methodological contributions are most needed in the future.

3.1.1 Sampling technique

Our initial sampling plan focussed on the use of "snowball" technique, which can help capture population-wide social networks. In this sampling method, initial respondents or "seeds" are asked to name their social contacts who are subsequently invited to take part in the survey themselves and then asked to also recruit the members of their network. This procedure can be repeated for a given number of iterations, until the desired sample size is reached (Kowald and Axhausen, 2014).

For ethical constraints, we could not collect the contact information of the alters and therefore we could not invite them to take part in the survey, an approach at least partly applied in the Swiss study described by Kowald and Axhausen (2014) where respondents could choose to send out the invitation cards or rely on the research team for this. We encountered strong resistance from respondents to agree to send the email to their social contact at the end of the survey. Focus groups and interviews carried out after the pilots revealed that the main worry of respondents was to disturb their social contacts by sending them the survey and making them feel morally obliged to complete it. We believe that a cultural difference between the UK and Switzerland may be at play in this case, as the respondents' motivations seemed to go beyond personal burden or privacy concerns, but relate to social norms.

It is important to notice that while snowball sampling has been applied in the UK, this has been done with the aim of investigating hidden populations, such as criminal gangs (Patrick, 1973), non-heterosexual women (Browne, 2005) and lone mothers (Duncan and Edwards, 1999). To our knowledge, there is no study that was not aimed at capturing such a hard-to-reach population which successfully collected a snowball sample in this country. The main phase of the survey thus relied on a single level egocentric sampling approach.

3.1.2 Incentives

A study requiring such a level of involvement needs to provide adequate incentives to make sure that respondents will sign up and complete the survey. Several different incentive structures have been attempted in the pilot studies. Similarly burdensome research studies provided monetary incentives to each participant (Greaves et al., 2014; Kowald et al., 2010; Montini et al., 2014). In particular, Kowald and Axhausen (2014) argue that a monetary reward is the best way to incentivise participants due to its universally understandable nature. We rewarded all respondents who completed the entirety of the survey with a £25 shopping voucher.

3.1.3 Number of contacts reported in the name generator

The name generator provides respondents with a limited number of spaces to report their network. As specified in Section 2.1.3, respondents in the final version of the survey are initially provided with 30 lines to input the names of their social contacts, and they can use 10 extra lines if needed. Such upper limits were designed on the basis of survey testing and findings from previous studies. Participants in a study in Toronto (Carrasco et al., 2008a) reported a mean of 23.76 alters; a study in Chile, surveying affective networks including both very close and somewhat close social contacts, reports a mean network size of 22.24 (Carrasco et al., 2013) while another study in Eindhoven, based on a 2-day interaction diary and a social network survey, reports an average network size of 23.28 alters (van den Berg et al., 2009).

Given these figures, in our pilot we presented respondents with 15 slots that they could fill in with names of their social contacts (so that the layout could be easily accommodated in a single screen of an internet browser). If needed, they could add 10 additional slots, up to a maximum of 60 spaces, a number rarely reached in previous studies. We observed that the tool we provided had an effect on the number of contacts that participants were naming. Figure 7.5 shows that when 15 slots where shown, a large number of respondents listed 10 or 15 contacts. While resulting from a small sample, this statistics gives us an indication of the fact that respondents might have felt like they needed to fill the grid they were provided with, or provide a round number of contacts. In a number of pilots studies, we observed that respondents never named more than 30 contacts, therefore the final version of the survey offered 30 spaces, with the possibility to add an additional 10, for a maximum of 40. As visible from the orange line in Figure 7.5, in the final survey we again observe a peak at 30 named contacts. We believe that this is a bias due to the instrument in question that could not easily addressed in the present study, but indeed requires further attention in the future. In both the pilot and the final survey, several respondents also only list one contact. While this will require further investigations, it could be due to fatigue effects.

3.1.4 Smartphone app issues

A well-known issue with surveys making use of smartphone apps is that of battery drainage. The reported travel activity could be affected by issues such

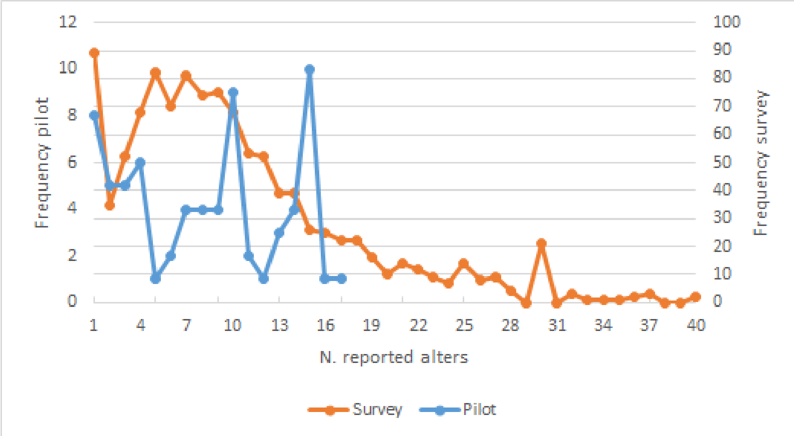

Fig. 7.5: Number of social network members in pilot and final study

as flat batteries or users turning off localisation services to preserve power, especially during days involving substantial travel activities. Unfortunately, the app does not allow us to check whether this is the case. Participants could have also actively prevented tracking for privacy concerns while performing specific activities. These issues are common to all studies making use of travel apps, and our decision to use such a tool is motivated by the fact that we concluded that smartphone apps were a better option than traditional travel diaries and GPS loggers. The former have indeed been shown to imply under-reporting in the number of trips (Wolf, 2006; Zmud and Wolf, 2003) and overestimation of trip durations (Kelly et al., 2013) and other inconsistent or missing trip information as well as missing route choice data (Bhat et al., 2005); while studies using the latter underlined the fact that participants found it hard to remember to carry the device with them Bohte and Maat (2009), while personal smartphones are rarely forgotten. We address the issues resulting from the data collection process at the data processing stage, censoring those participants who are likely to have not properly used the app.

3.2 Recruitment strategy

Participants were mainly recruited in the greater Leeds (UK) area, although people living elsewhere in the UK were also invited to take part. Participants were recruited through a number of different means. Our most reliable source came in the form of the *Leeds Citizens‘ Panel*, a repository of Leeds residents willing to engage in surveys and administered by *Leeds City Council*. A related group of people consisted of *Leeds Council* staff. We also made use of a number of commercial and community mailing lists as well as paper-based flyers and letters, manually distributed in the Leeds area. Flyers were mainly distributed in the city centre of Leeds, while letters were posted in a representative range of residential areas. A limited number of students were invited to participate by distributing flyers on campus at the University of Leeds.

As the present project is research-driven, the sampling strategy aimed at collecting a sample entailing a good variety in terms of socio-demographic characteristics as well as mobility and activity behaviour, rather than achieving representativeness of the population. The mere fact that respondents were supposed to use their own smartphones certainly implies a selection bias, probably leading to over-sampling of younger and high-income people. This is confirmed by statistics for the UK showing that older individuals from lower social grades are substantially less likely to own a smartphones than younger people from higher social grades (Local Level UK, 2014).

Previous experience suggests that long duration surveys can only succeed if the research team can gain respondents' trust (van den Berg et al., 2009; Kowald and Axhausen, 2014). In order to achieve this, the recruitment material (e-mail/flyer/letter) contained detailed information about the research team, the importance of the project for scientific research, the type of commitment implied by taking part and the incentive provided. Details were also given on the ethical clearance obtained for the survey. Respondents were able to contact the research team via e-mail, phone (both by call or text message) at any time and the team would respond promptly. Respondents needed to fulfil a number of criteria to be suitable to take part in the study. They needed to be aged 18 and over and own an Android or iOs smartphone with a phone data plan (for the smartphone app).

Table 7.1 shows the total number of people contacted and recruited as well as a breakdown of completion rates by survey component. As expected (given the highly burdensome nature of the study), the overall response rate is low, 2%. The number varies across recruitment sources, with very poor performance of flyers and letters and commercial mailing lists and good performance of the *Leeds City Council* mailing list and *Leeds Citizens' Panel*. The latter are cases where the message was sent by a source deemed trustworthy by the recipients, and this probably helped respondents believe that the survey was worth their attention and that there were guarantees that they would be rewarded upon completion. The average retention rate throughout the survey is 26%, and we observe more stability in this statistic across recruitment sources.

A low response rate should not come as a particular surprise for a survey of this nature, both given the amount of data collected, the type of information collected off respondents, and the time horizon over which respondents need to stay involved in the survey.

		Contacted	*Signed-up*	*BS*	*LCC*	*NG*	*rMove (install)*	*rMove (2 weeks)*
Total	N	27,500	1,747	1,416	1,290	1,109	643	452
	% contacted	.	6%	5%	5%	4%	2%	2%
	% signed-up	.	.	81%	74%	63%	37%	26%
Flyers and letters	N	10,000	117	101	94	83	44	31
	% contacted	.	1%	1%	1%	1%	0%	0%
	% signed-up	.	.	86%	80%	71%	38%	26%
Commercial mailing list	N	10,000	155	131	123	114	52	36
	% contacted	.	2%	1%	1%	1%	1%	0%
	% signed-up	.	.	85%	79%	74%	34%	23%
Leeds University Students and Staff	N	2,500	163	146	138	122	82	54
	% contacted	.	7%	6%	6%	5%	3%	2%
	% signed-up	.	.	90%	85%	75%	50%	33%
Community mailing lists	N	2,500	283	229	211	176	92	69
	% contacted	.	11%	9%	8%	7%	4%	3%
	% signed-up	.	.	81%	75%	62%	33%	24%
Leeds Citiziens Panel	N	2,000	465	382	334	275	157	117
	% contacted	.	23%	19%	17%	14%	8%	6%
	% signed-up	.	.	82%	72%	59%	34%	25%
Leeds Council Staff	N	500	285	227	212	189	126	84
	% contacted	.	57%	45%	42%	38%	25%	17%
	% signed-up	.	.	80%	74%	66%	44%	29%
Unknown	N	.	279	200	178	150	90	61

Table 7.1: Recruitment sources and survey completion statistics

4 Preliminary sample analysis

In this section we present overall sample characteristics, with particular attention paid to the differences between the groups of people who reached different levels of completion of the survey. This will allow us to assess whether survey engagement can be related to differences in participants' characteristics.

4.1 Background Questionnaire

Table 7.2 reports the main socio-demographic characteristics of respondents collected in the background questionnaire (BQ), split by the level of advancement in the survey, i.e. for people who only completed the BQ, for those who also completed the Life-Course Calendar (LCC), the Name Generator (NG) and finally for those who completed the survey in all its parts, including using the smartphone app for two weeks.

Table 7.2 shows that the sample includes a high share of women, young people and people with a high level of education. The average age of the sample, computed by using the midpoint of each category, is 39.5. Many surveys tend to have a higher share of women than men, and we believe the low number of elderly people was to be expected given the format of the research, including an online survey and a smartphone app.

We find that the percentage share of the different socio-demographic characteristics remain fairly stable across different people who have achieved different levels of survey completion, except for the levels of car availability, where we see a higher share in the group who reach the final stage of the

	Completed BQ		Completed BQ and LCC		Completed BQ, LCC and NG		Completed online survey and used rMove for 2 weeks	
Total	**1,416**		**1,290**		**1,109**		**452**	
	Freq.	*%*	*Freq.*	*%*	*Freq.*	*%*	*Freq.*	*%*
Gender								
Female	807	56.99	736	57.05	623	56.18	262	57.96
Male	609	43.01	554	42.95	486	43.82	190	42.04
Age								
18 - 24	248	17.51	234	18.14	217	19.57	67	14.82
25 - 29	152	10.73	143	11.09	129	11.63	44	9.73
30 - 39	358	25.28	331	25.66	292	26.33	134	29.65
40 - 49	307	21.68	276	21.4	227	20.47	93	20.58
50 - 59	219	15.47	191	14.81	158	14.25	82	18.14
60 - 65	76	5.37	69	5.35	51	4.6	19	4.2
66 and above	56	3.95	46	3.57	35	3.16	13	2.87
Education								
No education	30	2.12	29	2.25	24	2.16	6	1.33
O level	100	7.06	87	6.74	73	6.58	24	5.31
A level	128	9.04	115	8.91	97	8.75	28	6.19
Vocational school	219	15.47	200	15.5	165	14.88	66	14.6
Undergraduate	624	44.07	569	44.11	498	44.91	204	45.13
Masters	230	16.24	213	16.51	183	16.5	87	19.25
PhD	85	6	77	5.97	69	6.22	37	8.19
Marital status								
Single	468	33.05	441	34.19	392	35.35	119	26.33
Married	584	41.24	523	40.54	439	39.59	217	48.01
Cohabiting	275	19.42	248	19.22	215	19.39	91	20.13
Divorced	76	5.37	69	5.35	54	4.87	21	4.65
Widowed	13	0.92	9	0.7	9	0.81	4	0.88
Car availability								
No	453	31.99	416	32.25	369	33.27	124	27.43
Yes	963	68.01	874	67.75	740	66.73	328	72.57
Bicycle availability								
No	783	55.3	711	55.12	615	55.46	231	51.11
Yes	633	44.7	579	44.88	494	44.54	221	48.89
Household income								
Below 10k	79	5.58	75	5.81	68	6.13	21	4.65
10 - 20k	122	8.62	111	8.6	94	8.48	32	7.08
20 - 30k	183	12.92	167	12.95	146	13.17	55	12.17
30 - 40k	206	14.55	180	13.95	147	13.26	66	14.6
40 - 50k	211	14.9	191	14.81	167	15.06	63	13.94
50 - 75k	277	19.56	257	19.92	224	20.2	106	23.45
75 - 100k	110	7.77	99	7.67	83	7.48	48	10.62
100 - 125k	28	1.98	24	1.86	18	1.62	8	1.77
125 - 150k	16	1.13	16	1.24	13	1.17	4	0.88
Above - 150	9	0.64	8	0.62	8	0.72	5	1.11
Do not know	90	6.36	83	6.43	76	6.85	22	4.87
Prefer not to say	85	6	79	6.12	65	5.86	22	4.87
Location								
Leeds	899	63.49	821	63.64	704	63.48	298	65.93
Elsewhere in W Yorkshire	161	11.37	146	11.32	126	11.36	45	9.96
Elsewhere in the UK	356	25.14	323	25.04	279	25.16	109	24.12

Table 7.2: Socio-demographic characteristics - comparison across survey completion stages

survey. There is clearly a possibility that this higher rate is a reflection of greater survey engagement with the car ownership question. Overall, the stability in socio-demographics characteristics is reassuring in that we see that there are no major underlying differences in respondents who drop out or stay in the survey for its whole duration.

Approximately 65% of the recruited participants were from the greater Leeds area, reflecting the fact that several local recruitment channels were used, as discussed in Section 3.2. Approximately 10% of the sample lived elsewhere in West Yorkshire, while the rest of the sample was from elsewhere in the UK, with clusters in major cities such as London. These respondents were likely reached through the commercial mailing list.

	Share	**Still living with parents**		**N. of relocations while living with parents**		**N. of long-term partners**		**N. of children**		**N. of homes**		**N. of jobs**		**N. of cars**	
Age		*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*
18 - 24	18.14%	45%	0.50	1.72	1.90	0.36	0.64	0.14	1.09	1.60	1.93	1.96	1.88	0.39	0.85
25 - 29	11.09%	13%	0.34	2.17	2.39	1.00	1.27	0.19	0.60	3.80	2.71	3.45	2.23	1.20	2.27
30 - 39	25.66%	5%	0.21	1.97	2.43	1.41	1.86	0.91	1.09	4.63	2.89	4.68	3.73	2.02	1.95
40 - 49	21.40%	1%	0.12	1.81	2.09	1.53	1.01	1.35	1.29	4.92	2.99	4.62	3.45	3.75	3.20
50 - 59	14.81%	2%	0.12	1.74	1.80	1.50	1.31	1.54	1.19	5.16	3.00	5.37	3.87	5.34	4.55
60 - 65	5.35%	1%	0.12	2.48	2.41	1.42	0.86	1.49	1.15	4.96	2.92	4.83	3.04	7.64	6.45
66 and above	3.57%	0.00	0.00	2.30	2.26	1.61	0.95	1.63	1.20	5.07	2.90	6.26	5.57	6.41	4.71
Men	42.95%	0.12	0.33	2.01	2.13	1.29	1.76	1.01	1.34	4.12	3.05	4.21	3.89	3.60	4.55
Women	57.05%	0.11	0.31	1.85	2.21	1.17	0.97	0.88	1.16	4.20	3.02	4.19	3.25	2.46	2.96
All	.	0.12	0.32	1.92	2.18	1.22	1.37	0.94	1.24	4.16	3.03	4.20	3.54	2.95	3.77

Table 7.3: LCC descriptive statistics

4.2 Life-course Calendar

We now turn to a detailed descriptive analysis of the other parts of the survey data. In each case, we include in the statistics all the people who have completed up to that specific component, i.e. for example in the descriptive statistics of the LCC data, reported in Table 7.3, we use a sample of 1,290. This Table shows different life-course changes (listed as column headings) and the mean number of occurrences by age group and gender. We also report the shares the different age and gender groups in the sample. As expected, the highest percentage of respondents still living with their parents belongs to the age group $18-24$, followed by the group $25-29$. Somewhat surprisingly, about 13 respondents in the age range $60-65$ stated that they live with their parents, but this might be the case of people who took elderly parents in their home.

We asked participants to state how many times they relocated while living with their parents. We observe that over 60s report the highest means (with relatively high standard deviations) as well as people in the $25-29$ group, but statistical testing shows that there are no significant differences across age groups in this specific event. As expected, a rising number of long-term partners (defined as partners with whom a person has lived with) is reported with increased age, except for the age group $60-65$. The same is true for the number of children and the number of jobs, while the $60-65$ age category reports the highest number of cars owned during the life course. Statistical testing shows that the differences across age groups are significant, as expected.

There are no significant differences in the distribution of life course events across men and women, except in the case of car ownership, where women own significantly fewer cars than men over their life.

As in the case of the socio-demographics characteristics, we have prepared two additional versions of Table 7.3: one including the participants who have completed the entire online survey and one only included those who have in addition used the rMove for two weeks[2]. We also tested whether people who have completed different stages of the survey are different in terms of average number of the different life course events. Our results show that, for all events except number of people still living with parents and number of relocations while living with parents, there are significant differences at the 0.05 level. We believe this depends on survey involvement, as the events where the differences are present are those that involved inputting more information in the LCC, a relatively demanding and time consuming task.

4.3 Name Generator

Tables 7.4 and 7.5 report descriptive statistics for the name generator and name interpreter data. In particular, Table 7.4 shows, depending on the gender of the *ego* (i.e. the participant whose social network is analysed), the number and share of *alters* (i.e. social contacts) of each gender were listed in the NG. As expected, we observe that people are more likely to report alters of their own gender. This gender homophily was confirmed to be significant by statistical testing. The rightmost coloumn of the table represents the total number of contacts reported, showing that female egos reports slightly more contacts than male. The same type of information is displayed in Table 7.5 for the age of the egos and alters. We can see that there is a high age homophily, meaning that people report a high number of social contacts of their same age group. This finding was also confirmed by statistical tests of significance.

As in the previous cases, we compared these two tables with the corresponding ones including only those respondents who not only completed the online survey, but also used the smartphone app for two weeks[2]. We found

[2]Due to space limitations, we report those tables in an online appendix at http://www.stephanehess.me.uk/papers/Calastri_Crastes_Hess_2017_online_appendix.pdf

significant differences in the number of contacts by gender and by all age categories except $40-49$, $60-69$ and over 70.

		Alter		
		Female	Male	*Total*
Ego	Female	7.21	3.51	*10.72*
		67.24%	*32.76%*	.
	Male	3.92	5.37	*9.28*
		42.19%	*57.81%*	.

Table 7.4: NG descriptive statistics

		Alter								
	Age	Under 18	18 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 69	70 and above	*Total*
Ego	18 - 24	0.49	6.06	1.04	0.36	0.70	0.97	0.23	0.24	10.09
		4.9%	*60.0%*	*10.3%*	*3.6%*	*6.9%*	*9.6%*	*2.3%*	*2.3%*	.
	25 - 29	0.24	1.26	4.34	1.99	0.46	1.12	0.51	0.26	10.19
		2.4%	*12.3%*	*42.6%*	*19.6%*	*4.5%*	*11.0%*	*5.0%*	*2.6%*	.
	30 - 39	0.28	0.24	0.89	4.84	1.38	0.75	1.18	0.28	9.84
		2.8%	*2.4%*	*9.1%*	*49.1%*	*14.1%*	*7.6%*	*12.0%*	*2.9%*	.
	40 - 49	0.44	0.26	0.30	1.67	3.70	1.32	0.77	0.91	9.36
		4.8%	*2.8%*	*3.2%*	*17.8%*	*39.5%*	*14.1%*	*8.2%*	*9.7%*	.
	50 - 59	0.35	0.45	0.56	0.93	1.99	4.24	1.24	1.06	10.83
		3.2%	*4.1%*	*5.2%*	*8.6%*	*18.4%*	*39.2%*	*11.5%*	*9.8%*	.
	60 - 65	0.20	0.22	0.43	1.53	1.33	2.41	3.27	1.20	10.59
		1.9%	*2.0%*	*4.1%*	*14.4%*	*12.6%*	*22.8%*	*30.9%*	*11.3%*	.
	66 and above	0.46	0.46	0.69	1.06	1.49	1.89	4.09	2.46	12.57
		3.6%	*3.6%*	*5.5%*	*8.4%*	*11.8%*	*15.0%*	*32.5%*	*19.5%*	.

Table 7.5: NG descriptive statistics

4.3.1 Recall survey

As part of our ongoing work, we plan to survey our respondents again at different points in time to observe changes that may have occurred since the main data collection took place. At this stage, for illustration purposes, we have performed a pilot recall survey aimed at understanding changes in social network over time and limitations in the use of the name generator to address such survey question. Studies such as Calastri et al. (2017c) and Sharmeen et al. (2016) have used network data collected at different points in time using name generators, to study the stability and changes in social networks. Especially when the period of time between the two surveys is extended, recall issues may emerge and it might be difficult to distinguish people who are no longer part of the network from those who have been forgotten. On the other side, showing the initial name generator at the moment of the second survey and asking people to confirm that the network is unchanged may lead to bias.

For this reason, we adopted a different approach. In July 2017 we recontacted 10 people who had been surveyed in November 2016 and asked them to complete the NG from scratch. Once completed, we showed them the NG they filled out in November, and asked them to match the names of the people who were in both lists. If there was a perfect correspondence, the survey ended. This did not happen for any of the respondents. For the contacts who had only been reported in November but not in July, we asked if they were still in touch. If not, we asked for the reason why. For those people who were only reported in the July NG, we asked whether they were new acquaintances, or if they were already known to the participants in November, but had been forgotten in the NG at the time.

The average network size of these 10 people was 12.9 in November and 11.2 in July (not statistically different) and they on average matched 8.4 contacts. On average, there were 4.2 contacts who had not been named in July but with whom they were still in touch and 0.2 who were not named and with whom they were actually not in touch any more. While the former were spread across the sample, the latter were 2 contacts of a single participant, lost because he/she went to university. In addition, there were on average 2.6 people who were only named in the July list but were actually known in November already, spread across the sample, while only 0.1 (1 alter from one ego) was a new acquaintance. The present sample is of course very small, and a larger recall study is needed for any significant conclusion. Nevertheless, we find the results quite striking, as they highlight serious limitations of the name generator tool for eliciting social networks, suggesting it suffers from severe recall issues.

4.4 Smartphone travel and activity app

As shown in Table 7.2, 452 respondents used the smartphone app rMove for two weeks. A total of 40,672 trips were recorded, for which participants had to answer different questions, as explained in Section 2.2.1. 84.71% of trips were recorded correctly, and for 81.1% all details were provided by respondents. 12.34% of total trips were marked by users as GPS errors and 2.95% as other errors (e.g. the app recorded a movement when the person did not actually move).

Table 7.6 shows the share of rMove trips by purpose[3], where the most common destination is home or work, followed by social (all non-work activities that involve other people, such as going out and spending time with the family) and shopping (including both groceries and other shopping). Thanks to the link with the NG, we were able to determine that 55.63% of the trips were made by participants on their own, 15.62% were conducted only with people listed in the NG, 17.03% with both contacts from the NG and others, and the remaining 11.73% of trips was conducted with contacts unreported in the NG only.

[3]The purposes listed in the tables are macro-categories to give an overview of the trips, but a more detailed distinction is made in the data

Trip purpose	**%**
Going home	28.47%
Going to work	19.42%
Social	11.98%
Going shopping	10.23%
Other[1]	10.19%
Drop off/Pick up	6.62%
Errands	4.56%
Sports and exercise	4.52%
Leisure	2.31%
Going to School/ class/ University	1.15%
Petrol	0.57%

[1] includes "change travel mode" and "Other (non specified) purpose"

Table 7.6: Share of rMove trips by purpose

	Share of trips	**Average distance per trip (km)**
Walk	46.71%	11.88
Car	37.57%	1.55
Urban bus	6.95%	10.49
Rail	2.40%	54.33
Bicycle	2.27%	7.85
Taxi	1.76%	6.26
Urban rail	1.23%	18.99
Other bus	0.65%	186.40
Other modes	0.46%	42.13

Table 7.7: Share of trips and average distance by mode

Table 7.7 reports the share of trips by each mode, showing that most trips are performed by car and on foot. While the share is much lower, urban buses are used more than other public transport modes. This is to be expected in Leeds, as there is no metro/light rail service in the city. Rail trips are mainly non-urban, as the distance also shows. Modes other than those listed were grouped together, where the occasional presence of trips by plane pushes the mean distance (37.76 km) upwards.

5 Summary

Recent work in transport research has increasingly tried to broaden out beyond traditional areas such as mode choice or car ownership and has tried to position travel decisions within the broader life context. However, while important progress has been made in terms of how to capture these additional dimensions, both in terms of detailed tracking of movements and in-depth data collection on long term decisions or social network influences, surveys have tended to look at only a handful (or often one) of these issues in isolation. The ERC funded DECISIONS project set out to instead collect data in a unified approach by jointly looking at numerous dimensions. We believe that this is an unprecedented effort that joins complexity of the survey design, amount of information collected and sample size. The present paper has given an overview of the different components of this survey and provided initial insights into the resulting data. The full dataset will be made publicly available at the end of the DECISIONS project, in 2020.

The survey was made up of two different components, an online survey and a smartphone tracking app. The online survey was in turn divided into three elements, a background questionnaire, a life-course calendar and a name generator & name interpreter. These different tools were used to capture different aspects of participants' lives, including travel and energy choices, life-course events, social networks and short term activity and mobility behaviour. The level of complexity goes beyond what is typically expected of survey respondents, and the rate of retention across different survey components is consequently lower than in many other studies. Nevertheless, we end up with a usable sample of respondents who completed all parts of the survey, and initial analysis of the data shows high quality information and crucially allows us to understand the links between short-term and long-term decisions for the same individual while also making links with his/her social network.

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Chapter 8

Discussion and conclusions

1 Summary

This thesis has put forward a number of theoretical and applied contributions around the theme of modelling complex decision-making related to travel, time use and social networks. The Introduction outlined a number of areas that this thesis focused on, selected for their specific relevance not only for travel behaviour research, but for being transferrable across applications in other fields. This section returns to these themes, draws links across the different chapters of the thesis and summarises the findings of this work.

1.1 The role of social networks in decision making

1.1.1 Modelling social network use and evolution

A better modelling of how social networks evolve and operate will ultimately contribute to gaining a better understanding of their impact on other choice processes as well as developing joint models of social network processes and other decisions. Chapters 2 and 3 focussed on the modelling of patterns of social interactions and evolution of social networks (with a focus on maintenance of social contacts). In particular, Chapter 2 presented an application of the MDCEV model to investigate the determinants of communication frequency by four modes (face- to-face, phone, e-mail, and SMS) between people and their social network members, a topic previously mainly studied with multi-level models (Frei and Ohnmacht, 2016) and multi-level path analysis (van den Berg et al., 2012). The findings of this paper give a detailed picture of the ego and ego-alter level variables determining the choice of each mode, as well as providing a picture of the satiation accrued by each mode. These provide practically useful insights for understanding the patterns of social interactions amongst social contacts, which can have important connections with their involvement in activities and travel for social, leisure and other purposes.

Chapter 3 presents a hybrid model of social contact retention over time, where relationship strength is modelled as a latent construct. The results show that ego socio-demographics and life- course changes, as well as ego-alter characteristics, have a significant impact on retention. In addition, significant random ego-level heterogeneity in retention, as well as both ego and ego-alter level heterogeneity in strength is found.

These papers show the importance of using comprehensive frameworks that can accommodate the complexity of the choice process. Both in the case of the decision of how to interact with social contacts and in the one of social contact retention, it is crucial to include in the model both ego and ego-alter level variables. Moreover, the results of the paper presented in Chapter 2, highlighting that there is a strong preference for face-to-face interaction, especially with core social contacts, are reflected in the ones from the paper in Chapter 3, which indicate that emotionally stronger contacts are more likely to be retained in the network over time. This behavioural picture, where some social contacts are emotionally stronger, have more frequent face-to-face interactions and are more likely to remain in the network, is an important finding in light of the current research on potential substitution effects between ICT based modes of communication and more traditional ones, and the role of distance in social relationships. The implications of these findings have a direct impact on the demand for travel for social purposes and potentially for long-term social influence on choices. The results from the paper presented in Chapter 2 also showed that the frequency of communication seems to be unaffected by the availability of specific travel modes or public transport passes. As discussed in the paper, previous studies do not present clear-cut evidence on the significance of these factors for the patterns of social interactions (Frei and Axhausen, 2009; Frei and Ohnmacht, 2016; Sharmeen et al., 2014; Tillema et al., 2010), so it is acknowledged that the findings could be partially related to the specific context where the data was collected as well as to the lack of detailed information about the transport network.

The papers presented in Chapters 2 and 3 represent innovations with respect to the existing literature in that the first one is a new application of the MDCEV model and constitutes a particularly comprehensive effort to represent the decision process of social interactions; while the second one represents an important first step in using advanced choice models to study social network evolution. Given the relevance of social interactions and changes in social networks for travel behaviour analysis and other choices, it is important to pursue their analysis using advanced choice models. As mentioned above, the applied work for these papers highlighted important limitations of the name generator data, which inspired the search for more reliable tools in the survey presented in Chapter 7, where the main issues with recall using name generators were observed and methods to mitigate them were suggested.

1.1.2 Understanding links between choices and social context

The field of travel behaviour has seen an increased interest in understanding the role of social networks on travel and activity choices. Several studies have used simple choice models to incorporate social networks effects (e.g. the choices of others or the characteristics of the social network) as covariates (e.g. Páez et al., 2008; Scott et al., 2012), suggesting that the latter were influencing choices. The work presented in Chapters 2, 3 and 4 of this thesis revolves around the theme of social networks and choices. Chapters 2 and 3 focus on modelling social interactions and social network evolutions, processes that, as mentioned in the papers, are likely to have strong links with other decisions. In particular, understanding the pattern of interaction between leisure network members helps to understand travel for social and leisure purposes, while understanding the changes in social networks over time might help gain better insights into other long-term choices that are susceptible to the influence of social network members.

Chapter 4 is specifically focused on investigating the possible links between decisions related to time allocation and the social context. In this work, the difficulty in determining the direction of causality was highlighted, but at the same time the model results confirmed the presence of significant links between these two dimensions, not only in the case of social and leisure activities (as previously found in the literature) but also for other activities. The paper also investigated the presence of potential confounding between the socio-demographic and social network variables, showing that such an effect could be ruled out. This paper represents a successful application of the MDCNEV model, a complex model structure that had only been applied in a very limited number of occasions before, and found substantial correlation within the nests, differently from previous work (Ferdous et al., 2010; Pinjari and Bhat, 2010b; Rajagopalan et al., 2009). Forecasting results show that the nesting structure matters and its impact on time reallocation is in line with expectations. While in Chapter 4, the examples are purely illustrative and guided by model results, this can be practically useful for predicting how time allocation, and therefore the need for travel and services provisions, will change in the event of a change of socio-demographics, such as changes in the population income.

1.2 Modelling and forecasting discrete-continuous choices

The time use models developed in Chapters 4 and 5 accommodate heterogeneity as well as capturing correlation structures across days and activities. The first one explores the type of activity chosen and time spent in each of them across two days, relating the choice to socio-demographic characteristics as well as social network variables. Correlations between activities are explored by means of a nesting structure. The model results show that there are three nests, grouping "in home", "out of home" and "family" activities, with strong levels of correlation.

Chapter 5 makes use of two different datasets to delve more deeply into the topic of capturing correlation patterns across and within different days. Accommodating correlations and complementarities in the MDCEV model would require major changes in the model structure, and, as seen in solutions put forward in the past, often result in computationally intractable models. Therefore, a mixed MDCEV model that can accommodate positive and negative correlations between activities at the within-day and between-day level is applied. Differently from the work presented in Chapter 4, these results allow us to observe the presence of substantially different sensitivities during weekday and week-end days. In addition, they reveal substantial random heterogeneity, highlighting that different people have different sensitivities, both in terms of the participation and in the time invested in different activities. The estimation of the full covariance matrix made it possible to calculate correlations between the coefficients of the model, and therefore between the parameters representing the discrete and continuous part of the choice of each activity. This modeling approach allows us to report a wide amount of information concerning the correlations between activities.

Both Chapter 4 and Chapter 5 include model forecasting. Forecasting is clearly of major interest when using discrete-continuous models, yet most applications pay little attention to this, especially when using more advanced variants of the model. This is largely due to the complexity of the forecasting process, an issue addressed in this thesis. While in the case of the MDCNEV model, the (Pinjari and Bhat, 2010a) forecasting algorithm can be applied, this requires taking draws from a generalized extreme value distribution. The paper proposes a simpler method to take draws from a GEV distribution (necessary for forecasting) than the ones previously suggested in the literature (Bhat, 2009; McFadden, 1999) and adopted in the only application forecasting with this model (Bernardo et al., 2015). Forecasting is also performed in the work presented in Chapter 5, but in this case two new approaches are proposed, as the (Pinjari and Bhat, 2010a) would not accommodate redistributions of time across days. The new approaches are applied to the two datasets and give results that are in line with expectations.

1.3 Accommodating complex patterns of unobserved heterogeneity

While the work using discrete continuous models also looks at accommodating deterministic (Chapters 2 and 4) and random heterogeneity (Chapter 5), contributions to more conventional discrete choice modelling are made in Chapters 3 and 6.

In Chapter 3, a hybrid framework was developed to understand how social networks evolve in time and in particular which social contacts are retained over a 4 year period by an individual. In this framework, the binary outcome to retain each social contact is modelled as affected by ego and ego-alter characteristics. Moreover, in an attempt to disentangle different sources of heterogeneity in this process, random heterogeneity at the ego level in retention and at the ego and ego-alter level in the relationship strength are accommodated. The findings underline the impact of strength on retention as well as the relevance of random ego-level heterogeneity in retention, as well as both ego and ego-alter level heterogeneity in strength. In particular, the results show that the ego-alter level heterogeneity in strength is higher than the ego level one, as expected.

While much of the focus in choice modelling has been on explaining heterogeneity as variations in marginal utility coefficients, there is similarly major scope for heterogeneity in the process that people use to make a decision. Much of this has looked at information processing (Hess and Hensher, 2010; Layton and Hensher, 2010) and decision rules (Abou-Zeid and Ben-Akiva, 2010; Chorus et al., 2008; Tversky, 1972) but the heterogeneity has generally focussed at the person level rather than the choice level. Chapter 6 looks at the treatment of latent mode availability and consideration using high resolution GPS data for mode choice, where the latent availability is handled at the person level and the consideration at the trip level. The probabilistic treatment of availability takes into account differences across respondents as this is specified as a function of socio-demographic characteristics, while the probability of consideration depends on trip-level variables, such as distance, purpose and heat index.

1.4 Insights from existing RP data sources and new data collection

The first 5 papers in this thesis used four existing datasets containing revealed choice data. These range from typical name generator data, used from the analysis of social network processes (in Chapters 2 and 3), to time use and travel diaries (used in Chapters 4 and 5), to a GPS tracking app recording all travel activities (used in Chapter 6). As discussed in this thesis, capturing complex real-life behaviour can be challenging. It may involve asking respondents to recall detailed information about multiple aspects of their lives, often distant in time and with limited aids, potentially leading to omissions and misreporting due to fatigue and difficulty to recall. Additional error can be caused by the format of the survey and whether it requires manual data entry/handling.

Given these difficulties, rich datasets generally come with higher risk of error, and a compromise between quantity and quality of information is often unavoidable. For example, the Communities in *Concepción* dataset is an extremely rich survey that allowed us to perform social network and time use modelling accounting for many socio-demographic characteristics as well as social network variables. On the other side, this survey relied on a traditional name generator and a pen and pencil activity survey, which both have limitations in terms of data accuracy (Bell et al., 2007; Wolf, 2006; Zmud and Wolf, 2003). These limitations represented an encouragement to explore alternative data sources, such as the GPS mobility data collected within the *Tag My Day* project. As described at length in the related Chapters, the different types of data imply different challenges. This thesis has shown that these can be overcome by appropriate efforts in handling and modelling the data to obtain meaningful behavioural insights.

All the datasets used in these 5 papers were collected by research bodies but not all of them were initially designed for choice modelling. In particular, the *Tag My Day* dataset was collected for purposes other than the analyses normally conducted in our field and, as explained in the paper, data on travel mode availability was not initially collected. The paper in Chapter 6 shows how, despite these limitations, performing data cleaning and enriching, and developing models making different assumptions in terms of availability and consideration resulted in successful estimation of mode choice models that provided reasonable values of travel time (VTT). Not only does this paper model the complex behavioural structure of consideration and computes reasonable VTT measures using GPS data, but it also shows that GPS data without associated in-depth information about respondents can be successfully used in our analyses. This type of data entails two other important advantages. The first one is its real-life nature: the GPS technology provides a high level of precision in recording travel times and locations, and the use of an app/portal to prompt respondents to provide additional information has great benefits in improving accuracy of recall. Secondly, the *Tag My Day* data is longitudinal, i.e. a high number of observations are collected for each individual over time. This experience inspired the use of a similar tool in our data collection, presented in Chapter 7. The rMove app is of course a more advanced tool with respect to the logger used in the *Tag My Day* survey. Nevertheless, the lessons learnt from the *Tag My Day* data management and modelling will be essential when applied to the GPS data collected in the *DECISIONS* survey.

The use of longitudinal data is a recurrent theme of this thesis. All the datasets used in this thesis include multiple observations for each respondent (either in the form of alters, or in the form of trips, activities...), and all except the one used in Chapter 2 record the information at multiple points in time. Unfortunately, the high variability in the number of trips recorded across people in the *Tag My Day* dataset did not make it possible to fully exploit the panel nature of the dataset to infer habitual behaviour and observe differences across days.

The application of the MDCNEV model performed in Chapter 4 makes use of a two-day dataset, but while the modelling approach adopted (using an overall budget of 48 hours) allows to accommodate a link between different days, acknowledging the presence of correlations between them, it does not make it possible to understand the differences in the utilities of activities across days. The limitations of this approach and of the work performed with the *Tag My Day* dataset partly motivated the effort in Chapter 5, were a longer-term longitudinal dataset (*Mobidrive*) was employed in addition to the two-day dataset used in Chapter 4. The appropriate treatment of multi-day activity diary data in Chapter 5 showed the potential of this type of data in unveiling substitution dynamics across and within days. The performance of the analysis with two different datasets validates the model and forecasting results.

Time use modelling with the *Mobidrive* and *Concepción* data highlighted the importance of data quality in this type of work. In both these traditional "paper and pencil" surveys, participants could freely describe the activity they were undertaking. For this reason, researcher had to recode the activities into a finite number of categories increasing the probability of errors and misinterpretations. Moreover, in this type of surveys, there is generally a lack of detailed information about the time spent at home, which led us to treat a substantial amount of time as the "outside good". This modelling experience was again crucial in shaping the data collection presented in Chapter 7, where the choice of the activities conducted was constrained in rMove (although a wide range of options were provided to respondents) and respondents also received surveys about their in-home activities.

The work on social contacts retention presented in Chapter 3 also makes use of longitudinal data, as the name generator is filled out by the same respondents at two different points in time. As explained in the paper, the small sample usable for the analysis constitutes a challenge, and the survey protocol required a substantial amount of work to match the social contacts named in the two waves, as respondents would sometimes only use names, surnames or nicknames in one of the waves. This represented an obstacle that affected previous efforts to model these data (Sharmeen et al., 2016). Like in other cases, a correct handling and modelling of the data made it possible not only to model contact maintenance but also to obtain a detailed and meaningful picture of behaviour.

Finally, the work with the different datasets in the first 5 Chapters of this thesis inspired the development of the data collection described in Chapter 7. In this case, the different survey tools are designed to address the limitations of previous data collections. Preliminary analysis of the data shows high quality information from a large usable sample of respondents who completed all parts of the survey. This dataset will be a useful tool for testing advanced model structures and behavioural hypotheses involving complex choice behaviour.

2 Objectives and contributions

The Introduction to this thesis outlined six separate objectives, three of them relating to model methodology, two to applications, and one to data. In what follows, a brief discussion of how the work described in the thesis has addressed these objectives and a description of the contributions are provided.

M1: Modelling inter and intra-agent heterogeneity in longitudinal data This objective was met with the developments in Chapter 3. The presence of both inter and intra-agent heterogeneity in longitudinal data was highlighted and it was shown how the use of a hybrid model structure can help in this context. While the hybrid structure is not essential when the choice process is not a simple binary outcome with the heterogeneity linked to the constant only, the framework should still have benefits in other cases too.

M2: Modelling complex correlation patterns in discrete-continuous models and recognising their role in forecasting This objective was met in different ways in Chapter 4 and Chapter 5. In Chapter 4, one of the first applications of the nested MDCEV model was provided, showing stronger correlations than in most other applications. The correlations addressed here are between different activities. Chapter 5 proposes further developments by allowing for correlations within and between activities at the day-level and intra-day level, putting forward the use of a mixed MDCEV model. In both chapters, new practical solutions for using the models in forecasting are provided.

M3: Capturing the latent aspects of alternative availability and consideration in high resolution data This objective was met in Chapter 6, where high resolution data collected by means of a GPS logger are exploited. Travel mode choice is modelled by taking into account the availability of each mode and consideration of two modes depending on trip characteristics. Due to missing information, probabilistic approaches to infer availability are adopted, and more flexible models are shown to provide better fit and more plausible VTTs. The use of high resolution GPS data, enriched with environmental data, adds value to the modelling effort.

A1: Novel applications to high resolution and/or longitudinal data and exploitation of non-traditional data sources This thesis is a rare example of a travel behaviour research PhD thesis that makes use of RP data alone and which uses multiple datasets. The objective is met with applications to both high resolution data (Chapter 4, 5 and 6), longitudinal data (Chapter 3 and 5) and data not collected for choice modelling purposes (Chapter 6).

A2: Applying advanced choice models in the area of social networks This objective was met with the contributions in Chapters 2, 3, 4. In Chapter 2, the MDCEV model was applied to explain the mode and frequency of interaction with social network members. A forecasting exercise allowed to show the effects of relocation of a social contact on interactions and distance travelled. Chapter 3 put forward a hybrid framework to represent the process of social contact retention over time, showing the importance of relationship strength and of other observable ego- and dyad-level variables. Finally, 4 explored the correlations between social network characteristics and activity engagements, also highlighting the difficulty of determining the direction of causality of such effects.

D1: Highlighting issues with existing datasets and guidance for integrated data collection efforts This objective was met with the work presented in different Chapters. Chapter 3 discussed the limitations of name generator data in terms of the associated recall issues. Chapters 4 and 5 make use of traditional time use and travel diary data, that are subject to known issues, e.g. underreporting of short trips, rounding of start/end times. The work in Chapter 6, while making use of more accurate data, highlighted the challenges associated with passively collected data, and the necessary steps to be undertaken to make such data usable in choice modelling. Chapter 7 presents a detailed summary of these issues while introducing a new integrated data collection effort. By integrating a rich survey and a smarphone mobility app, this data collection exploits the lessons learnt from the Chapters 2-6 and provides guidance for scholars aiming at collecting similarly rich and detailed data to be used for advanced modelling.

3 Outlook

This thesis has discussed different topics in choice modelling around the general theme of capturing and modelling complex decisions.

As highlighted in the conclusions of the single papers, more work is needed on the topics proposed in this thesis. As mentioned above, the modelling of social network processes using choice models is at its infancy. There are other decision processes that could be studied by means of advanced choice modelling, and different framework to be tested to model different choices. The work in psychology provides important elements of guidance in this process, as shown in Chapter 3. Indeed, there might be other psychological factors affecting social network evolution, such as personality traits, that could be captured and included in choice models as indicators. Some examples of the possible next steps in this area of work would be the formulation of a more general model of network evolution, that does not only focus on the process of retention but also includes the processes of contact formation. This last point seems particularly challenging in terms of defining the choice set, and existing studies have recurred to the use of a synthetic population or approximated the entire population by the local distribution of socio-demographics.

The area of social network effects on choices (often referred to as social influence) has received more attention than social network dynamics itself although it still counts a limited number of contributions. As highlighted in Chapter 4, the issues of potential confounding as well as the directionality of the effects are important aspects that are often underestimated and should be considered more carefully by studies in this area.

Differently from social networks, time use is an area that has received a substantial amount of attention within the greater area of travel behaviour research. Nevertheless, the MDCEV model is a relatively new approach that could benefit from extensions to accommodate further aspects of real-life behaviour. This thesis moved a first step towards addressing the issue of correlation across days in time use applications, but recognised that changes in the utility function would be needed to properly accommodate substitutions and complementarities. While such a model has been suggested, its complexity makes it so difficult to estimate that there have been no applications of it in the literature. Multiple discrete-continuous choices are of such complex nature that several possible aspects of real-life behaviour could still be accommodated as extensions of the model, although this would require a substantial methodological effort to ensure applicability of the models.

The work presented in this thesis modelled different complex decisions using advanced choice models. One of the datasets used, the *Concepción* dataset, is a rare example of a survey including multiple aspects of participants lives, such as time use, social networks and socio-demographic characteristics. The dataset described in Chapter 7 not only includes this information, but also collected details about participants' life history and energy behaviour. A challenging next step in this work would consist in building stronger links between the different choice domains, such as travel behaviour, social interactions and energy choices to develop a comprehensive framework that would create links across these decisions across the life course.

All the papers collected in this thesis made use of RP data, a source of data that has great benefits in terms of the ability to capture real-life behaviour, but at the same time has important limitations that were discussed in the thesis. In each case, the lessons learnt about the different data sources and how to handle them were shared. At the same time, the successful effort reported in Chapter 7 shows that it is possible to collect very rich RP data minimising the issues that were found in many of the datasets used. As discussed in Chapter 7, there are plans to carry out a full recall survey on the name generator, as the paper in this thesis only presents a pilot of that specific part, and to also perform additional recall surveys about other aspects of respondent's life that were collected in this first wave, for example life-course events.

The future work outlined in this section would continue the effort carried out in this thesis to propose new methods and applications to better capture and understand complex decision-making in different fields. This could not only advance academic research but also provide valuable advice to policy making in different areas. In particular, this work and its future developments could contribute to the understanding of travel demand, especially as derived from the need to perform activities and interact with people, which could in turn inform policy makers about the need for travel investments and infrastructures. In addition, the understanding of social networks and social interactions has implications in terms of understanding social inclusion and can provide useful information with respect to related social policies.

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Appendix A

Appendix to Chapter 2

In this appendix, we present the results of our MDCEV model for mode and frequency of interaction when different assumptions about the cost of the different modes of communication and the budget are used. We also show that such assumptions do not have a large impact on forecasts from the model.

1 Model estimation

1.1 Price differentiation

In Chapter 2, we assume that all the modes of communication have equal unitary cost. We now modify the assumption, and assume that face-to-face is more expensive (with a cost equal to 2), followed by phone (with cost of 1) and that SMS and e-mail are cheaper, costing, respectively, 0.1 and 0.5. The model results are presented in Table A.1. Statistical testing shows that the only parameters that are significantly different between the two models at the 0.05 level are the translation parameters, the distance coefficient for face-to-face and the baseline utility constant for email.

1.2 Budget change

In the paper, we assume that the budget for a person is equal to the overall number of interactions for that person. We compute the mean of the sample budget and add it to the budget of each individual, so that a generic fixed increase is perceived by everyone. The model results are presented in Table A.2. In this case, the only parameters that are significantly different are the baseline utility constants (the γ parameters) for all modes, which all change by the same amount.

	face-to-face		*phone*		*e-mail*		*sms*	
	est	t-stat	est	t-stat	est	t-stat	est	t-stat
Gamma parameters (γ)	1.04	22.4	4.07	44.46	7.12	43.85	9.89	40.59
Baseline constants (δ)	4.38	17.4	1.32	5.295	-2.36	9.176	-0.29	1.12
Ego characteristics								
Age								
Age = 18	0.09	0.17	-0.05	0.10	-1.90	3.51	0.64	1.25
Age 19-30	-0.12	0.58	-0.34	1.60	-0.44	2.03	0.66	3.04
Age 31-45	-0.03	0.23	-0.08	0.57	0.06	0.45	0.50	3.41
Age 46-60	-0.09	0.68	-0.17	1.25	-0.02	0.18	0.36	2.54
Education duration (years)	-0.01	1.42	-0.01	0.99	0.03	2.67	-0.02	1.86
Civil status								
Married	-0.07	0.56	-0.24	1.87	-0.36	2.81	-0.52	4.07
Widowed	-0.06	0.29	-0.30	1.38	-0.81	3.54	-0.39	1.74
Divorced	-0.15	0.88	-0.26	1.48	-0.44	2.49	-0.35	2.00
Living separately	-0.23	0.69	-0.05	0.14	-0.57	1.64	-0.28	0.79
Employment status								
Student	0.23	0.86	-0.17	0.66	0.31	1.17	0.08	0.32
Homemaker	-0.04	0.37	-0.07	0.54	-0.20	1.62	-0.14	1.13
Retired	-0.16	1.05	-0.17	1.11	-0.43	2.70	-0.40	2.45
Looking for work	-0.28	1.00	-0.06	0.22	0.12	0.41	-0.06	0.21
Number of contacts	-0.01	2.41	-0.01	3.48	0.00	0.57	0.00	0.20
Ego-alter characteristics								
Distance	-0.29	43.97	-0.07	10.82	0.05	7.48	-0.05	5.43
Distance=0	0.44	6.92	-0.56	8.68	0.00	0.05	-0.04	0.58
Relationship duration	-0.21	18.94	0.03	2.76	-0.09	6.29	-0.20	12.39
Sex homophily								
Both male	0.06	2.46	0.06	2.18	0.28	8.93	-0.24	6.37
Both female	0.01	0.30	0.22	10.03	0.08	2.72	0.41	13.94
Age difference	0.01	10.83	0.00	5.32	-0.01	8.06	-0.01	6.57
Help & Problems								
Ask for help	0.25	5.40	0.41	8.33	0.29	4.69	0.27	3.78
Discuss problems	0.21	9.54	0.39	16.27	0.20	6.77	0.43	13.18
Ask for help x Discuss problems	0.14	2.82	-0.05	0.96	-0.12	1.81	-0.12	1.56
Type of relationship								
Spouse	2.08	30.34	1.07	15.83	0.19	2.26	0.87	10.62
Relative 1st degree	0.45	15.37	0.46	14.84	0.01	0.24	0.31	7.35
Relative	-0.03	0.69	0.05	1.39	-0.34	6.17	-0.06	1.16
Married into family	0.10	2.75	0.12	3.05	-0.49	8.34	-0.29	4.67
Acquaintance	-0.21	9.43	-0.33	13.95	-0.10	3.57	-0.50	14.95
Same level of education	-0.04	2.04	-0.02	1.02	0.11	4.30	0.09	3.56
Same citizenship	0.09	3.85	0.02	0.83	0.02	0.77	0.09	2.71
Missing values coefficients								
Ego education duration	0.76	1.54	-0.38	0.77	0.72	1.43	-0.44	0.85
Distance	-0.89	29.04	-0.21	7.00	-0.04	1.04	-0.12	3.03
Relationship duration	-0.54	6.58	0.30	3.69	-0.61	5.63	-0.79	7.33
Age difference	-0.42	7.49	-0.44	7.25	0.40	5.33	0.03	0.36
Ask for help	0.17	1.68	0.32	2.88	-0.38	2.42	-0.40	2.15
Discuss problems	0.35	2.99	-0.10	0.76	0.32	2.01	-0.59	2.57
Type of relationship	-0.02	0.25	-0.16	1.48	-0.09	0.67	-0.03	0.24
Same level of education	-0.09	2.66	-0.14	4.13	0.04	1.08	-0.07	1.58
Log-likelihood: -161,681.9								

Table A.1: Model results - Price differentiation

	face-to-face		*phone*		*e-mail*		*sms*	
	est	t-stat	est	t-stat	est	t-stat	est	t-stat
Gamma parameters (γ)	0.55	23.93	3.01	51.77	5.59	47.46	7.68	43.48
Baseline constants (δ)	-3.39	11.55	-6.28	21.46	-7.87	26.14	-7.34	23.97
Ego characteristics								
Age								
Age = 18	0.05	0.08	-0.06	0.10	-2.20	3.48	0.76	1.26
Age 19-30	-0.13	0.53	-0.39	1.54	-0.50	1.97	0.78	3.05
Age 31-45	-0.03	0.21	-0.09	1.54	0.08	0.47	0.58	3.42
Age 46-60	-0.10	0.60	-0.19	1.19	-0.02	0.15	0.42	2.55
Education duration (years)	-0.01	1.27	-0.01	0.91	0.03	2.68	-0.02	1.82
Civil status								
Married	-0.08	0.56	-0.27	1.82	-0.41	2.76	-0.60	4.02
Widowed	-0.08	0.33	-0.36	1.39	-0.94	3.51	-0.45	1.72
Divorced	-0.17	0.83	-0.30	1.48	-0.51	2.48	-0.42	2.01
Living separately	-0.25	0.63	-0.04	0.10	-0.67	1.63	-0.32	0.78
Employment status								
Student	0.25	0.81	-0.20	0.65	0.36	1.16	0.10	0.31
Homemaker	-0.05	0.38	-0.07	0.52	-0.23	1.62	-0.16	1.12
Retired	-0.19	1.03	-0.19	1.03	-0.49	2.66	-0.47	2.42
Looking for work	-0.30	0.89	-0.05	0.15	0.16	0.46	-0.04	0.12
Number of contacts	-0.01	2.09	-0.01	3.24	0.00	0.43	0.00	0.06
Ego-alter characteristics								
Distance	-0.33	43.42	-0.08	10.28	0.06	7.49	-0.05	5.33
Distance=0	0.39	5.22	-0.64	8.51	0.00	0.01	-0.05	0.52
Relationship duration	-0.24	17.92	0.04	3.04	-0.11	6.21	-0.23	12.27
Sex homophily								
Both male	0.07	2.32	0.07	2.19	0.32	8.94	-0.27	6.28
Both female	0.01	0.38	0.25	9.79	0.09	2.65	0.47	13.84
Age difference	0.01	10.17	0.01	4.96	-0.01	8.10	-0.01	6.55
Help & Problems								
Ask for help	0.27	5.03	0.47	8.18	0.34	4.65	0.30	3.69
Discuss problems	0.24	9.07	0.45	16.07	0.23	6.65	0.49	13.07
Ask for help x Discuss problems	0.15	2.58	-0.07	1.12	-0.15	1.84	-0.14	1.54
Type of relationship								
Spouse	2.15	26.85	1.19	15.18	0.22	2.25	0.99	10.37
Relative 1st degree	0.50	14.46	0.51	14.03	0.01	0.27	0.35	7.25
Relative	-0.03	0.69	0.06	1.35	-0.39	6.15	-0.08	1.20
Married into family	0.12	2.65	0.14	2.95	-0.58	8.32	-0.34	4.69
Acquaintance	-0.22	8.82	-0.39	13.86	-0.12	3.52	-0.58	14.91
Same level of education	-0.04	2	-0.02	1.049	0.13	4.298	0.11	3.515
Same citizenship	0.11	3.90	0.03	0.95	0.03	0.76	0.11	2.70
Missing values coefficients								
Ego education duration	0.79	1.36	-0.42	0.73	0.85	1.43	-0.48	0.80
Distance	-0.98	27.87	-0.24	6.70	-0.04	0.97	-0.13	2.89
Relationship duration	-0.59	6.18	0.35	3.67	-0.72	5.60	-0.91	7.24
Age difference	-0.46	7.09	-0.49	6.97	0.47	5.35	0.03	0.34
Ask for help	0.19	1.59	0.36	2.79	-0.44	2.44	-0.48	2.17
Discuss problems	0.40	2.91	-0.12	0.79	0.36	1.96	-0.70	2.60
Type of relationship	-0.02	0.18	-0.18	1.42	-0.10	0.62	-0.03	0.18
Same level of education	-0.10	2.70	-0.17	4.14	0.05	0.99	-0.08	1.65
Log-likelihood: -166,397.9								

Table A.2: Model results - Budget change

2 Model forecasting

We adopt the same price differentiation and change in the budget as above and apply the forecasting procedure. Table A.3 shows that the elasticities are of the same sign and magnitude in the three model applications (except for the case of the Overall elasticity of the frequency of interaction, but this tends to zero anyway).

Elasticities of the frequency of interaction by each mode	ORIGINAL MODEL	INCREASE IN BUDGET	PRICE DIFFERENTIATION
face-to-face	-0.004	-0.006	-0.002
phone	0.002	0.000	0.004
e-mail	0.008	0.005	0.011
SMS	0.003	0.000	0.006
Elasticities of the frequency of interaction with relocated alter by each mode			
face-to-face	-0.162	-0.164	-0.149
phone	-0.037	-0.041	-0.032
e-mail	0.052	0.049	0.056
SMS	-0.028	-0.033	-0.023
Overall elasticity of the frequency of interaction	-8.00E-06	-0.002	0.003
Elasticity of the frequency of interaction with the relocated alter	-0.075	-0.081	-0.064
Elasticity of consumption of the outside good	0.006	0.001	0.008
Distance elasticity	0.007	0.004	0.010
Distance elasticity for relocated alter	-0.011	-0.014	-0.006

Table A.3: Elasticities

Appendix B

Appendix to Chapter 5

In this appendix, we report the full covariance matrices for each of the four estimated models, i.e. the models with and without basic socio-demographic characteristics (gender effect) with the *Concepción* and the *Mobidrive* datasets. For ease of display, we report the posterior mean of the covariance and the posterior standard deviation of the covariance between each pair of parameters in columns instead of reporting a matrix.

Table B.1: Covariance matrix for the Mobidrive dataset - base model

Covariance matrix for the Mobidrive dataset - base model

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ work^{WD}	γ work^{WD}	3.0265	0.5147	γ work^{WD}	δ social^{SUN}	-0.4887	0.1607	γ school^{WD}	δ drop pick^{SUN}	-0.3168	0.1144
γ work^{WD}	γ school^{WD}	-0.2480	0.1700	γ work^{WD}	δ leisure^{SUN}	-0.0156	0.1992	γ school^{WD}	δ daily shop^{SUN}	0.1713	0.0892
γ work^{WD}	γ drop pick^{WD}	0.8318	0.1621	γ work^{WD}	δ private business^{SUN}	-0.0923	0.1373	γ school^{WD}	δ non daily shop^{SUN}	0.1339	0.0924
γ work^{WD}	γ daily shop^{WD}	0.2024	0.1085	γ work^{WD}	δ travel^{SUN}	-0.1711	0.1659	γ school^{WD}	δ social^{SUN}	-0.2773	0.0965
γ work^{WD}	γ non daily shop^{WD}	0.0285	0.0840	γ school^{WD}	γ school^{WD}	0.7166	0.1802	γ school^{WD}	δ leisure^{SUN}	-0.0480	0.1003
γ work^{WD}	γ social^{WD}	0.4946	0.1219	γ school^{WD}	γ drop pick^{WD}	-0.0212	0.0822	γ school^{WD}	δ private business^{SUN}	0.1745	0.0893
γ work^{WD}	γ leisure^{WD}	0.2452	0.1141	γ school^{WD}	γ daily shop^{WD}	-0.2931	0.0704	γ school^{WD}	δ travel^{SUN}	-0.0376	0.0956
γ work^{WD}	γ private business^{WD}	0.2602	0.1756	γ school^{WD}	γ non daily shop^{WD}	0.0337	0.0810	γ drop pick^{WD}	γ drop pick^{WD}	0.3468	0.0640
γ work^{WD}	γ travel^{WD}	0.0816	0.1132	γ school^{WD}	γ social^{WD}	0.0047	0.0564	γ drop pick^{WD}	γ daily shop^{WD}	0.0620	0.0572
γ work^{WD}	δ work^{WD}	-5.4142	0.8694	γ school^{WD}	γ leisure^{WD}	0.0982	0.0446	γ drop pick^{WD}	γ non daily shop^{WD}	0.0137	0.0404
γ work^{WD}	δ school^{WD}	2.8421	0.5865	γ school^{WD}	γ private business^{WD}	-0.2446	0.0822	γ drop pick^{WD}	γ social^{WD}	0.1588	0.0514
γ work^{WD}	δ drop pick^{WD}	-1.1146	0.2986	γ school^{WD}	γ travel^{WD}	0.1249	0.0651	γ drop pick^{WD}	γ leisure^{WD}	0.0833	0.0422
γ work^{WD}	δ daily shop^{WD}	-0.1925	0.1756	γ school^{WD}	δ work^{WD}	0.5890	0.2750	γ drop pick^{WD}	γ private business^{WD}	0.0582	0.0651
γ work^{WD}	δ non daily shop^{WD}	0.0239	0.1261	γ school^{WD}	δ school^{WD}	-2.5082	0.4649	γ drop pick^{WD}	γ travel^{WD}	0.0428	0.0345
γ work^{WD}	δ social^{WD}	-0.0338	0.1580	γ school^{WD}	δ drop pick^{WD}	-0.0496	0.1905	γ drop pick^{WD}	δ work^{WD}	-1.5294	0.2963
γ work^{WD}	δ leisure^{WD}	0.1615	0.2217	γ school^{WD}	δ daily shop^{WD}	0.6656	0.1434	γ drop pick^{WD}	δ school^{WD}	0.7675	0.2869
γ work^{WD}	δ private business^{WD}	0.0270	0.1274	γ school^{WD}	δ non daily shop^{WD}	0.3013	0.0807	γ drop pick^{WD}	δ drop pick^{WD}	-0.4334	0.1225
γ work^{WD}	δ travel^{WD}	-0.4901	0.1280	γ school^{WD}	δ social^{WD}	-0.4059	0.0899	γ drop pick^{WD}	δ daily shop^{WD}	-0.0138	0.0925
γ work^{WD}	γ work^{SAT}	-0.4971	0.1568	γ school^{WD}	δ leisure^{WD}	-0.2002	0.1884	γ drop pick^{WD}	δ non daily shop^{WD}	0.0636	0.0430
γ work^{WD}	γ school^{SAT}	0.0839	0.2438	γ school^{WD}	δ private business^{WD}	0.2620	0.0974	γ drop pick^{WD}	δ social^{WD}	-0.1430	0.0821
γ work^{WD}	γ drop pick^{SAT}	-0.1196	0.1908	γ school^{WD}	δ travel^{WD}	-0.2221	0.0926	γ drop pick^{WD}	δ leisure^{WD}	0.2887	0.1097
γ work^{WD}	γ daily shop^{SAT}	-0.1537	0.1131	γ school^{WD}	γ work^{SAT}	-0.2263	0.0921	γ drop pick^{WD}	δ private business^{WD}	-0.1099	0.0575
γ work^{WD}	γ non daily shop^{SAT}	-0.3322	0.1987	γ school^{WD}	γ school^{SAT}	0.4197	0.0984	γ drop pick^{WD}	δ travel^{WD}	-0.1649	0.0425
γ work^{WD}	γ social^{SAT}	0.0652	0.1138	γ school^{WD}	γ drop pick^{SAT}	-0.7885	0.1378	γ drop pick^{WD}	γ work^{SAT}	-0.2233	0.0746
γ work^{WD}	γ leisure^{SAT}	0.2440	0.1297	γ school^{WD}	γ daily shop^{SAT}	-0.1326	0.0924	γ drop pick^{WD}	γ school^{SAT}	0.0581	0.0833
γ work^{WD}	γ private business^{SAT}	0.4619	0.2297	γ school^{WD}	γ non daily shop^{SAT}	-0.5020	0.1062	γ drop pick^{WD}	γ drop pick^{SAT}	-0.1375	0.0986
γ work^{WD}	γ travel^{SAT}	0.0513	0.1105	γ school^{WD}	γ social^{SAT}	0.1328	0.0705	γ drop pick^{WD}	γ daily shop^{SAT}	-0.0691	0.0408
γ work^{WD}	δ work^{SAT}	-0.9906	0.2222	γ school^{WD}	γ leisure^{SAT}	0.0273	0.1142	γ drop pick^{WD}	γ non daily shop^{SAT}	-0.1609	0.0951
γ work^{WD}	δ school^{SAT}	1.8932	0.3307	γ school^{WD}	γ private business^{SAT}	-0.4753	0.1208	γ drop pick^{WD}	γ social^{SAT}	0.0248	0.0478
γ work^{WD}	δ drop pick^{SAT}	-0.5672	0.2340	γ school^{WD}	γ travel^{SAT}	0.0185	0.0502	γ drop pick^{WD}	γ leisure^{SAT}	0.0446	0.0525
γ work^{WD}	δ daily shop^{SAT}	-0.1629	0.1845	γ school^{WD}	δ work^{SAT}	0.3135	0.2021	γ drop pick^{WD}	γ private business^{SAT}	0.2003	0.0652
γ work^{WD}	δ non daily shop^{SAT}	0.3232	0.1485	γ school^{WD}	δ school^{SAT}	-0.3855	0.1780	γ drop pick^{WD}	γ travel^{SAT}	0.0277	0.0328
γ work^{WD}	δ social^{SAT}	-0.0677	0.1249	γ school^{WD}	δ drop pick^{SAT}	-0.0681	0.1106	γ drop pick^{WD}	δ work^{SAT}	-0.3035	0.1138
γ work^{WD}	δ leisure^{SAT}	-0.1811	0.2055	γ school^{WD}	δ daily shop^{SAT}	0.2081	0.0615	γ drop pick^{WD}	δ school^{SAT}	0.4873	0.1240
γ work^{WD}	δ private business^{SAT}	0.1684	0.1610	γ school^{WD}	δ non daily shop^{SAT}	-0.0442	0.0859	γ drop pick^{WD}	δ drop pick^{SAT}	-0.2797	0.1123
γ work^{WD}	δ travel^{SAT}	-0.0722	0.1007	γ school^{WD}	δ social^{SAT}	-0.3844	0.0810	γ drop pick^{WD}	δ daily shop^{SAT}	0.0013	0.0656
γ work^{WD}	γ work^{SUN}	-0.5836	0.2284	γ school^{WD}	δ leisure^{SAT}	-0.2962	0.1497	γ drop pick^{WD}	δ non daily shop^{SAT}	0.0259	0.0414
γ work^{WD}	γ school^{SUN}	-0.5067	0.1880	γ school^{WD}	δ private business^{SAT}	0.0942	0.0695	γ drop pick^{WD}	δ social^{SAT}	-0.0590	0.0648
γ work^{WD}	γ drop pick^{SUN}	1.7489	0.2943	γ school^{WD}	δ travel^{SAT}	-0.1295	0.0413	γ drop pick^{WD}	δ leisure^{SAT}	0.1046	0.0670
γ work^{WD}	γ daily shop^{SUN}	0.1535	0.1291	γ school^{WD}	γ work^{SUN}	-0.3740	0.1219	γ drop pick^{WD}	δ private business^{SAT}	-0.0848	0.0469
γ work^{WD}	γ non daily shop^{SUN}	-0.9114	0.1558	γ school^{WD}	γ school^{SUN}	0.2774	0.0732	γ drop pick^{WD}	δ travel^{SAT}	-0.0384	0.0431
γ work^{WD}	γ social^{SUN}	-0.0554	0.1076	γ school^{WD}	γ drop pick^{SUN}	0.1979	0.1876	γ drop pick^{WD}	γ work^{SUN}	-0.2514	0.0810
γ work^{WD}	γ leisure^{SUN}	0.1032	0.1472	γ school^{WD}	γ daily shop^{SUN}	-0.0745	0.1186	γ drop pick^{WD}	γ school^{SUN}	-0.1133	0.0510
γ work^{WD}	γ private business^{SUN}	0.7849	0.1821	γ school^{WD}	γ non daily shop^{SUN}	0.2703	0.0732	γ drop pick^{WD}	γ drop pick^{SUN}	0.4524	0.0930
γ work^{WD}	γ travel^{SUN}	-0.1216	0.1432	γ school^{WD}	γ social^{SUN}	-0.0826	0.0823	γ drop pick^{WD}	γ daily shop^{SUN}	0.1319	0.0592
γ work^{WD}	δ work^{SUN}	-1.0922	0.2310	γ school^{WD}	γ leisure^{SUN}	0.0745	0.0743	γ drop pick^{WD}	γ non daily shop^{SUN}	-0.2335	0.0670
γ work^{WD}	δ school^{SUN}	1.4290	0.3162	γ school^{WD}	γ private business^{SUN}	-0.7664	0.1520	γ drop pick^{WD}	γ social^{SUN}	-0.0167	0.0334
γ work^{WD}	δ drop pick^{SUN}	-0.7049	0.3052	γ school^{WD}	γ travel^{SUN}	0.0214	0.0784	γ drop pick^{WD}	γ leisure^{SUN}	-0.0443	0.0640
γ work^{WD}	δ daily shop^{SUN}	0.1099	0.1602	γ school^{WD}	δ work^{SUN}	0.8573	0.2039	γ drop pick^{WD}	γ private business^{SUN}	0.1658	0.0940
γ work^{WD}	δ non daily shop^{SUN}	0.2056	0.0904	γ school^{WD}	δ school^{SUN}	-0.6152	0.1394	γ drop pick^{WD}	γ travel^{SUN}	-0.0519	0.0481

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{work}}^{SUN}$	-0.2979	0.1209	$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{travel}}^{SUN}$	0.1177	0.0683	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{travel}}^{SUN}$	0.0593	0.0329
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{school}}^{SUN}$	0.3691	0.0839	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{work}}^{SUN}$	-0.2105	0.0955	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{work}}^{SUN}$	0.1200	0.0805
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{drop pick}}^{SUN}$	-0.1136	0.1222	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{school}}^{SUN}$	0.4050	0.1069	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{school}}^{SUN}$	-0.0102	0.0617
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{daily shop}}^{SUN}$	-0.0400	0.0752	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{SUN}$	-0.0736	0.1064	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{SUN}$	-0.1155	0.0639
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.0017	0.0364	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{SUN}$	-0.2180	0.0672	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{SUN}$	-0.0598	0.0329
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{social}}^{SUN}$	-0.2263	0.0577	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.0749	0.0486	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{SUN}$	0.0079	0.0233
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{leisure}}^{SUN}$	0.2013	0.0843	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{social}}^{SUN}$	-0.0567	0.0588	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{social}}^{SUN}$	-0.1006	0.0586
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{private business}}^{SUN}$	-0.0795	0.0783	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{leisure}}^{SUN}$	-0.0060	0.0994	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{leisure}}^{SUN}$	-0.0281	0.0568
$\gamma_{\text{drop pick}}^{WD}$	$\delta_{\text{travel}}^{SUN}$	-0.0213	0.0540	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{private business}}^{SUN}$	-0.3362	0.0607	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{private business}}^{SUN}$	-0.1123	0.0615
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{daily shop}}^{WD}$	0.3241	0.0615	$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{travel}}^{SUN}$	-0.1808	0.0988	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{travel}}^{SUN}$	-0.0960	0.0441
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{WD}$	0.0631	0.0434	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{WD}$	0.0742	0.0343	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{social}}^{WD}$	0.1848	0.0814
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{social}}^{WD}$	0.1143	0.0411	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{social}}^{WD}$	0.0538	0.0386	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{leisure}}^{WD}$	0.0829	0.0539
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{WD}$	0.0251	0.0299	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{WD}$	0.0457	0.0255	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{private business}}^{WD}$	0.0213	0.0361
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{private business}}^{WD}$	0.1072	0.0437	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{private business}}^{WD}$	-0.0033	0.0252	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	0.0661	0.0372
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	0.0095	0.0499	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	0.0284	0.0278	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{work}}^{WD}$	-0.7795	0.2211
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{work}}^{WD}$	-0.2362	0.1987	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{work}}^{WD}$	0.0776	0.1315	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{school}}^{WD}$	0.3813	0.1947
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{school}}^{WD}$	1.2123	0.2192	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{school}}^{WD}$	-0.1306	0.2433	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{drop pick}}^{WD}$	-0.3742	0.1657
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{WD}$	-0.2952	0.1169	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{WD}$	-0.1412	0.1071	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{daily shop}}^{WD}$	-0.1644	0.0707
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{WD}$	-0.6051	0.1014	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{WD}$	-0.1164	0.0982	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{non daily shop}}^{WD}$	0.0254	0.0443
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{WD}$	-0.1216	0.0377	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{WD}$	0.0258	0.0468	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{social}}^{WD}$	-0.1657	0.0942
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{social}}^{WD}$	-0.0102	0.0638	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{social}}^{WD}$	-0.0999	0.0607	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{leisure}}^{WD}$	-0.0192	0.1253
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{leisure}}^{WD}$	0.1171	0.1116	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{leisure}}^{WD}$	0.0169	0.0826	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{private business}}^{WD}$	-0.0554	0.0678
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{private business}}^{WD}$	-0.2130	0.0531	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{private business}}^{WD}$	-0.0126	0.0592	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{travel}}^{WD}$	-0.1487	0.0497
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{travel}}^{WD}$	0.0129	0.0552	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{travel}}^{WD}$	-0.0401	0.0364	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{work}}^{SAT}$	-0.1228	0.0676
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{work}}^{SAT}$	0.0734	0.0584	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{work}}^{SAT}$	-0.0146	0.0381	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{school}}^{SAT}$	0.1107	0.1116
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{school}}^{SAT}$	-0.0750	0.0746	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{school}}^{SAT}$	0.0870	0.0459	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{drop pick}}^{SAT}$	-0.0656	0.0659
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{drop pick}}^{SAT}$	0.3393	0.0745	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{drop pick}}^{SAT}$	-0.0624	0.0915	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{daily shop}}^{SAT}$	-0.0119	0.0251
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{daily shop}}^{SAT}$	0.0909	0.0402	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{daily shop}}^{SAT}$	0.0106	0.0257	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{non daily shop}}^{SAT}$	-0.0779	0.0530
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{SAT}$	0.2510	0.0543	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{SAT}$	0.0095	0.0539	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{social}}^{SAT}$	0.0548	0.0226
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{social}}^{SAT}$	0.0165	0.0508	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{social}}^{SAT}$	0.0459	0.0318	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{leisure}}^{SAT}$	0.0641	0.0602
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{SAT}$	0.0119	0.0524	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{SAT}$	0.0211	0.0434	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{private business}}^{SAT}$	0.0840	0.0388
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{private business}}^{SAT}$	0.2945	0.0645	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{private business}}^{SAT}$	-0.0044	0.0464	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{travel}}^{SAT}$	0.0474	0.0396
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{travel}}^{SAT}$	0.0624	0.0474	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{travel}}^{SAT}$	0.0317	0.0314	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{work}}^{SAT}$	-0.0826	0.0855
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{work}}^{SAT}$	-0.0145	0.0728	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{work}}^{SAT}$	0.0770	0.0510	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{school}}^{SAT}$	0.3206	0.0831
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{school}}^{SAT}$	0.2291	0.0868	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{school}}^{SAT}$	-0.0148	0.0533	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{drop pick}}^{SAT}$	-0.1814	0.0874
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{SAT}$	-0.1605	0.0900	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{SAT}$	-0.0989	0.0883	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{daily shop}}^{SAT}$	-0.0286	0.0463
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{SAT}$	-0.1553	0.0444	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{SAT}$	-0.0309	0.0369	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{non daily shop}}^{SAT}$	0.0553	0.0438
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{SAT}$	0.0527	0.0403	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{SAT}$	0.0179	0.0302	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{social}}^{SAT}$	-0.1374	0.0912
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{social}}^{SAT}$	0.0150	0.0705	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{social}}^{SAT}$	-0.0928	0.0458	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{leisure}}^{SAT}$	-0.0787	0.0979
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{leisure}}^{SAT}$	0.1122	0.0902	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{leisure}}^{SAT}$	-0.0194	0.0630	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{private business}}^{SAT}$	0.0270	0.0449
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{private business}}^{SAT}$	-0.0507	0.0566	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{private business}}^{SAT}$	0.0087	0.0524	$\gamma_{\text{social}}^{WD}$	$\delta_{\text{travel}}^{SAT}$	-0.0727	0.0403
$\gamma_{\text{daily shop}}^{WD}$	$\delta_{\text{travel}}^{SAT}$	-0.0424	0.0418	$\gamma_{\text{non daily shop}}^{WD}$	$\delta_{\text{travel}}^{SAT}$	-0.0491	0.0286	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{work}}^{SUN}$	-0.1104	0.0913
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{work}}^{SUN}$	0.1425	0.0727	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{work}}^{SUN}$	-0.0314	0.0700	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{school}}^{SUN}$	-0.1317	0.0650
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{school}}^{SUN}$	-0.2548	0.0656	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{school}}^{SUN}$	-0.0439	0.0415	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{drop pick}}^{SUN}$	0.3953	0.1623
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{drop pick}}^{SUN}$	0.0740	0.0973	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{drop pick}}^{SUN}$	0.0590	0.0744	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{daily shop}}^{SUN}$	0.1271	0.0782
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{daily shop}}^{SUN}$	0.2170	0.0904	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{daily shop}}^{SUN}$	0.0745	0.0453	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.1581	0.0596
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.1690	0.0686	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.0154	0.0533	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{social}}^{SUN}$	0.0275	0.0368
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{social}}^{SUN}$	0.0925	0.0309	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{social}}^{SUN}$	0.0323	0.0305	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{leisure}}^{SUN}$	0.0651	0.0398
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{SUN}$	0.0491	0.1003	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{SUN}$	0.0638	0.0343	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{private business}}^{SUN}$	0.1212	0.0685
$\gamma_{\text{daily shop}}^{WD}$	$\gamma_{\text{private business}}^{SUN}$	0.4056	0.0736	$\gamma_{\text{non daily shop}}^{WD}$	$\gamma_{\text{private business}}^{SUN}$	-0.0124	0.0810	$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{travel}}^{SUN}$	0.0718	0.0839

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ social^{WD}	δ work^{SUN}	-0.0359	0.0954	γ leisure^{WD}	δ drop pick^{SUN}	-0.2383	0.1109	γ private business^{WD}	δ social^{SUN}	0.0743	0.0464
γ social^{WD}	δ school^{SUN}	0.2761	0.1043	γ leisure^{WD}	δ daily shop^{SUN}	-0.0215	0.0560	γ private business^{WD}	δ leisure^{SUN}	0.0498	0.0811
γ social^{WD}	δ drop pick^{SUN}	-0.2570	0.1317	γ leisure^{WD}	δ non daily shop^{SUN}	0.0434	0.0312	γ private business^{WD}	δ private business^{SUN}	-0.0540	0.0445
γ social^{WD}	δ daily shop^{SUN}	-0.0248	0.0665	γ leisure^{WD}	δ social^{SUN}	-0.1657	0.0501	γ private business^{WD}	δ travel^{SUN}	0.0303	0.0498
γ social^{WD}	δ non daily shop^{SUN}	0.0234	0.0323	γ leisure^{WD}	δ leisure^{SUN}	-0.0513	0.1325	γ travel^{WD}	γ travel^{WD}	0.0870	0.0253
γ social^{WD}	δ social^{SUN}	-0.2117	0.0734	γ leisure^{WD}	δ private business^{SUN}	-0.0935	0.0574	γ travel^{WD}	δ work^{WD}	-0.1000	0.1926
γ social^{WD}	δ leisure^{SUN}	-0.0379	0.0806	γ leisure^{WD}	δ travel^{SUN}	-0.1209	0.0659	γ travel^{WD}	δ school^{WD}	-0.2879	0.2719
γ social^{WD}	δ private business^{SUN}	-0.1473	0.0686	γ private business^{WD}	γ private business^{WD}	0.1371	0.0696	γ travel^{WD}	δ drop pick^{WD}	-0.1160	0.1208
γ social^{WD}	δ travel^{SUN}	-0.1655	0.1120	γ private business^{WD}	γ travel^{WD}	-0.0472	0.0334	γ travel^{WD}	δ daily shop^{WD}	0.0278	0.1075
γ leisure^{WD}	γ leisure^{WD}	0.1164	0.0545	γ private business^{WD}	δ work^{WD}	-0.5046	0.3165	γ travel^{WD}	δ non daily shop^{WD}	0.0616	0.0259
γ leisure^{WD}	γ private business^{WD}	-0.0055	0.0271	γ private business^{WD}	δ school^{WD}	0.9373	0.3536	γ travel^{WD}	δ social^{WD}	-0.1752	0.0455
γ leisure^{WD}	γ travel^{WD}	0.0437	0.0270	γ private business^{WD}	δ drop pick^{WD}	-0.0233	0.1239	γ travel^{WD}	δ leisure^{WD}	-0.0907	0.1009
γ leisure^{WD}	δ work^{WD}	-0.3147	0.2535	γ private business^{WD}	δ daily shop^{WD}	-0.2319	0.0787	γ travel^{WD}	δ private business^{WD}	0.0180	0.0452
γ leisure^{WD}	δ school^{WD}	-0.2138	0.2167	γ private business^{WD}	δ non daily shop^{WD}	-0.0823	0.0361	γ travel^{WD}	δ travel^{WD}	-0.1107	0.0412
γ leisure^{WD}	δ drop pick^{WD}	-0.2586	0.1257	γ private business^{WD}	δ social^{WD}	0.1679	0.0475	γ travel^{WD}	γ work^{SAT}	-0.0505	0.0587
γ leisure^{WD}	δ daily shop^{WD}	-0.0070	0.0571	γ private business^{WD}	δ leisure^{WD}	0.1731	0.1374	γ travel^{WD}	γ school^{SAT}	0.0758	0.0803
γ leisure^{WD}	δ non daily shop^{WD}	0.0630	0.0275	γ private business^{WD}	δ private business^{WD}	-0.0460	0.0423	γ travel^{WD}	γ drop pick^{SAT}	-0.1336	0.0928
γ leisure^{WD}	δ social^{WD}	-0.1664	0.0703	γ private business^{WD}	δ travel^{WD}	0.0575	0.0414	γ travel^{WD}	γ daily shop^{SAT}	-0.0232	0.0359
γ leisure^{WD}	δ leisure^{WD}	-0.0460	0.1641	γ private business^{WD}	γ work^{SAT}	0.0492	0.0614	γ travel^{WD}	γ non daily shop^{SAT}	-0.0964	0.0749
γ leisure^{WD}	δ private business^{WD}	0.0148	0.0570	γ private business^{WD}	γ school^{SAT}	-0.1036	0.0385	γ travel^{WD}	γ social^{SAT}	0.0396	0.0254
γ leisure^{WD}	δ travel^{WD}	-0.1076	0.0400	γ private business^{WD}	γ drop pick^{SAT}	0.2329	0.0861	γ travel^{WD}	γ leisure^{SAT}	0.0242	0.0477
γ leisure^{WD}	γ work^{SAT}	-0.0829	0.0565	γ private business^{WD}	γ daily shop^{SAT}	0.0329	0.0394	γ travel^{WD}	γ private business^{SAT}	-0.0536	0.0665
γ leisure^{WD}	γ school^{SAT}	0.1538	0.0604	γ private business^{WD}	γ non daily shop^{SAT}	0.1627	0.0539	γ travel^{WD}	γ travel^{SAT}	0.0224	0.0313
γ leisure^{WD}	γ drop pick^{SAT}	-0.1844	0.0788	γ private business^{WD}	γ social^{SAT}	-0.0284	0.0335	γ travel^{WD}	δ work^{SAT}	0.0129	0.0765
γ leisure^{WD}	γ daily shop^{SAT}	-0.0242	0.0398	γ private business^{WD}	γ leisure^{SAT}	-0.0025	0.0425	γ travel^{WD}	δ school^{SAT}	0.0378	0.0761
γ leisure^{WD}	γ non daily shop^{SAT}	-0.0991	0.0548	γ private business^{WD}	γ private business^{SAT}	0.1859	0.0976	γ travel^{WD}	δ drop pick^{SAT}	-0.0045	0.0953
γ leisure^{WD}	γ social^{SAT}	0.0624	0.0392	γ private business^{WD}	γ travel^{SAT}	0.0133	0.0177	γ travel^{WD}	δ daily shop^{SAT}	0.0446	0.0555
γ leisure^{WD}	γ leisure^{SAT}	0.0354	0.0391	γ private business^{WD}	δ work^{SAT}	-0.1608	0.1316	γ travel^{WD}	δ non daily shop^{SAT}	0.0176	0.0561
γ leisure^{WD}	γ private business^{SAT}	-0.0499	0.0727	γ private business^{WD}	δ school^{SAT}	0.1948	0.1249	γ travel^{WD}	δ social^{SAT}	-0.1328	0.0495
γ leisure^{WD}	γ travel^{SAT}	0.0410	0.0315	γ private business^{WD}	δ drop pick^{SAT}	-0.0540	0.0870	γ travel^{WD}	δ leisure^{SAT}	-0.1050	0.0714
γ leisure^{WD}	δ work^{SAT}	0.0225	0.0825	γ private business^{WD}	δ daily shop^{SAT}	-0.1031	0.0461	γ travel^{WD}	δ private business^{SAT}	0.0315	0.0361
γ leisure^{WD}	δ school^{SAT}	0.1073	0.0651	γ private business^{WD}	δ non daily shop^{SAT}	0.0395	0.0449	γ travel^{WD}	δ travel^{SAT}	-0.0449	0.0196
γ leisure^{WD}	δ drop pick^{SAT}	-0.1430	0.0594	γ private business^{WD}	δ social^{SAT}	0.1353	0.0403	γ travel^{WD}	γ work^{SUN}	-0.0923	0.0501
γ leisure^{WD}	δ daily shop^{SAT}	0.0154	0.0487	γ private business^{WD}	δ leisure^{SAT}	0.1287	0.0742	γ travel^{WD}	γ school^{SUN}	0.0147	0.0404
γ leisure^{WD}	δ non daily shop^{SAT}	0.0342	0.0314	γ private business^{WD}	δ private business^{SAT}	-0.0110	0.0376	γ travel^{WD}	γ drop pick^{SUN}	0.1671	0.1025
γ leisure^{WD}	δ social^{SAT}	-0.1594	0.0557	γ private business^{WD}	δ travel^{SAT}	0.0338	0.0218	γ travel^{WD}	γ daily shop^{SUN}	0.0355	0.0345
γ leisure^{WD}	δ leisure^{SAT}	-0.0990	0.0881	γ private business^{WD}	γ work^{SUN}	0.0607	0.0572	γ travel^{WD}	γ non daily shop^{SUN}	0.0232	0.0501
γ leisure^{WD}	δ private business^{SAT}	0.0404	0.0387	γ private business^{WD}	γ school^{SUN}	-0.1265	0.0555	γ travel^{WD}	γ social^{SUN}	-0.0021	0.0198
γ leisure^{WD}	δ travel^{SAT}	-0.0713	0.0245	γ private business^{WD}	γ drop pick^{SUN}	-0.0078	0.0954	γ travel^{WD}	γ leisure^{SUN}	0.0327	0.0288
γ leisure^{WD}	γ work^{SUN}	-0.1056	0.0646	γ private business^{WD}	γ daily shop^{SUN}	0.0245	0.0530	γ travel^{WD}	γ private business^{SUN}	-0.1027	0.0712
γ leisure^{WD}	γ school^{SUN}	-0.0681	0.0394	γ private business^{WD}	γ non daily shop^{SUN}	-0.1375	0.0689	γ travel^{WD}	γ travel^{SUN}	0.0704	0.0345
γ leisure^{WD}	γ drop pick^{SUN}	0.2824	0.1219	γ private business^{WD}	γ social^{SUN}	0.0216	0.0221	γ travel^{WD}	δ work^{SUN}	0.1659	0.0943
γ leisure^{WD}	γ daily shop^{SUN}	0.0751	0.0339	γ private business^{WD}	γ leisure^{SUN}	-0.0142	0.0299	γ travel^{WD}	δ school^{SUN}	0.0145	0.0792
γ leisure^{WD}	γ non daily shop^{SUN}	-0.0588	0.0388	γ private business^{WD}	γ private business^{SUN}	0.2728	0.0877	γ travel^{WD}	δ drop pick^{SUN}	-0.1400	0.0771
γ leisure^{WD}	γ social^{SUN}	0.0035	0.0270	γ private business^{WD}	γ travel^{SUN}	-0.0359	0.0372	γ travel^{WD}	δ daily shop^{SUN}	0.0316	0.0659
γ leisure^{WD}	γ leisure^{SUN}	0.0588	0.0322	γ private business^{WD}	δ work^{SUN}	-0.3578	0.1394	γ travel^{WD}	δ non daily shop^{SUN}	0.0218	0.0355
γ leisure^{WD}	γ private business^{SUN}	-0.0351	0.0527	γ private business^{WD}	δ school^{SUN}	0.2491	0.1072	γ travel^{WD}	δ social^{SUN}	-0.1500	0.0438
γ leisure^{WD}	γ travel^{SUN}	0.0585	0.0376	γ private business^{WD}	δ drop pick^{SUN}	0.0959	0.0646	γ travel^{WD}	δ leisure^{SUN}	-0.0297	0.0506
γ leisure^{WD}	δ work^{SUN}	0.1336	0.1216	γ private business^{WD}	δ daily shop^{SUN}	-0.0748	0.0530	γ travel^{WD}	δ private business^{SUN}	-0.0392	0.0533
γ leisure^{WD}	δ school^{SUN}	0.0663	0.0610	γ private business^{WD}	δ non daily shop^{SUN}	-0.0235	0.0291	γ travel^{WD}	δ travel^{SUN}	-0.1011	0.0398

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{WD}}$	10.3948	1.5582
$\delta_{\text{work}^{WD}}$	$\delta_{\text{school}^{WD}}$	-5.9185	0.9672
$\delta_{\text{work}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	1.2011	0.4713
$\delta_{\text{work}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	0.0839	0.3160
$\delta_{\text{work}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	-0.0751	0.1889
$\delta_{\text{work}^{WD}}$	$\delta_{\text{social}^{WD}}$	-0.0452	0.2821
$\delta_{\text{work}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	-0.6218	0.3751
$\delta_{\text{work}^{WD}}$	$\delta_{\text{private business}^{WD}}$	-0.1453	0.2223
$\delta_{\text{work}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.7435	0.2192
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	0.8059	0.2901
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	0.2303	0.4593
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.0759	0.3131
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.3374	0.1884
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.5859	0.3561
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	0.0817	0.1798
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.3298	0.3063
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.9393	0.3128
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0212	0.2082
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{SAT}}$	2.4015	0.4385
$\delta_{\text{work}^{WD}}$	$\delta_{\text{school}^{SAT}}$	-3.5425	0.5655
$\delta_{\text{work}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.4630	0.4274
$\delta_{\text{work}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.2104	0.3204
$\delta_{\text{work}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	-0.6013	0.2196
$\delta_{\text{work}^{WD}}$	$\delta_{\text{social}^{SAT}}$	-0.1057	0.2341
$\delta_{\text{work}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.0155	0.4026
$\delta_{\text{work}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	-0.2659	0.3128
$\delta_{\text{work}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	-0.0543	0.1876
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	1.1465	0.3912
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	0.7273	0.3619
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-2.7417	0.5084
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.1011	0.2404
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	1.5297	0.2901
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.2115	0.1546
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0552	0.2890
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	-1.3372	0.3151
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	0.3258	0.2696
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{SUN}}$	2.5613	0.4356
$\delta_{\text{work}^{WD}}$	$\delta_{\text{school}^{SUN}}$	-2.6684	0.5442
$\delta_{\text{work}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	0.6748	0.5576
$\delta_{\text{work}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.4744	0.2722
$\delta_{\text{work}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.2773	0.1603
$\delta_{\text{work}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.7575	0.2524
$\delta_{\text{work}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	-0.4426	0.3536
$\delta_{\text{work}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	-0.1940	0.2545
$\delta_{\text{work}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	-0.0334	0.3318
$\delta_{\text{school}^{WD}}$	$\delta_{\text{school}^{WD}}$	11.1802	1.2740
$\delta_{\text{school}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	-0.6008	0.5115
$\delta_{\text{school}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	-2.4187	0.3883
$\delta_{\text{school}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	-0.9964	0.2335
$\delta_{\text{school}^{WD}}$	$\delta_{\text{social}^{WD}}$	1.0018	0.2774

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{school}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	0.9948	0.4128
$\delta_{\text{school}^{WD}}$	$\delta_{\text{private business}^{WD}}$	-1.1498	0.2554
$\delta_{\text{school}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.3711	0.3008
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	0.3791	0.3660
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	-1.5107	0.3680
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	2.7510	0.4692
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.3048	0.2980
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	1.3830	0.3284
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.4727	0.2896
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.0346	0.4389
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	2.2332	0.3288
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0145	0.1600
$\delta_{\text{school}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-1.9780	0.6663
$\delta_{\text{school}^{WD}}$	$\delta_{\text{school}^{SAT}}$	2.7368	0.4682
$\delta_{\text{school}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.0268	0.3696
$\delta_{\text{school}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	-0.6865	0.2162
$\delta_{\text{school}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.3185	0.2718
$\delta_{\text{school}^{WD}}$	$\delta_{\text{social}^{SAT}}$	1.2048	0.2543
$\delta_{\text{school}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	1.0659	0.3561
$\delta_{\text{school}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	-0.4267	0.2405
$\delta_{\text{school}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.3891	0.1553
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	0.8058	0.3129
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	-1.2524	0.2818
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	0.5197	0.4569
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	0.5508	0.3968
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-1.4730	0.2834
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.1985	0.2482
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.3766	0.2667
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	3.1559	0.4634
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0804	0.2662
$\delta_{\text{school}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-3.6996	0.6227
$\delta_{\text{school}^{WD}}$	$\delta_{\text{school}^{SUN}}$	3.3217	0.4234
$\delta_{\text{school}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	0.7773	0.4158
$\delta_{\text{school}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.4881	0.2819
$\delta_{\text{school}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.4763	0.2282
$\delta_{\text{school}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.4093	0.2811
$\delta_{\text{school}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.5071	0.3756
$\delta_{\text{school}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	-0.7551	0.2743
$\delta_{\text{school}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	-0.0213	0.3629
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	2.0775	0.3344
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	0.4140	0.1735
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.1124	0.1059
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{social}^{WD}}$	0.3672	0.1530
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	0.3128	0.2282
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{private business}^{WD}}$	0.5859	0.1359
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.4220	0.1374
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	0.4647	0.1851
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	-0.5365	0.1434
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	0.4364	0.1759
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	-0.0030	0.1204

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.2483	0.1674
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.2776	0.1414
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.2075	0.1665
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.2732	0.1911
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0954	0.1003
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.4942	0.2066
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{school}^{SAT}}$	-0.6101	0.2498
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	1.2175	0.2607
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0000	0.1120
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.1214	0.1606
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{social}^{SAT}}$	0.3535	0.1221
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.3753	0.1687
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	0.2240	0.1316
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.2991	0.0874
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	-0.0451	0.1539
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	0.4868	0.1655
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-1.3864	0.2573
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.5260	0.1239
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.5814	0.1335
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	-0.1516	0.1048
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.1701	0.1414
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	-0.6253	0.2286
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.1289	0.1441
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-0.3624	0.2188
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{school}^{SUN}}$	-0.6206	0.1947
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	1.0522	0.2510
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	0.4536	0.1687
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.0574	0.1314
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.4263	0.1548
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.5000	0.1712
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.7101	0.1560
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.6093	0.1378
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	1.2770	0.1781
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.2972	0.0780
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{social}^{WD}}$	-0.1319	0.1013
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	-0.1865	0.1456
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{private business}^{WD}}$	0.3830	0.0886
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{travel}^{WD}}$	-0.1197	0.1141
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	-0.2404	0.1035
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	0.2042	0.1409
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.7946	0.1464
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	-0.2111	0.0919
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.6180	0.1069
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.0103	0.0836
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.0233	0.0908
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.5638	0.1072
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.1085	0.0824
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.0451	0.1163
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{school}^{SAT}}$	-0.3305	0.1397
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.2455	0.1707

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ daily shop^{WD}	δ daily shop^{SAT}	0.3621	0.1038
δ daily shop^{WD}	δ non daily shop^{SAT}	-0.1110	0.0785
δ daily shop^{WD}	δ social^{SAT}	-0.1274	0.1020
δ daily shop^{WD}	δ leisure^{SAT}	-0.2319	0.1223
δ daily shop^{WD}	δ private business^{SAT}	0.0707	0.0920
δ daily shop^{WD}	δ travel^{SAT}	0.0477	0.0653
δ daily shop^{WD}	γ work^{SUN}	-0.3933	0.1228
δ daily shop^{WD}	γ school^{SUN}	0.4939	0.1285
δ daily shop^{WD}	γ drop pick^{SUN}	0.0368	0.1789
δ daily shop^{WD}	γ daily shop^{SUN}	-0.3543	0.1764
δ daily shop^{WD}	γ non daily shop^{SUN}	0.3124	0.1388
δ daily shop^{WD}	γ social^{SUN}	-0.2053	0.0648
δ daily shop^{WD}	γ leisure^{SUN}	-0.1102	0.2010
δ daily shop^{WD}	γ private business^{SUN}	-0.8335	0.1507
δ daily shop^{WD}	γ travel^{SUN}	-0.2097	0.1005
δ daily shop^{WD}	δ work^{SUN}	0.4556	0.1455
δ daily shop^{WD}	δ school^{SUN}	-0.7182	0.2026
δ daily shop^{WD}	δ drop pick^{SUN}	0.0637	0.1603
δ daily shop^{WD}	δ daily shop^{SUN}	0.4515	0.1111
δ daily shop^{WD}	δ non daily shop^{SUN}	0.1446	0.0865
δ daily shop^{WD}	δ social^{SUN}	-0.0297	0.0932
δ daily shop^{WD}	δ leisure^{SUN}	0.0761	0.1476
δ daily shop^{WD}	δ private business^{SUN}	0.6257	0.1147
δ daily shop^{WD}	δ travel^{SUN}	0.3170	0.1347
δ non daily shop^{WD}	δ non daily shop^{WD}	0.2410	0.0464
δ non daily shop^{WD}	δ social^{WD}	-0.2274	0.0698
δ non daily shop^{WD}	δ leisure^{WD}	0.1777	0.0776
δ non daily shop^{WD}	δ private business^{WD}	0.1522	0.0463
δ non daily shop^{WD}	δ travel^{WD}	-0.1013	0.0360
δ non daily shop^{WD}	γ work^{SAT}	-0.1165	0.0497
δ non daily shop^{WD}	γ school^{SAT}	0.1609	0.0716
δ non daily shop^{WD}	γ drop pick^{SAT}	-0.3809	0.0806
δ non daily shop^{WD}	γ daily shop^{SAT}	-0.0835	0.0483
δ non daily shop^{WD}	γ non daily shop^{SAT}	-0.2337	0.0534
δ non daily shop^{WD}	γ social^{SAT}	0.0431	0.0613
δ non daily shop^{WD}	γ leisure^{SAT}	-0.0027	0.0418
δ non daily shop^{WD}	γ private business^{SAT}	-0.1912	0.0614
δ non daily shop^{WD}	γ travel^{SAT}	0.0294	0.0348
δ non daily shop^{WD}	δ work^{SAT}	-0.0598	0.0910
δ non daily shop^{WD}	δ school^{SAT}	-0.1068	0.0909
δ non daily shop^{WD}	δ drop pick^{SAT}	0.0292	0.1089
δ non daily shop^{WD}	δ daily shop^{SAT}	0.0802	0.0701
δ non daily shop^{WD}	δ non daily shop^{SAT}	0.0202	0.0426
δ non daily shop^{WD}	δ social^{SAT}	-0.1837	0.0460
δ non daily shop^{WD}	δ leisure^{SAT}	0.0237	0.0644
δ non daily shop^{WD}	δ private business^{SAT}	0.0405	0.0590
δ non daily shop^{WD}	δ travel^{SAT}	-0.0448	0.0335
δ non daily shop^{WD}	γ work^{SUN}	-0.3085	0.0700
δ non daily shop^{WD}	γ school^{SUN}	0.1440	0.0424
δ non daily shop^{WD}	γ drop pick^{SUN}	0.0034	0.0785

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ non daily shop^{WD}	γ daily shop^{SUN}	-0.0274	0.0482
δ non daily shop^{WD}	γ non daily shop^{SUN}	0.1347	0.0423
δ non daily shop^{WD}	γ social^{SUN}	-0.0461	0.0358
δ non daily shop^{WD}	γ leisure^{SUN}	-0.0059	0.0770
δ non daily shop^{WD}	γ private business^{SUN}	-0.4077	0.0783
δ non daily shop^{WD}	γ travel^{SUN}	-0.0072	0.0575
δ non daily shop^{WD}	δ work^{SUN}	0.2173	0.1074
δ non daily shop^{WD}	δ school^{SUN}	-0.2475	0.0882
δ non daily shop^{WD}	δ drop pick^{SUN}	-0.0255	0.0902
δ non daily shop^{WD}	δ daily shop^{SUN}	0.0863	0.0699
δ non daily shop^{WD}	δ non daily shop^{SUN}	0.0326	0.0310
δ non daily shop^{WD}	δ social^{SUN}	-0.2038	0.0617
δ non daily shop^{WD}	δ leisure^{SUN}	0.1962	0.1003
δ non daily shop^{WD}	δ private business^{SUN}	0.1121	0.0618
δ non daily shop^{WD}	δ travel^{SUN}	0.0488	0.0568
δ social^{WD}	δ social^{WD}	0.7789	0.1306
δ social^{WD}	δ leisure^{WD}	0.1286	0.1211
δ social^{WD}	δ private business^{WD}	0.0999	0.0745
δ social^{WD}	δ travel^{WD}	0.2592	0.0655
δ social^{WD}	γ work^{SAT}	0.2040	0.1070
δ social^{WD}	γ school^{SAT}	-0.2819	0.1147
δ social^{WD}	γ drop pick^{SAT}	0.4654	0.1058
δ social^{WD}	γ daily shop^{SAT}	0.0767	0.0643
δ social^{WD}	γ non daily shop^{SAT}	0.3498	0.1016
δ social^{WD}	γ social^{SAT}	-0.1018	0.0654
δ social^{WD}	γ leisure^{SAT}	0.0035	0.1301
δ social^{WD}	γ private business^{SAT}	0.1585	0.1238
δ social^{WD}	γ travel^{SAT}	-0.0567	0.0605
δ social^{WD}	δ work^{SAT}	-0.0235	0.0995
δ social^{WD}	δ school^{SAT}	-0.0240	0.1205
δ social^{WD}	δ drop pick^{SAT}	0.0368	0.1215
δ social^{WD}	δ daily shop^{SAT}	-0.2096	0.0640
δ social^{WD}	δ non daily shop^{SAT}	0.0119	0.1099
δ social^{WD}	δ social^{SAT}	0.5097	0.0998
δ social^{WD}	δ leisure^{SAT}	0.1568	0.0991
δ social^{WD}	δ private business^{SAT}	0.0423	0.0653
δ social^{WD}	δ travel^{SAT}	0.1624	0.0513
δ social^{WD}	γ work^{SUN}	0.2720	0.0912
δ social^{WD}	γ school^{SUN}	-0.0658	0.0802
δ social^{WD}	γ drop pick^{SUN}	-0.3896	0.1298
δ social^{WD}	γ daily shop^{SUN}	-0.2551	0.1173
δ social^{WD}	γ non daily shop^{SUN}	-0.1106	0.0887
δ social^{WD}	γ social^{SUN}	0.0117	0.0557
δ social^{WD}	γ leisure^{SUN}	-0.0372	0.0716
δ social^{WD}	γ private business^{SUN}	0.3735	0.1098
δ social^{WD}	γ travel^{SUN}	-0.2461	0.0875
δ social^{WD}	δ work^{SUN}	-0.5627	0.1601
δ social^{WD}	δ school^{SUN}	0.0355	0.1006
δ social^{WD}	δ drop pick^{SUN}	0.3983	0.1283
δ social^{WD}	δ daily shop^{SUN}	-0.0657	0.1192

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ social^{WD}	δ non daily shop^{SUN}	0.0243	0.0493
δ social^{WD}	δ social^{SUN}	0.5279	0.0934
δ social^{WD}	δ leisure^{SUN}	-0.1120	0.1361
δ social^{WD}	δ private business^{SUN}	0.1987	0.0908
δ social^{WD}	δ travel^{SUN}	0.2942	0.0865
δ leisure^{WD}	δ leisure^{WD}	1.7419	0.2751
δ leisure^{WD}	δ private business^{WD}	-0.1513	0.1043
δ leisure^{WD}	δ travel^{WD}	0.1757	0.1071
δ leisure^{WD}	γ work^{SAT}	-0.1134	0.1854
δ leisure^{WD}	γ school^{SAT}	-0.1187	0.1586
δ leisure^{WD}	γ drop pick^{SAT}	0.0566	0.1746
δ leisure^{WD}	γ daily shop^{SAT}	-0.0740	0.1034
δ leisure^{WD}	γ non daily shop^{SAT}	0.1345	0.2197
δ leisure^{WD}	γ social^{SAT}	-0.0882	0.1123
δ leisure^{WD}	γ leisure^{SAT}	-0.0890	0.1273
δ leisure^{WD}	γ private business^{SAT}	0.4993	0.1629
δ leisure^{WD}	γ travel^{SAT}	0.0993	0.1143
δ leisure^{WD}	δ work^{SAT}	-0.4268	0.1552
δ leisure^{WD}	δ school^{SAT}	-0.1390	0.1933
δ leisure^{WD}	δ drop pick^{SAT}	-0.3416	0.2053
δ leisure^{WD}	δ daily shop^{SAT}	-0.2173	0.0945
δ leisure^{WD}	δ non daily shop^{SAT}	-0.0770	0.1082
δ leisure^{WD}	δ social^{SAT}	0.2744	0.1071
δ leisure^{WD}	δ leisure^{SAT}	1.0723	0.1744
δ leisure^{WD}	δ private business^{SAT}	-0.3621	0.1443
δ leisure^{WD}	δ travel^{SAT}	0.0512	0.0951
δ leisure^{WD}	γ work^{SUN}	-0.4327	0.1965
δ leisure^{WD}	γ school^{SUN}	0.0280	0.0917
δ leisure^{WD}	γ drop pick^{SUN}	-0.7940	0.2168
δ leisure^{WD}	γ daily shop^{SUN}	0.1335	0.1496
δ leisure^{WD}	γ non daily shop^{SUN}	0.0320	0.1501
δ leisure^{WD}	γ social^{SUN}	0.0223	0.0792
δ leisure^{WD}	γ leisure^{SUN}	-0.2557	0.0935
δ leisure^{WD}	γ private business^{SUN}	-0.0486	0.1813
δ leisure^{WD}	γ travel^{SUN}	-0.2826	0.1127
δ leisure^{WD}	δ work^{SUN}	-0.7042	0.2203
δ leisure^{WD}	δ school^{SUN}	-0.0972	0.1575
δ leisure^{WD}	δ drop pick^{SUN}	0.8664	0.1874
δ leisure^{WD}	δ daily shop^{SUN}	-0.3543	0.1483
δ leisure^{WD}	δ non daily shop^{SUN}	-0.2133	0.0864
δ leisure^{WD}	δ social^{SUN}	-0.0327	0.1252
δ leisure^{WD}	δ leisure^{SUN}	1.1317	0.1837
δ leisure^{WD}	δ private business^{SUN}	-0.0375	0.1567
δ leisure^{WD}	δ travel^{SUN}	0.4900	0.1170
δ private business^{WD}	δ private business^{WD}	0.5508	0.0944
δ private business^{WD}	δ travel^{WD}	-0.0298	0.0482
δ private business^{WD}	γ work^{SAT}	0.0463	0.0680
δ private business^{WD}	γ school^{SAT}	0.0675	0.1071
δ private business^{WD}	γ drop pick^{SAT}	-0.2211	0.1053
δ private business^{WD}	γ daily shop^{SAT}	-0.0637	0.0427

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.1321	0.0965	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.0964	0.0342	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.0462	0.0573
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	0.0007	0.0693	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	0.2083	0.0576	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	0.2188	0.0944
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	0.0276	0.0715	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	0.0317	0.0468	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0806	0.1170
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.3652	0.0738	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.5414	0.1388	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	0.0069	0.0747
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0108	0.0684	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.0669	0.0584	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	0.0312	0.1240
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.0772	0.1293	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.0920	0.0573	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{school}^{SAT}}$	0.5200	0.1231
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{school}^{SAT}}$	-0.1178	0.0970	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.0115	0.0325	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.5960	0.1117
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.3041	0.1486	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.0723	0.0468	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{daily shop}^{SAT}}$	-0.0565	0.0684
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	-0.0098	0.0614	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	0.0914	0.0996	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.3272	0.0837
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.1499	0.0708	$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0634	0.0480	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{social}^{SAT}}$	0.1879	0.0551
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{social}^{SAT}}$	-0.0452	0.0720	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-0.2127	0.1331	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{leisure}^{SAT}}$	0.0983	0.1398
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	-0.1951	0.0864	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{school}^{SUN}}$	-0.1228	0.0754	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{private business}^{SAT}}$	-0.2482	0.0860
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	0.3124	0.0753	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	0.3784	0.1075	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{travel}^{SAT}}$	0.0722	0.0627
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.0298	0.0619	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.0555	0.0873	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{work}^{SAT}}$	0.3935	0.1032
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	-0.2444	0.0806	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.0842	0.0507	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{school}^{SAT}}$	-0.1528	0.1303
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	0.1759	0.1180	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.2713	0.0563	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.4432	0.1302
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.0423	0.1534	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.1081	0.0664	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0464	0.0757
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.3028	0.0705	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.0525	0.0595	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{non daily shop}^{SAT}}$	-0.0443	0.0584
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.1506	0.0710	$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.1731	0.0657	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{social}^{SAT}}$	-0.3469	0.0923
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	-0.0964	0.0934	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{work}^{SAT}}$	0.3326	0.0936	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{leisure}^{SAT}}$	-0.2431	0.1552
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	0.1095	0.0749	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{school}^{SAT}}$	-0.2605	0.0884	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{private business}^{SAT}}$	0.0616	0.0886
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	-0.4531	0.0999	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{drop pick}^{SAT}}$	0.4120	0.1337	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{travel}^{SAT}}$	-0.1831	0.0502
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0540	0.1035	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.0897	0.0473	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{work}^{SUN}}$	-0.2187	0.0928
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{work}^{SUN}}$	0.1574	0.1192	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.3294	0.0917	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{school}^{SUN}}$	-0.0154	0.0760
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{school}^{SUN}}$	-0.3228	0.1121	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{social}^{SAT}}$	-0.0756	0.0435	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{drop pick}^{SUN}}$	0.4080	0.2815
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.0079	0.1315	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.0771	0.0560	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{daily shop}^{SUN}}$	0.0860	0.0752
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	0.2931	0.0807	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{private business}^{SAT}}$	0.0158	0.0852	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.0070	0.0820
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.1823	0.0569	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0203	0.0369	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	0.0093	0.0869
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.0263	0.0922	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{work}^{SAT}}$	0.0133	0.1159	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	0.1451	0.0798
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0768	0.0934	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{school}^{SAT}}$	-0.1994	0.1123	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	-0.3252	0.1064
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.3648	0.0751	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{drop pick}^{SAT}}$	0.3494	0.1507	$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	0.0466	0.0888
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.1459	0.0934	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{daily shop}^{SAT}}$	-0.0614	0.0703	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	0.6272	0.1359
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.2507	0.0649	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.0533	0.0409	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	-0.2831	0.1713
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	0.1907	0.0847	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{social}^{SAT}}$	0.1740	0.0916	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.5026	0.1617
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	-0.2025	0.1135	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{leisure}^{SAT}}$	0.0466	0.1636	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.0637	0.1355
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	0.3260	0.1039	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{private business}^{SAT}}$	0.0507	0.0693	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.1187	0.0973
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.0653	0.0507	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{travel}^{SAT}}$	0.0929	0.0481	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	-0.2431	0.0874
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.2541	0.0947	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{work}^{SUN}}$	0.2696	0.0721	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	-0.1629	0.1005
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.0904	0.0336	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{school}^{SUN}}$	0.0049	0.0655	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	-0.0982	0.0744
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.0796	0.0632	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.4332	0.2206	$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	-0.1823	0.1064
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	0.0814	0.0512	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.0784	0.0606	$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{drop pick}^{SAT}}$	1.1290	0.2095
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0287	0.0452	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.1103	0.0727	$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.1937	0.1293
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{work}^{SAT}}$	0.0047	0.0919	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	0.0153	0.0425	$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.6479	0.1094
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{school}^{SAT}}$	-0.2486	0.1068	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0013	0.0522	$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{social}^{SAT}}$	-0.1863	0.0974
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.1729	0.1071	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	0.1141	0.1047	$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.0843	0.1236
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	-0.0718	0.0679	$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	0.0529	0.0886	$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{private business}^{SAT}}$	0.5059	0.1252
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	-0.0336	0.0737	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	-0.1025	0.1714	$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0334	0.0615
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{social}^{SAT}}$	0.2308	0.0716	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	-0.0260	0.1410	$\gamma_{\text{drop pick}^{SAT}}$	$\delta_{\text{work}^{SAT}}$	-0.3321	0.1492
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.2371	0.1106	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	0.2440	0.1401	$\gamma_{\text{drop pick}^{SAT}}$	$\delta_{\text{school}^{SAT}}$	0.2959	0.2061
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	-0.0604	0.0489	$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.0037	0.1037	$\gamma_{\text{drop pick}^{SAT}}$	$\delta_{\text{drop pick}^{SAT}}$	0.3862	0.1523

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ drop pick^{SAT}	δ daily shop^{SAT}	-0.2349	0.1142	γ daily shop^{SAT}	δ drop pick^{SUN}	0.0086	0.0559	γ social^{SAT}	δ private business^{SAT}	0.0324	0.0436
γ drop pick^{SAT}	δ non daily shop^{SAT}	0.0868	0.1079	γ daily shop^{SAT}	δ daily shop^{SUN}	-0.0751	0.0514	γ social^{SAT}	δ travel^{SAT}	-0.0837	0.0286
γ drop pick^{SAT}	δ social^{SAT}	0.4599	0.0988	γ daily shop^{SAT}	δ non daily shop^{SUN}	-0.0396	0.0292	γ social^{SAT}	γ work^{SUN}	-0.0599	0.0538
γ drop pick^{SAT}	δ leisure^{SAT}	0.2874	0.1346	γ daily shop^{SAT}	δ social^{SUN}	0.0846	0.0653	γ social^{SAT}	γ school^{SUN}	-0.0419	0.0612
γ drop pick^{SAT}	δ private business^{SAT}	-0.0393	0.0970	γ daily shop^{SAT}	δ leisure^{SUN}	-0.0960	0.0722	γ social^{SAT}	γ drop pick^{SUN}	0.1885	0.0771
γ drop pick^{SAT}	δ travel^{SAT}	0.1807	0.0504	γ daily shop^{SAT}	δ private business^{SUN}	-0.0885	0.0531	γ social^{SAT}	γ daily shop^{SUN}	0.0592	0.0612
γ drop pick^{SAT}	γ work^{SUN}	0.5268	0.1097	γ daily shop^{SAT}	δ travel^{SUN}	-0.0553	0.0565	γ social^{SAT}	γ non daily shop^{SUN}	-0.0172	0.0428
γ drop pick^{SAT}	γ school^{SUN}	-0.2523	0.0943	γ non daily shop^{SAT}	γ non daily shop^{SAT}	0.5585	0.1015	γ social^{SAT}	γ social^{SUN}	0.0182	0.0231
γ drop pick^{SAT}	γ drop pick^{SUN}	-0.4589	0.1855	γ non daily shop^{SAT}	γ social^{SAT}	-0.0905	0.0577	γ social^{SAT}	γ leisure^{SUN}	0.0703	0.0423
γ drop pick^{SAT}	γ daily shop^{SUN}	0.0341	0.1294	γ non daily shop^{SAT}	γ leisure^{SAT}	-0.0573	0.0692	γ social^{SAT}	γ private business^{SUN}	-0.0638	0.1136
γ drop pick^{SAT}	γ non daily shop^{SUN}	-0.1620	0.1048	γ non daily shop^{SAT}	γ private business^{SAT}	0.2836	0.0937	γ social^{SAT}	γ travel^{SUN}	0.0409	0.0325
γ drop pick^{SAT}	γ social^{SUN}	0.0717	0.0858	γ non daily shop^{SAT}	γ travel^{SAT}	0.0031	0.0611	γ social^{SAT}	δ work^{SUN}	0.2556	0.0963
γ drop pick^{SAT}	γ leisure^{SUN}	-0.0840	0.1434	γ non daily shop^{SAT}	δ work^{SAT}	0.0056	0.1088	γ social^{SAT}	δ school^{SUN}	-0.0584	0.0849
γ drop pick^{SAT}	γ private business^{SUN}	0.7829	0.1590	γ non daily shop^{SAT}	δ school^{SAT}	-0.0871	0.1527	γ social^{SAT}	δ drop pick^{SUN}	-0.2467	0.0773
γ drop pick^{SAT}	γ travel^{SUN}	0.0543	0.0934	γ non daily shop^{SAT}	δ drop pick^{SAT}	0.1220	0.1580	γ social^{SAT}	δ daily shop^{SUN}	-0.0657	0.0755
γ drop pick^{SAT}	δ work^{SUN}	-0.8669	0.1882	γ non daily shop^{SAT}	δ daily shop^{SAT}	-0.1995	0.0801	γ social^{SAT}	δ non daily shop^{SUN}	0.0408	0.0437
γ drop pick^{SAT}	δ school^{SUN}	0.6309	0.1611	γ non daily shop^{SAT}	δ non daily shop^{SAT}	0.0370	0.0463	γ social^{SAT}	δ social^{SUN}	-0.1017	0.0679
γ drop pick^{SAT}	δ drop pick^{SUN}	0.4592	0.1801	γ non daily shop^{SAT}	δ social^{SAT}	0.3012	0.0858	γ social^{SAT}	δ leisure^{SUN}	-0.1150	0.0762
γ drop pick^{SAT}	δ daily shop^{SUN}	-0.1043	0.1228	γ non daily shop^{SAT}	δ leisure^{SAT}	0.2356	0.1642	γ social^{SAT}	δ private business^{SUN}	-0.0905	0.0777
γ drop pick^{SAT}	δ non daily shop^{SUN}	-0.1730	0.0782	γ non daily shop^{SAT}	δ private business^{SAT}	-0.0466	0.0973	γ social^{SAT}	δ travel^{SUN}	-0.1180	0.0493
γ drop pick^{SAT}	δ social^{SUN}	0.3933	0.1108	γ non daily shop^{SAT}	δ travel^{SAT}	0.0919	0.0469	γ leisure^{SAT}	γ leisure^{SAT}	0.1112	0.0637
γ drop pick^{SAT}	δ leisure^{SUN}	0.0166	0.2042	γ non daily shop^{SAT}	γ work^{SUN}	0.3834	0.0896	γ leisure^{SAT}	γ private business^{SAT}	-0.0323	0.0677
γ drop pick^{SAT}	δ private business^{SUN}	-0.1400	0.1014	γ non daily shop^{SAT}	γ school^{SUN}	-0.1607	0.0802	γ leisure^{SAT}	γ travel^{SAT}	0.0139	0.0331
γ drop pick^{SAT}	δ travel^{SUN}	0.0415	0.1381	γ non daily shop^{SAT}	γ drop pick^{SUN}	-0.4787	0.1877	γ leisure^{SAT}	δ work^{SAT}	0.0649	0.1467
γ daily shop^{SAT}	γ daily shop^{SAT}	0.0976	0.0422	γ non daily shop^{SAT}	γ daily shop^{SUN}	0.0253	0.1282	γ leisure^{SAT}	δ school^{SAT}	0.1104	0.1145
γ daily shop^{SAT}	γ non daily shop^{SAT}	0.1426	0.0605	γ non daily shop^{SAT}	γ non daily shop^{SUN}	-0.0529	0.1074	γ leisure^{SAT}	δ drop pick^{SAT}	-0.1375	0.0967
γ daily shop^{SAT}	γ social^{SAT}	0.0049	0.0263	γ non daily shop^{SAT}	γ social^{SUN}	0.0948	0.0537	γ leisure^{SAT}	δ daily shop^{SAT}	-0.0362	0.0445
γ daily shop^{SAT}	γ leisure^{SAT}	-0.0136	0.0231	γ non daily shop^{SAT}	γ leisure^{SUN}	-0.0052	0.0711	γ leisure^{SAT}	δ non daily shop^{SAT}	0.0139	0.0465
γ daily shop^{SAT}	γ private business^{SAT}	0.0608	0.0581	γ non daily shop^{SAT}	γ private business^{SUN}	0.4529	0.1205	γ leisure^{SAT}	δ social^{SAT}	-0.0524	0.1121
γ daily shop^{SAT}	γ travel^{SAT}	0.0090	0.0318	γ non daily shop^{SAT}	γ travel^{SUN}	0.0223	0.0902	γ leisure^{SAT}	δ leisure^{SAT}	-0.1138	0.1179
γ daily shop^{SAT}	δ work^{SAT}	0.0769	0.0886	γ non daily shop^{SAT}	δ work^{SUN}	-0.4020	0.1639	γ leisure^{SAT}	δ private business^{SAT}	0.0490	0.0501
γ daily shop^{SAT}	δ school^{SAT}	-0.0182	0.0990	γ non daily shop^{SAT}	δ school^{SUN}	0.2079	0.1249	γ leisure^{SAT}	δ travel^{SAT}	-0.0399	0.0503
γ daily shop^{SAT}	δ drop pick^{SAT}	0.0179	0.1031	γ non daily shop^{SAT}	δ drop pick^{SUN}	0.3335	0.1157	γ leisure^{SAT}	γ work^{SUN}	-0.0429	0.0501
γ daily shop^{SAT}	δ daily shop^{SAT}	-0.0597	0.0615	γ non daily shop^{SAT}	δ daily shop^{SUN}	-0.2026	0.1145	γ leisure^{SAT}	γ school^{SUN}	-0.0503	0.0448
γ daily shop^{SAT}	δ non daily shop^{SAT}	0.0130	0.0369	γ non daily shop^{SAT}	δ non daily shop^{SUN}	-0.1027	0.0667	γ leisure^{SAT}	γ drop pick^{SUN}	0.2301	0.1265
γ daily shop^{SAT}	δ social^{SAT}	0.0484	0.0538	γ non daily shop^{SAT}	δ social^{SUN}	0.2794	0.0902	γ leisure^{SAT}	γ daily shop^{SUN}	-0.0086	0.0625
γ daily shop^{SAT}	δ leisure^{SAT}	0.0075	0.0652	γ non daily shop^{SAT}	δ leisure^{SUN}	-0.0245	0.0979	γ leisure^{SAT}	γ non daily shop^{SUN}	-0.0905	0.0579
γ daily shop^{SAT}	δ private business^{SAT}	0.0004	0.0353	γ non daily shop^{SAT}	δ private business^{SUN}	-0.1777	0.0804	γ leisure^{SAT}	γ social^{SUN}	0.0179	0.0281
γ daily shop^{SAT}	δ travel^{SAT}	0.0044	0.0301	γ non daily shop^{SAT}	δ travel^{SUN}	0.0149	0.1082	γ leisure^{SAT}	γ leisure^{SUN}	0.0688	0.0633
γ daily shop^{SAT}	γ work^{SUN}	0.1589	0.0609	γ social^{SAT}	γ social^{SAT}	0.1149	0.0520	γ leisure^{SAT}	γ private business^{SUN}	0.0334	0.1209
γ daily shop^{SAT}	γ school^{SUN}	-0.0733	0.0392	γ social^{SAT}	γ leisure^{SAT}	0.0424	0.0517	γ leisure^{SAT}	γ travel^{SUN}	0.0100	0.0688
γ daily shop^{SAT}	γ drop pick^{SUN}	-0.0958	0.0882	γ social^{SAT}	γ private business^{SAT}	-0.0691	0.0535	γ leisure^{SAT}	δ work^{SUN}	0.0346	0.2336
γ daily shop^{SAT}	γ daily shop^{SUN}	0.0341	0.0327	γ social^{SAT}	γ travel^{SAT}	0.0425	0.0436	γ leisure^{SAT}	δ school^{SUN}	0.0551	0.1120
γ daily shop^{SAT}	γ non daily shop^{SUN}	-0.0156	0.0422	γ social^{SAT}	δ work^{SAT}	0.1812	0.0707	γ leisure^{SAT}	δ drop pick^{SUN}	-0.1820	0.1502
γ daily shop^{SAT}	γ social^{SUN}	0.0347	0.0223	γ social^{SAT}	δ school^{SAT}	-0.0140	0.0849	γ leisure^{SAT}	δ daily shop^{SUN}	-0.0032	0.0374
γ daily shop^{SAT}	γ leisure^{SUN}	0.0221	0.0437	γ social^{SAT}	δ drop pick^{SAT}	-0.1864	0.0662	γ leisure^{SAT}	δ non daily shop^{SUN}	0.0651	0.0406
γ daily shop^{SAT}	γ private business^{SUN}	0.1464	0.0861	γ social^{SAT}	δ daily shop^{SAT}	-0.0078	0.0328	γ leisure^{SAT}	δ social^{SUN}	-0.0415	0.0716
γ daily shop^{SAT}	γ travel^{SUN}	0.0408	0.0446	γ social^{SAT}	δ non daily shop^{SAT}	-0.0056	0.0275	γ leisure^{SAT}	δ leisure^{SUN}	-0.1113	0.0876
γ daily shop^{SAT}	δ work^{SUN}	-0.0315	0.1234	γ social^{SAT}	δ social^{SAT}	-0.1367	0.0505	γ leisure^{SAT}	δ private business^{SUN}	-0.0280	0.0914
γ daily shop^{SAT}	δ school^{SUN}	0.0653	0.0733	γ social^{SAT}	δ leisure^{SAT}	-0.1194	0.0829	γ leisure^{SAT}	δ travel^{SUN}	-0.0692	0.1119

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov	Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{private business}}^{SAT}$	0.6095	0.0960	$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	-0.0563	0.1055	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	0.0267	0.1177
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{travel}}^{SAT}$	0.0330	0.0576	$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	-0.0686	0.0825	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	-0.9354	0.2297
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{work}}^{SAT}$	-0.2900	0.1190	$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.0055	0.0496	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	1.2392	0.2574
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{school}}^{SAT}$	0.4154	0.1302	$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	-0.0770	0.0640	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	-0.4322	0.2246
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	-0.2271	0.1543	$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	0.0393	0.0764	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	0.1319	0.1253
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	-0.1661	0.0634	$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	-0.0848	0.0666	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	0.0489	0.0824
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.0099	0.0626	$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	-0.0503	0.0645	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	-0.2577	0.0983
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	0.2506	0.0828	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{work}}^{SAT}$	1.0915	0.3617	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	-0.0868	0.1419
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	0.3843	0.1212	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{school}}^{SAT}$	-0.8155	0.2497	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	-0.1017	0.1190
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	-0.2183	0.0613	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	-0.4791	0.2376	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	-0.1994	0.1501
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.0433	0.0469	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	-0.0099	0.1188	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	1.1050	0.3588
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	0.1198	0.1056	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.1760	0.0821	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	0.1382	0.1107
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	-0.2666	0.0831	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	-0.1680	0.0914	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	0.1228	0.0806
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.0162	0.1797	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	-0.3031	0.1352	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	0.1057	0.1132
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	0.2134	0.0883	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	-0.0445	0.0953	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	-0.0522	0.1322
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.2645	0.1347	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	-0.1648	0.0655	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	0.2188	0.1120
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	0.0693	0.0605	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	0.2780	0.1617	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.1995	0.0662
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	-0.1184	0.1008	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	0.0211	0.1543	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	0.0974	0.1079
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	0.6215	0.1752	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.1010	0.1586	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	0.2719	0.0895
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	-0.0500	0.0752	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	0.0585	0.0969	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.5430	0.2022
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	-0.6678	0.1476	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	0.1779	0.1100	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	-0.3007	0.0887
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	0.5946	0.1249	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	0.1013	0.0650	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	0.3260	0.1065
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	0.2453	0.1555	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	0.1865	0.1491	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	-0.1011	0.0967
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	-0.2618	0.0709	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	-0.2321	0.1875	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	-0.1140	0.1583
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.1565	0.0674	$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	0.0783	0.0876	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	-0.2645	0.1468
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	0.0462	0.0772	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	1.0432	0.3477	$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	0.0957	0.1209
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	0.2673	0.1936	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	-0.6559	0.3196	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	-0.2214	0.2047
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	-0.2717	0.0893	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	-0.3801	0.1414	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	-0.0792	0.1584
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	0.0170	0.0851	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	-0.2930	0.0895	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	0.4247	0.1506
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{travel}}^{SAT}$	0.0723	0.0426	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	0.0677	0.1181	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	0.4622	0.1666
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{work}}^{SAT}$	0.0338	0.0596	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	0.1113	0.0874	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.0422	0.1286
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{school}}^{SAT}$	0.0065	0.0625	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	-0.5048	0.1701	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	0.1451	0.0981
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	-0.0879	0.0508	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	-0.2593	0.0941	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	0.0837	0.1271
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	-0.0396	0.0340	$\delta_{\text{work}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	-0.2217	0.0975	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	0.4243	0.1561
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	0.0150	0.0246	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{school}}^{SAT}$	1.4698	0.2233	$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	0.1659	0.0961
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	-0.0530	0.0535	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	-0.0813	0.2217	$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	0.2298	0.0740
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	0.0364	0.0892	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	-0.0879	0.1105	$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.0689	0.0609
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	0.0056	0.0522	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	0.2407	0.0952	$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	-0.1212	0.0550
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	-0.0479	0.0341	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	0.0048	0.0929	$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	-0.1352	0.0802
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	-0.0624	0.0483	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	-0.1568	0.1973	$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	-0.0337	0.0583
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	-0.0568	0.0361	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	0.1191	0.1682	$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.0023	0.0348
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	0.0295	0.1372	$\delta_{\text{school}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.0052	0.0759	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	-0.0457	0.0946
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	0.0499	0.0391	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	-0.1576	0.1757	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	0.1468	0.0626
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.0042	0.0455	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	-0.4068	0.1283	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	0.0944	0.1245
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	0.0157	0.0266	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	1.1198	0.2431	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	-0.0254	0.0559
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	0.0165	0.0409	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	0.1525	0.1065	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	0.1095	0.0667
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	-0.0085	0.0459	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.6293	0.1074	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	-0.0563	0.0409
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	0.0311	0.0420	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	-0.0234	0.0590	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	-0.0620	0.0986
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	0.0511	0.0963	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	0.0170	0.0741	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	-0.2160	0.0758
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	0.0266	0.0483	$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	0.7627	0.1362	$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	0.0240	0.0548

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ daily shop^{SAT}	δ work^{SUN}	0.2272	0.1169
δ daily shop^{SAT}	δ school^{SUN}	-0.1400	0.0968
δ daily shop^{SAT}	δ drop pick^{SUN}	-0.0477	0.1181
δ daily shop^{SAT}	δ daily shop^{SUN}	0.1558	0.0730
δ daily shop^{SAT}	δ non daily shop^{SUN}	0.0018	0.0477
δ daily shop^{SAT}	δ social^{SUN}	-0.0912	0.0855
δ daily shop^{SAT}	δ leisure^{SUN}	-0.0122	0.1119
δ daily shop^{SAT}	δ private business^{SUN}	0.1109	0.0734
δ daily shop^{SAT}	δ travel^{SUN}	-0.0120	0.0691
δ non daily shop^{SAT}	δ non daily shop^{SAT}	0.1744	0.0533
δ non daily shop^{SAT}	δ social^{SAT}	-0.0202	0.0476
δ non daily shop^{SAT}	δ leisure^{SAT}	-0.0797	0.0975
δ non daily shop^{SAT}	δ private business^{SAT}	0.1484	0.0475
δ non daily shop^{SAT}	δ travel^{SAT}	0.0079	0.0289
δ non daily shop^{SAT}	γ work^{SUN}	-0.0686	0.0787
δ non daily shop^{SAT}	γ school^{SUN}	-0.0661	0.0793
δ non daily shop^{SAT}	γ drop pick^{SUN}	0.1550	0.1159
δ non daily shop^{SAT}	γ daily shop^{SUN}	-0.0402	0.0520
δ non daily shop^{SAT}	γ non daily shop^{SUN}	-0.0689	0.0600
δ non daily shop^{SAT}	γ social^{SUN}	-0.0197	0.0518
δ non daily shop^{SAT}	γ leisure^{SUN}	0.0675	0.0507
δ non daily shop^{SAT}	γ private business^{SUN}	0.0465	0.1128
δ non daily shop^{SAT}	γ travel^{SUN}	0.0328	0.0424
δ non daily shop^{SAT}	δ work^{SUN}	-0.1373	0.1294
δ non daily shop^{SAT}	δ school^{SUN}	0.1957	0.0925
δ non daily shop^{SAT}	δ drop pick^{SUN}	-0.0897	0.1024
δ non daily shop^{SAT}	δ daily shop^{SUN}	0.0724	0.0735
δ non daily shop^{SAT}	δ non daily shop^{SUN}	0.0476	0.0452
δ non daily shop^{SAT}	δ social^{SUN}	-0.0510	0.0880
δ non daily shop^{SAT}	δ leisure^{SUN}	-0.0590	0.0953
δ non daily shop^{SAT}	δ private business^{SUN}	0.0248	0.0769
δ non daily shop^{SAT}	δ travel^{SUN}	-0.0377	0.0791
δ social^{SAT}	δ social^{SAT}	0.4631	0.1119
δ social^{SAT}	δ leisure^{SAT}	0.2884	0.0840
δ social^{SAT}	δ private business^{SAT}	-0.0881	0.0679
δ social^{SAT}	δ travel^{SAT}	0.1641	0.0517
δ social^{SAT}	γ work^{SUN}	0.2010	0.0744
δ social^{SAT}	γ school^{SUN}	-0.0162	0.0581
δ social^{SAT}	γ drop pick^{SUN}	-0.4253	0.1354
δ social^{SAT}	γ daily shop^{SUN}	-0.1448	0.0806
δ social^{SAT}	γ non daily shop^{SUN}	-0.0592	0.0594
δ social^{SAT}	γ social^{SUN}	-0.0031	0.0526
δ social^{SAT}	γ leisure^{SUN}	-0.1248	0.0627
δ social^{SAT}	γ private business^{SUN}	0.3404	0.1099
δ social^{SAT}	γ travel^{SUN}	-0.1984	0.0936

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ social^{SAT}	δ social^{SUN}	0.3826	0.0950
δ social^{SAT}	δ leisure^{SUN}	0.1139	0.1089
δ social^{SAT}	δ private business^{SUN}	0.1300	0.0718
δ social^{SAT}	δ travel^{SUN}	0.2798	0.0839
δ leisure^{SAT}	δ leisure^{SAT}	0.8118	0.1555
δ leisure^{SAT}	δ private business^{SAT}	-0.2990	0.0899
δ leisure^{SAT}	δ travel^{SAT}	0.0916	0.0794
δ leisure^{SAT}	γ work^{SUN}	-0.0946	0.1326
δ leisure^{SAT}	γ school^{SUN}	0.0231	0.0922
δ leisure^{SAT}	γ drop pick^{SUN}	-0.7589	0.1848
δ leisure^{SAT}	γ daily shop^{SUN}	0.0873	0.0989
δ leisure^{SAT}	γ non daily shop^{SUN}	0.0530	0.0707
δ leisure^{SAT}	γ social^{SUN}	0.0191	0.0595
δ leisure^{SAT}	γ leisure^{SUN}	-0.2268	0.0616
δ leisure^{SAT}	γ private business^{SUN}	0.1026	0.1173
δ leisure^{SAT}	γ travel^{SUN}	-0.1726	0.0770
δ leisure^{SAT}	δ work^{SUN}	-0.5973	0.1807
δ leisure^{SAT}	δ school^{SUN}	-0.0361	0.1534
δ leisure^{SAT}	δ drop pick^{SUN}	0.7427	0.1584
δ leisure^{SAT}	δ daily shop^{SUN}	-0.2338	0.1096
δ leisure^{SAT}	δ non daily shop^{SUN}	-0.2186	0.0683
δ leisure^{SAT}	δ social^{SUN}	0.1067	0.0991
δ leisure^{SAT}	δ leisure^{SUN}	0.7472	0.1282
δ leisure^{SAT}	δ private business^{SUN}	-0.0323	0.1003
δ leisure^{SAT}	δ travel^{SUN}	0.3585	0.0872
δ private business^{SAT}	δ private business^{SAT}	0.3106	0.1082
δ private business^{SAT}	δ travel^{SAT}	-0.0109	0.0510
δ private business^{SAT}	γ work^{SUN}	-0.0621	0.0674
δ private business^{SAT}	γ school^{SUN}	-0.0087	0.0894
δ private business^{SAT}	γ drop pick^{SUN}	0.1901	0.1619
δ private business^{SAT}	γ daily shop^{SUN}	-0.1477	0.0727
δ private business^{SAT}	γ non daily shop^{SUN}	0.0146	0.0608
δ private business^{SAT}	γ social^{SUN}	-0.0299	0.0682
δ private business^{SAT}	γ leisure^{SUN}	0.1344	0.0614
δ private business^{SAT}	γ private business^{SUN}	-0.1348	0.0839
δ private business^{SAT}	γ travel^{SUN}	0.0635	0.0790
δ private business^{SAT}	δ work^{SUN}	0.0959	0.0914
δ private business^{SAT}	δ school^{SUN}	0.0087	0.1390
δ private business^{SAT}	δ drop pick^{SUN}	-0.2269	0.1409
δ private business^{SAT}	δ daily shop^{SUN}	0.1855	0.0860
δ private business^{SAT}	δ non daily shop^{SUN}	0.1382	0.0420
δ private business^{SAT}	δ social^{SUN}	-0.0136	0.0794
δ private business^{SAT}	δ leisure^{SUN}	-0.2523	0.0767
δ private business^{SAT}	δ private business^{SUN}	0.1421	0.0859
δ private business^{SAT}	δ travel^{SUN}	-0.0690	0.0667

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ travel^{SAT}	γ non daily shop^{SUN}	0.0231	0.0393
δ travel^{SAT}	γ social^{SUN}	-0.0242	0.0372
δ travel^{SAT}	γ leisure^{SUN}	-0.0688	0.0563
δ travel^{SAT}	γ private business^{SUN}	0.0611	0.0615
δ travel^{SAT}	γ travel^{SUN}	-0.0672	0.0478
δ travel^{SAT}	δ work^{SUN}	-0.2498	0.0691
δ travel^{SAT}	δ school^{SUN}	0.0187	0.0653
δ travel^{SAT}	δ drop pick^{SUN}	0.2430	0.0756
δ travel^{SAT}	δ daily shop^{SUN}	0.0705	0.0731
δ travel^{SAT}	δ non daily shop^{SUN}	-0.0291	0.0494
δ travel^{SAT}	δ social^{SUN}	0.1431	0.0528
δ travel^{SAT}	δ leisure^{SUN}	0.0739	0.0632
δ travel^{SAT}	δ private business^{SUN}	0.1288	0.0572
δ travel^{SAT}	δ travel^{SUN}	0.1380	0.0497
γ work^{SUN}	γ work^{SUN}	0.6189	0.1704
γ work^{SUN}	γ school^{SUN}	-0.1315	0.0956
γ work^{SUN}	γ drop pick^{SUN}	-0.2194	0.2049
γ work^{SUN}	γ daily shop^{SUN}	0.0417	0.0903
γ work^{SUN}	γ non daily shop^{SUN}	-0.0454	0.0697
γ work^{SUN}	γ social^{SUN}	0.0889	0.0634
γ work^{SUN}	γ leisure^{SUN}	0.0065	0.0861
γ work^{SUN}	γ private business^{SUN}	0.4528	0.1124
γ work^{SUN}	γ travel^{SUN}	0.0917	0.0840
γ work^{SUN}	δ work^{SUN}	-0.0605	0.1705
γ work^{SUN}	δ school^{SUN}	0.1377	0.1165
γ work^{SUN}	δ drop pick^{SUN}	0.0439	0.1208
γ work^{SUN}	δ daily shop^{SUN}	-0.1293	0.1053
γ work^{SUN}	δ non daily shop^{SUN}	-0.0796	0.0605
γ work^{SUN}	δ social^{SUN}	0.3354	0.1255
γ work^{SUN}	δ leisure^{SUN}	-0.3775	0.1434
γ work^{SUN}	δ private business^{SUN}	-0.1739	0.0735
γ work^{SUN}	δ travel^{SUN}	-0.1290	0.0844
γ school^{SUN}	γ school^{SUN}	0.3468	0.0833
γ school^{SUN}	γ drop pick^{SUN}	-0.3673	0.1027
γ school^{SUN}	γ daily shop^{SUN}	-0.1785	0.0740
γ school^{SUN}	γ non daily shop^{SUN}	0.2897	0.0840
γ school^{SUN}	γ social^{SUN}	-0.0720	0.0348
γ school^{SUN}	γ leisure^{SUN}	-0.0667	0.0871
γ school^{SUN}	γ private business^{SUN}	-0.4901	0.1152
γ school^{SUN}	γ travel^{SUN}	-0.0749	0.0504
γ school^{SUN}	δ work^{SUN}	0.2486	0.1152
γ school^{SUN}	δ school^{SUN}	-0.5054	0.0958
γ school^{SUN}	δ drop pick^{SUN}	0.2554	0.0989
γ school^{SUN}	δ daily shop^{SUN}	0.1849	0.1177
γ school^{SUN}	δ non daily shop^{SUN}	0.0072	0.0603

Table B.2: Covariance matrix for the Mobidrive dataset - model with basic socio-demographic characteristics

Covariance matrix for the Mobidrive dataset - model with basic socio-demographic characteristics

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ work^{WD}	γ work^{WD}	3.0922	0.4898
γ work^{WD}	γ school^{WD}	-0.5606	0.2210
γ work^{WD}	γ drop pick^{WD}	0.9913	0.3243
γ work^{WD}	γ daily shop^{WD}	0.0843	0.1627
γ work^{WD}	γ non daily shop^{WD}	0.1549	0.1498
γ work^{WD}	γ social^{WD}	0.4912	0.1312
γ work^{WD}	γ leisure^{WD}	0.1867	0.1038
γ work^{WD}	γ private business^{WD}	0.2647	0.1506
γ work^{WD}	γ travel^{WD}	0.0592	0.0881
γ work^{WD}	δ work^{WD}	-5.4499	0.7441
γ work^{WD}	δ school^{WD}	3.4570	0.6582
γ work^{WD}	δ drop pick^{WD}	-1.0336	0.3002
γ work^{WD}	δ daily shop^{WD}	-0.1467	0.1659
γ work^{WD}	δ non daily shop^{WD}	-0.1107	0.1090
γ work^{WD}	δ social^{WD}	-0.3266	0.1654
γ work^{WD}	δ leisure^{WD}	0.2318	0.1983
γ work^{WD}	δ private business^{WD}	0.0656	0.1311
γ work^{WD}	δ travel^{WD}	-0.4910	0.1206
γ work^{WD}	γ work^{SAT}	-1.7840	0.2568
γ work^{WD}	γ school^{SAT}	0.8891	0.2077
γ work^{WD}	γ drop pick^{SAT}	0.2566	0.1713
γ work^{WD}	γ daily shop^{SAT}	-0.0809	0.1453
γ work^{WD}	γ non daily shop^{SAT}	-0.3485	0.2564
γ work^{WD}	γ social^{SAT}	0.0615	0.1466
γ work^{WD}	γ leisure^{SAT}	0.5110	0.2015
γ work^{WD}	γ private business^{SAT}	0.0121	0.0976
γ work^{WD}	γ travel^{SAT}	0.1071	0.1287
γ work^{WD}	δ work^{SAT}	-2.1756	0.3070
γ work^{WD}	δ school^{SAT}	0.9516	0.2229
γ work^{WD}	δ drop pick^{SAT}	-0.0134	0.1426
γ work^{WD}	δ daily shop^{SAT}	-0.1583	0.1719
γ work^{WD}	δ non daily shop^{SAT}	-0.4490	0.1591
γ work^{WD}	δ social^{SAT}	-0.0708	0.1522
γ work^{WD}	δ leisure^{SAT}	-0.1786	0.1842
γ work^{WD}	δ private business^{SAT}	0.1171	0.1518
γ work^{WD}	δ travel^{SAT}	-0.2785	0.1343
γ work^{WD}	γ work^{SUN}	0.4031	0.2082
γ work^{WD}	γ school^{SUN}	-0.9338	0.2869
γ work^{WD}	γ drop pick^{SUN}	0.8568	0.2057
γ work^{WD}	γ daily shop^{SUN}	0.6166	0.2677
γ work^{WD}	γ non daily shop^{SUN}	0.7366	0.1666
γ work^{WD}	γ social^{SUN}	-0.0751	0.1155
γ work^{WD}	γ leisure^{SUN}	0.0911	0.1007
γ work^{WD}	γ private business^{SUN}	-0.4527	0.1697
γ work^{WD}	γ travel^{SUN}	-0.3016	0.1471
γ work^{WD}	δ work^{SUN}	-0.0799	0.1666
γ work^{WD}	δ school^{SUN}	1.8019	0.2816
γ work^{WD}	δ drop pick^{SUN}	-0.2510	0.2041
γ work^{WD}	δ daily shop^{SUN}	0.3146	0.1692
γ work^{WD}	δ non daily shop^{SUN}	0.5102	0.1629

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ work^{WD}	δ social^{SUN}	-0.3132	0.1388
γ work^{WD}	δ leisure^{SUN}	0.0429	0.1569
γ work^{WD}	δ private business^{SUN}	-0.0321	0.1124
γ work^{WD}	δ travel^{SUN}	0.1831	0.1371
γ school^{WD}	γ school^{WD}	1.6492	0.3361
γ school^{WD}	γ drop pick^{WD}	-0.5391	0.1232
γ school^{WD}	γ daily shop^{WD}	-0.3881	0.1708
γ school^{WD}	γ non daily shop^{WD}	0.0511	0.1183
γ school^{WD}	γ social^{WD}	0.0636	0.1010
γ school^{WD}	γ leisure^{WD}	0.2100	0.1102
γ school^{WD}	γ private business^{WD}	-0.3231	0.0843
γ school^{WD}	γ travel^{WD}	0.2295	0.0786
γ school^{WD}	δ work^{WD}	1.0195	0.3749
γ school^{WD}	δ school^{WD}	-4.6777	0.7540
γ school^{WD}	δ drop pick^{WD}	0.5456	0.2163
γ school^{WD}	δ daily shop^{WD}	0.9485	0.1992
γ school^{WD}	δ non daily shop^{WD}	0.3521	0.0850
γ school^{WD}	δ social^{WD}	-0.6116	0.1275
γ school^{WD}	δ leisure^{WD}	-0.1027	0.2196
γ school^{WD}	δ private business^{WD}	0.4166	0.1146
γ school^{WD}	δ travel^{WD}	-0.2965	0.0812
γ school^{WD}	γ work^{SAT}	0.3445	0.1632
γ school^{WD}	γ school^{SAT}	-0.0907	0.1830
γ school^{WD}	γ drop pick^{SAT}	-0.2230	0.1366
γ school^{WD}	γ daily shop^{SAT}	-0.2132	0.1132
γ school^{WD}	γ non daily shop^{SAT}	-0.3029	0.0963
γ school^{WD}	γ social^{SAT}	0.0475	0.0948
γ school^{WD}	γ leisure^{SAT}	-0.1745	0.1497
γ school^{WD}	γ private business^{SAT}	-0.2638	0.1241
γ school^{WD}	γ travel^{SAT}	-0.2694	0.1323
γ school^{WD}	δ work^{SAT}	0.6036	0.2329
γ school^{WD}	δ school^{SAT}	-0.5461	0.2209
γ school^{WD}	δ drop pick^{SAT}	0.2630	0.1133
γ school^{WD}	δ daily shop^{SAT}	0.6479	0.1780
γ school^{WD}	δ non daily shop^{SAT}	0.3807	0.0953
γ school^{WD}	δ social^{SAT}	-0.3609	0.1134
γ school^{WD}	δ leisure^{SAT}	0.0761	0.1527
γ school^{WD}	δ private business^{SAT}	0.2355	0.1497
γ school^{WD}	δ travel^{SAT}	0.3275	0.1330
γ school^{WD}	γ work^{SUN}	-0.3805	0.1542
γ school^{WD}	γ school^{SUN}	0.6137	0.2441
γ school^{WD}	γ drop pick^{SUN}	-0.4188	0.1573
γ school^{WD}	γ daily shop^{SUN}	-0.2652	0.1060
γ school^{WD}	γ non daily shop^{SUN}	-0.1604	0.1602
γ school^{WD}	γ social^{SUN}	0.0151	0.0864
γ school^{WD}	γ leisure^{SUN}	-0.0123	0.0946
γ school^{WD}	γ private business^{SUN}	-0.3195	0.2116
γ school^{WD}	γ travel^{SUN}	0.0535	0.0845
γ school^{WD}	δ work^{SUN}	0.1341	0.1953
γ school^{WD}	δ school^{SUN}	-0.5482	0.2198

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ school^{WD}	δ drop pick^{SUN}	-0.3318	0.1904
γ school^{WD}	δ daily shop^{SUN}	0.3499	0.1287
γ school^{WD}	δ non daily shop^{SUN}	0.3127	0.1019
γ school^{WD}	δ social^{SUN}	-0.2493	0.1116
γ school^{WD}	δ leisure^{SUN}	0.2990	0.2152
γ school^{WD}	δ private business^{SUN}	-0.0185	0.1055
γ school^{WD}	δ travel^{SUN}	0.0593	0.0982
γ drop pick^{WD}	γ drop pick^{WD}	0.5835	0.1318
γ drop pick^{WD}	γ daily shop^{WD}	0.1845	0.1204
γ drop pick^{WD}	γ non daily shop^{WD}	0.0736	0.0519
γ drop pick^{WD}	γ social^{WD}	0.1549	0.0749
γ drop pick^{WD}	γ leisure^{WD}	-0.0291	0.0619
γ drop pick^{WD}	γ private business^{WD}	0.1918	0.0687
γ drop pick^{WD}	γ travel^{WD}	-0.0685	0.0415
γ drop pick^{WD}	δ work^{WD}	-1.6482	0.5653
γ drop pick^{WD}	δ school^{WD}	2.0638	0.3447
γ drop pick^{WD}	δ drop pick^{WD}	-0.5630	0.1807
γ drop pick^{WD}	δ daily shop^{WD}	-0.3818	0.1209
γ drop pick^{WD}	δ non daily shop^{WD}	-0.0757	0.0592
γ drop pick^{WD}	δ social^{WD}	-0.0428	0.0813
γ drop pick^{WD}	δ leisure^{WD}	0.3876	0.1226
γ drop pick^{WD}	δ private business^{WD}	-0.2210	0.1300
γ drop pick^{WD}	δ travel^{WD}	-0.0411	0.0850
γ drop pick^{WD}	γ work^{SAT}	-0.5870	0.1999
γ drop pick^{WD}	γ school^{SAT}	0.4483	0.1260
γ drop pick^{WD}	γ drop pick^{SAT}	0.0783	0.0808
γ drop pick^{WD}	γ daily shop^{SAT}	0.0894	0.0903
γ drop pick^{WD}	γ non daily shop^{SAT}	-0.0971	0.0861
γ drop pick^{WD}	γ social^{SAT}	-0.0293	0.0643
γ drop pick^{WD}	γ leisure^{SAT}	0.2183	0.0754
γ drop pick^{WD}	γ private business^{SAT}	0.0792	0.0576
γ drop pick^{WD}	γ travel^{SAT}	0.2337	0.0701
γ drop pick^{WD}	δ work^{SAT}	-0.6767	0.1506
γ drop pick^{WD}	δ school^{SAT}	0.3143	0.1720
γ drop pick^{WD}	δ drop pick^{SAT}	-0.0538	0.0736
γ drop pick^{WD}	δ daily shop^{SAT}	-0.2665	0.0983
γ drop pick^{WD}	δ non daily shop^{SAT}	-0.1973	0.0605
γ drop pick^{WD}	δ social^{SAT}	-0.0058	0.0766
γ drop pick^{WD}	δ leisure^{SAT}	0.0731	0.0828
γ drop pick^{WD}	δ private business^{SAT}	-0.0528	0.1038
γ drop pick^{WD}	δ travel^{SAT}	-0.2929	0.1084
γ drop pick^{WD}	γ work^{SUN}	0.0548	0.0718
γ drop pick^{WD}	γ school^{SUN}	-0.4393	0.1210
γ drop pick^{WD}	γ drop pick^{SUN}	0.4312	0.1134
γ drop pick^{WD}	γ daily shop^{SUN}	0.3076	0.1148
γ drop pick^{WD}	γ non daily shop^{SUN}	0.4073	0.1066
γ drop pick^{WD}	γ social^{SUN}	-0.0727	0.0569
γ drop pick^{WD}	γ leisure^{SUN}	0.0095	0.0427
γ drop pick^{WD}	γ private business^{SUN}	0.0231	0.1205
γ drop pick^{WD}	γ travel^{SUN}	-0.0669	0.0898

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{work}^{SUN}}$	0.0930	0.0957
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{school}^{SUN}}$	0.6244	0.1674
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.0695	0.1151
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.0779	0.1174
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.0434	0.1227
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{social}^{SUN}}$	-0.1248	0.0617
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.1108	0.0803
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	-0.1118	0.0670
$\gamma_{\text{drop pick}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	-0.0178	0.0829
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{daily shop}^{WD}}$	0.1963	0.0863
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{non daily shop}^{WD}}$	-0.0171	0.0364
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.0409	0.0329
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{leisure}^{WD}}$	-0.0696	0.0346
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{private business}^{WD}}$	0.0735	0.0349
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.0601	0.0286
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.0388	0.2597
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{school}^{WD}}$	1.1503	0.4751
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	-0.2352	0.1528
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	-0.3684	0.1013
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	-0.0524	0.0317
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{social}^{WD}}$	0.0046	0.0696
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	0.0980	0.1015
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{private business}^{WD}}$	-0.1993	0.0748
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.0900	0.0383
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	-0.0343	0.0724
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	0.0759	0.0620
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	0.0525	0.0519
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.1198	0.0492
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.0593	0.0364
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	0.0176	0.0339
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	0.0769	0.0678
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	0.0328	0.0462
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	0.1557	0.0741
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.1140	0.1316
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{school}^{SAT}}$	0.0267	0.1045
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.0506	0.0486
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	-0.1805	0.0575
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	-0.0456	0.0564
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{social}^{SAT}}$	-0.0170	0.0487
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	-0.0113	0.0556
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	-0.0742	0.0571
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	-0.1736	0.0952
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	-0.0098	0.0484
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	-0.0949	0.0772
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	0.1965	0.0978
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	0.1376	0.0652
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.1350	0.0673
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	-0.0289	0.0239
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0241	0.0249
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	0.1261	0.0898

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{daily shop}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	0.0431	0.0405
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{work}^{SUN}}$	0.0721	0.0385
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{school}^{SUN}}$	0.1357	0.1207
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.0184	0.0850
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.1564	0.0585
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.1185	0.0536
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{social}^{SUN}}$	-0.0076	0.0460
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0537	0.0710
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	-0.0703	0.0485
$\gamma_{\text{daily shop}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	-0.0854	0.0453
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{non daily shop}^{WD}}$	0.0732	0.0235
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.0256	0.0355
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{leisure}^{WD}}$	0.0143	0.0267
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{private business}^{WD}}$	0.0145	0.0377
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.0086	0.0316
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.2637	0.2944
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{school}^{WD}}$	-0.0467	0.3238
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	-0.0867	0.1371
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	0.0387	0.0958
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.0096	0.0270
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{social}^{WD}}$	-0.0467	0.0591
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	0.1286	0.0775
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{private business}^{WD}}$	-0.0305	0.0710
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{travel}^{WD}}$	-0.0327	0.0401
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	-0.1027	0.0817
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	0.1226	0.0503
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.0225	0.0535
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	-0.0071	0.0294
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.0583	0.0431
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.0238	0.0374
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	0.0157	0.0330
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	0.0095	0.0290
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	0.0167	0.0560
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.0677	0.1227
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{school}^{SAT}}$	0.0119	0.1396
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.0130	0.0661
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0147	0.0621
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	-0.0343	0.0457
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{social}^{SAT}}$	-0.0192	0.0471
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.0709	0.0509
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	0.0046	0.0382
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	-0.0258	0.0656
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	-0.0407	0.0599
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	-0.0873	0.0619
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	0.0376	0.0722
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	0.0376	0.0507
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.0829	0.0561
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	-0.0238	0.0281
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.0109	0.0283
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	-0.0355	0.0474

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{non daily shop}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0170	0.0424
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{work}^{SUN}}$	0.0395	0.0505
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{school}^{SUN}}$	0.0728	0.1118
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.0236	0.0800
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	0.0067	0.0664
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.0392	0.0810
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{social}^{SUN}}$	-0.0416	0.0305
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.0954	0.0708
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	-0.0387	0.0444
$\gamma_{\text{non daily shop}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.0116	0.0646
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.2273	0.0548
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{leisure}^{WD}}$	0.0603	0.0424
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{private business}^{WD}}$	-0.0129	0.0632
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0457	0.0329
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.7228	0.2171
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{school}^{WD}}$	0.1831	0.2327
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	-0.2144	0.1315
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	-0.0693	0.0611
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.0364	0.0454
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{social}^{WD}}$	-0.3277	0.0770
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	-0.0146	0.1419
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{private business}^{WD}}$	-0.0092	0.0557
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{travel}^{WD}}$	-0.1201	0.0514
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	-0.2421	0.0791
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	0.1604	0.1094
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	0.0737	0.0760
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.0308	0.0294
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.0581	0.0920
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	0.0867	0.0476
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	0.0913	0.0605
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.1137	0.0448
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	0.0729	0.0593
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.3347	0.0905
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{school}^{SAT}}$	0.0375	0.0864
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.0574	0.0638
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0326	0.0583
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.0304	0.0395
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{social}^{SAT}}$	-0.1905	0.0549
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	-0.0916	0.0812
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	0.0454	0.0336
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	-0.0949	0.0640
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	-0.0621	0.0675
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	-0.0027	0.0815
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	0.2187	0.0806
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	0.1476	0.0457
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.2432	0.0683
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	-0.0531	0.0350
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0695	0.0303
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	-0.0873	0.0695
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	0.0136	0.0501

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{work}^{SUN}}$	0.0598	0.0426
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{school}^{SUN}}$	0.3165	0.0834
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.2029	0.0923
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	0.0297	0.0399
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.1161	0.0481
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{social}^{SUN}}$	-0.1559	0.0467
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0247	0.1004
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	-0.0758	0.0571
$\gamma_{\text{social}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	-0.0442	0.0495
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{leisure}^{WD}}$	0.1289	0.0370
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{private business}^{WD}}$	-0.0546	0.0420
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0503	0.0304
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.2844	0.1772
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{school}^{WD}}$	-0.6246	0.2130
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	-0.1180	0.1372
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	0.1490	0.0654
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.0322	0.0407
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{social}^{WD}}$	-0.0982	0.0825
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	-0.2105	0.1071
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{private business}^{WD}}$	0.1414	0.0484
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{travel}^{WD}}$	-0.1215	0.0411
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	-0.0880	0.0629
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	0.0058	0.0561
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	0.0663	0.0656
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	-0.0395	0.0376
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.0674	0.0589
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	0.0750	0.0366
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	0.0106	0.0290
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.1109	0.0327
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0400	0.0385
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.0563	0.0764
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{school}^{SAT}}$	-0.0959	0.0689
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.0367	0.0562
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0910	0.0680
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.0736	0.0493
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{social}^{SAT}}$	-0.1095	0.0550
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	-0.1269	0.0506
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	0.0976	0.0322
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.0003	0.0439
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	0.0066	0.0516
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	0.0965	0.0983
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	0.0720	0.0746
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.0705	0.0519
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.0070	0.0757
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.0037	0.0274
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0586	0.0289
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	-0.1915	0.0534
$\gamma_{\text{leisure}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0181	0.0311
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-0.0427	0.0311
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{school}^{SUN}}$	0.0111	0.0911

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.1877	0.0782
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	0.0800	0.0472
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.0720	0.0590
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{social}^{SUN}}$	-0.0623	0.0351
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0922	0.0865
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	-0.0104	0.0355
$\gamma_{\text{leisure}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	-0.0193	0.0464
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{private business}^{WD}}$	0.1554	0.0336
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.0385	0.0230
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.5408	0.2341
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{school}^{WD}}$	1.1398	0.2311
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	0.0358	0.0991
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	-0.2121	0.0562
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	-0.0512	0.0327
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{social}^{WD}}$	0.1647	0.0698
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	0.2501	0.0745
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{private business}^{WD}}$	-0.0402	0.0623
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.0492	0.0429
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	-0.1717	0.0829
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	0.1229	0.0681
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.0701	0.0556
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.0290	0.0236
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.0159	0.0328
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.0887	0.0326
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	0.0231	0.0303
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	0.1273	0.0528
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	0.0418	0.0370
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.2335	0.0750
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{school}^{SAT}}$	0.2877	0.0812
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.0242	0.0383
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	-0.2003	0.0671
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	-0.0978	0.0500
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{social}^{SAT}}$	0.1468	0.0570
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.1238	0.0496
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	-0.0170	0.0657
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	-0.0262	0.0470
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	0.1293	0.0469
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	-0.2207	0.0674
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.0065	0.0692
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	0.1023	0.0384
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.0585	0.0862
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	-0.0007	0.0319
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.0302	0.0419
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	0.0943	0.0512
$\gamma_{\text{private business}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0647	0.0251
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-0.0003	0.0361
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{school}^{SUN}}$	0.2135	0.0930
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	0.1837	0.0631
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.0445	0.0346
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.0158	0.0492

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.0277	0.0490
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.1206	0.0651
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.0263	0.0370
$\gamma_{\text{private business}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.0836	0.0340
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0850	0.0408
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.1200	0.1518
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{school}^{WD}}$	-0.5154	0.1982
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	0.1735	0.1353
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	0.1378	0.0473
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.0532	0.0378
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{social}^{WD}}$	-0.1044	0.0517
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	-0.0874	0.0636
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{private business}^{WD}}$	0.1335	0.0471
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{WD}}$	-0.0881	0.0430
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	-0.0119	0.0574
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	-0.0495	0.0379
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.0365	0.0639
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	-0.0398	0.0188
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.0274	0.0427
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	0.0146	0.0411
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.0265	0.0322
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.0508	0.0328
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0765	0.0273
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-0.0473	0.0771
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{school}^{SAT}}$	0.0333	0.0799
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.0816	0.0649
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0965	0.0508
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.0727	0.0388
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{social}^{SAT}}$	-0.0396	0.0354
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	-0.0349	0.0420
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	0.0734	0.0279
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.0961	0.0493
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	0.0171	0.0352
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	0.1156	0.0668
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.0902	0.0719
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.0358	0.0437
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.0379	0.0547
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.0135	0.0339
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0196	0.0175
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	-0.0659	0.0623
$\gamma_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0206	0.0386
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-0.0208	0.0292
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{school}^{SUN}}$	0.0178	0.0574
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.0236	0.0527
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	0.0951	0.0391
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.1039	0.0520
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{social}^{SUN}}$	-0.0398	0.0290
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.0172	0.0613
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.0424	0.0366
$\gamma_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.0497	0.0445

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{WD}}$	10.0503	1.2528
$\delta_{\text{work}^{WD}}$	$\delta_{\text{school}^{WD}}$	-6.4935	1.1312
$\delta_{\text{work}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	1.2048	0.4870
$\delta_{\text{work}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	0.0510	0.2824
$\delta_{\text{work}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.2226	0.1924
$\delta_{\text{work}^{WD}}$	$\delta_{\text{social}^{WD}}$	0.2757	0.2910
$\delta_{\text{work}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	-0.6146	0.3443
$\delta_{\text{work}^{WD}}$	$\delta_{\text{private business}^{WD}}$	-0.2429	0.2346
$\delta_{\text{work}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.8358	0.1917
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	3.2290	0.4731
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	-1.4778	0.3752
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.2250	0.2918
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.2598	0.2450
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.5568	0.3867
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	0.0934	0.2480
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.7868	0.3366
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.2364	0.1783
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	0.0390	0.2386
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{SAT}}$	3.9955	0.5526
$\delta_{\text{work}^{WD}}$	$\delta_{\text{school}^{SAT}}$	-2.1443	0.3971
$\delta_{\text{work}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.1604	0.2716
$\delta_{\text{work}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.2901	0.2807
$\delta_{\text{work}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.9530	0.3258
$\delta_{\text{work}^{WD}}$	$\delta_{\text{social}^{SAT}}$	-0.2238	0.2615
$\delta_{\text{work}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.0764	0.3059
$\delta_{\text{work}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	-0.2032	0.2992
$\delta_{\text{work}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.1785	0.2292
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	-0.9380	0.3941
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	1.8404	0.5353
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-1.0719	0.3269
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-1.0771	0.5374
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-1.1155	0.2751
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.0702	0.2236
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.0304	0.1766
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	0.7117	0.2722
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	0.6557	0.2417
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{SUN}}$	0.2681	0.2844
$\delta_{\text{work}^{WD}}$	$\delta_{\text{school}^{SUN}}$	-3.2432	0.4595
$\delta_{\text{work}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.0433	0.3591
$\delta_{\text{work}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.6736	0.2764
$\delta_{\text{work}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	-1.0278	0.2770
$\delta_{\text{work}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.4014	0.2319
$\delta_{\text{work}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	-0.3292	0.2739
$\delta_{\text{work}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	-0.1520	0.1941
$\delta_{\text{work}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	-0.5954	0.2540
$\delta_{\text{school}^{WD}}$	$\delta_{\text{school}^{WD}}$	16.0319	1.9583
$\delta_{\text{school}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	-0.9675	0.6064
$\delta_{\text{school}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	-2.7247	0.4627
$\delta_{\text{school}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	-0.9804	0.2967
$\delta_{\text{school}^{WD}}$	$\delta_{\text{social}^{WD}}$	1.2423	0.3476
$\delta_{\text{school}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	0.9051	0.4774
$\delta_{\text{school}^{WD}}$	$\delta_{\text{private business}^{WD}}$	-1.2057	0.3200
$\delta_{\text{school}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.6089	0.2099
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	-2.0417	0.5078
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	0.6832	0.4684
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	0.3640	0.3981
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.5054	0.2621
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.7177	0.3001
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.3528	0.3103
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	0.5713	0.3473
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	0.9897	0.3828
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	0.5458	0.3362
$\delta_{\text{school}^{WD}}$	$\delta_{\text{work}^{SAT}}$	-3.4767	0.7032
$\delta_{\text{school}^{WD}}$	$\delta_{\text{school}^{SAT}}$	2.8930	0.6545
$\delta_{\text{school}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.1382	0.3577
$\delta_{\text{school}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	-1.8320	0.3925
$\delta_{\text{school}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	-1.4498	0.3392
$\delta_{\text{school}^{WD}}$	$\delta_{\text{social}^{SAT}}$	1.2070	0.3249
$\delta_{\text{school}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.0596	0.3593
$\delta_{\text{school}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	-0.6004	0.4704
$\delta_{\text{school}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	-0.6025	0.4133
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	1.3426	0.4218
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	-2.2743	0.6777
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	1.0368	0.4362
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	1.4432	0.3799
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.9006	0.4121
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	-0.0864	0.2261
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.1067	0.2159
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	0.8864	0.4923
$\delta_{\text{school}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.3425	0.2245
$\delta_{\text{school}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-0.3184	0.4708
$\delta_{\text{school}^{WD}}$	$\delta_{\text{school}^{SUN}}$	3.0148	0.7397
$\delta_{\text{school}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	1.4691	0.5284
$\delta_{\text{school}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.6902	0.3756
$\delta_{\text{school}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.2858	0.2842
$\delta_{\text{school}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.4834	0.2883
$\delta_{\text{school}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	-0.2447	0.4890
$\delta_{\text{school}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.2809	0.2960
$\delta_{\text{school}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.2947	0.2789
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{drop pick}^{WD}}$	2.4034	0.3957
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	0.3402	0.1967
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.1263	0.1075
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{social}^{WD}}$	0.2880	0.1628
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	0.3493	0.2112
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{private business}^{WD}}$	0.5002	0.1471
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.1650	0.1471
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	0.6283	0.1880
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	-0.6334	0.1710
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.7597	0.2277
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	-0.1439	0.1287
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.2679	0.1530
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.4147	0.1665
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.5529	0.1387
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	0.3015	0.1170
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.5850	0.1925
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{work}^{SAT}}$	0.3048	0.2289
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{school}^{SAT}}$	0.9104	0.2476
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.7268	0.1957
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0608	0.1911
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.1931	0.1375
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{social}^{SAT}}$	0.5687	0.1574
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.5509	0.1802
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	0.1706	0.1480
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.9511	0.2537
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	0.2899	0.1687
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	0.4148	0.1925
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-1.4940	0.2844
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.1919	0.1818
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.5355	0.1603
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.1445	0.0986
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.2007	0.1414
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	0.4386	0.1652
$\delta_{\text{drop pick}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.1318	0.1006
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-0.1365	0.1278
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{school}^{SUN}}$	-0.3306	0.2039
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	1.1255	0.2628
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	0.2232	0.2126
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.3627	0.1816
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.2224	0.1298
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.6576	0.1929
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.5363	0.1357
$\delta_{\text{drop pick}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.6190	0.1951
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{daily shop}^{WD}}$	0.9361	0.1361
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{non daily shop}^{WD}}$	0.1496	0.0631
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{social}^{WD}}$	-0.1651	0.1165
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{leisure}^{WD}}$	-0.2132	0.1337
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{private business}^{WD}}$	0.2848	0.0814
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{travel}^{WD}}$	-0.2355	0.0545
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	0.0442	0.1179
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	-0.1350	0.1213
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.0864	0.0960
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	-0.2697	0.0771
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.1832	0.0627
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.0164	0.0720
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.1145	0.1101
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.0980	0.0943
$\delta_{\text{daily shop}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.3119	0.1029
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{work}^{SAT}}$	0.2096	0.1482
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{school}^{SAT}}$	-0.2013	0.1570
$\delta_{\text{daily shop}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.1302	0.0796

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{SAT}$	0.5365	0.1258
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{SAT}$	0.0295	0.0857
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{social}}^{SAT}$	-0.0412	0.0844
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{leisure}}^{SAT}$	0.0156	0.0805
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{private business}}^{SAT}$	0.0930	0.1184
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{travel}}^{SAT}$	0.3281	0.1147
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{work}}^{SUN}$	-0.1020	0.0914
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{school}}^{SUN}$	0.2157	0.1482
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.3382	0.1147
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{daily shop}}^{SUN}$	-0.2516	0.0851
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.2473	0.1140
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{social}}^{SUN}$	0.0456	0.0632
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{SUN}$	-0.0823	0.0621
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{private business}}^{SUN}$	-0.2988	0.1734
$\delta_{\text{daily shop}}^{WD}$	$\gamma_{\text{travel}}^{SUN}$	-0.0536	0.0748
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{work}}^{SUN}$	-0.1000	0.0985
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{school}}^{SUN}$	-0.2861	0.1387
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{SUN}$	-0.0587	0.1571
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{SUN}$	0.3485	0.0728
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{SUN}$	0.2369	0.0781
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{social}}^{SUN}$	-0.0236	0.0787
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{leisure}}^{SUN}$	0.1395	0.1024
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{private business}}^{SUN}$	0.1020	0.0870
$\delta_{\text{daily shop}}^{WD}$	$\delta_{\text{travel}}^{SUN}$	0.1296	0.0736
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{WD}$	0.1204	0.0422
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{social}}^{WD}$	-0.1669	0.0710
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{leisure}}^{WD}$	0.0936	0.0707
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{private business}}^{WD}$	0.0728	0.0452
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{travel}}^{WD}$	-0.0648	0.0418
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{work}}^{SAT}$	0.0662	0.0714
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{school}}^{SAT}$	0.0301	0.0540
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{drop pick}}^{SAT}$	-0.0859	0.0455
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{daily shop}}^{SAT}$	-0.0257	0.0226
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{SAT}$	-0.0736	0.0268
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{social}}^{SAT}$	-0.0005	0.0315
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{SAT}$	-0.0195	0.0471
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{private business}}^{SAT}$	-0.0538	0.0419
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{travel}}^{SAT}$	-0.0188	0.0399
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{work}}^{SAT}$	0.1366	0.0894
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{school}}^{SAT}$	-0.1093	0.0818
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{SAT}$	0.0914	0.0569
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{SAT}$	0.1068	0.0650
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{SAT}$	0.0979	0.0444
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{social}}^{SAT}$	-0.0931	0.0504
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{leisure}}^{SAT}$	0.0720	0.0401
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{private business}}^{SAT}$	0.0507	0.0292
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{travel}}^{SAT}$	0.0430	0.0410
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{work}}^{SUN}$	-0.1068	0.0378
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{school}}^{SUN}$	0.1210	0.0855
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.0833	0.0721

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{daily shop}}^{SUN}$	-0.0184	0.0577
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{non daily shop}}^{SUN}$	0.0215	0.0577
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{social}}^{SUN}$	-0.0095	0.0243
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{leisure}}^{SUN}$	-0.0026	0.0265
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{private business}}^{SUN}$	-0.0164	0.0757
$\delta_{\text{non daily shop}}^{WD}$	$\gamma_{\text{travel}}^{SUN}$	0.0157	0.0309
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{work}}^{SUN}$	0.0780	0.0731
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{school}}^{SUN}$	-0.1028	0.0795
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{drop pick}}^{SUN}$	-0.0692	0.0662
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{daily shop}}^{SUN}$	0.0578	0.0435
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{non daily shop}}^{SUN}$	0.0810	0.0433
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{social}}^{SUN}$	-0.0871	0.0311
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{leisure}}^{SUN}$	0.1341	0.0556
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{private business}}^{SUN}$	-0.0341	0.0356
$\delta_{\text{non daily shop}}^{WD}$	$\delta_{\text{travel}}^{SUN}$	0.0172	0.0336
$\delta_{\text{social}}^{WD}$	$\delta_{\text{social}}^{WD}$	0.8301	0.1343
$\delta_{\text{social}}^{WD}$	$\delta_{\text{leisure}}^{WD}$	0.0533	0.1217
$\delta_{\text{social}}^{WD}$	$\delta_{\text{private business}}^{WD}$	0.0951	0.0814
$\delta_{\text{social}}^{WD}$	$\delta_{\text{travel}}^{WD}$	0.2074	0.0639
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{work}}^{SAT}$	0.1359	0.1065
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{school}}^{SAT}$	-0.1886	0.1191
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{drop pick}}^{SAT}$	-0.1046	0.1049
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{daily shop}}^{SAT}$	-0.0165	0.0545
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{non daily shop}}^{SAT}$	0.1612	0.0944
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{social}}^{SAT}$	-0.1720	0.0653
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{leisure}}^{SAT}$	-0.0919	0.0891
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{private business}}^{SAT}$	0.2630	0.0916
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{travel}}^{SAT}$	-0.0840	0.0767
$\delta_{\text{social}}^{WD}$	$\delta_{\text{work}}^{SAT}$	0.1823	0.1605
$\delta_{\text{social}}^{WD}$	$\delta_{\text{school}}^{SAT}$	0.2914	0.1565
$\delta_{\text{social}}^{WD}$	$\delta_{\text{drop pick}}^{SAT}$	-0.1526	0.0815
$\delta_{\text{social}}^{WD}$	$\delta_{\text{daily shop}}^{SAT}$	-0.3163	0.1282
$\delta_{\text{social}}^{WD}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.1277	0.0735
$\delta_{\text{social}}^{WD}$	$\delta_{\text{social}}^{SAT}$	0.4755	0.0907
$\delta_{\text{social}}^{WD}$	$\delta_{\text{leisure}}^{SAT}$	0.1287	0.0910
$\delta_{\text{social}}^{WD}$	$\delta_{\text{private business}}^{SAT}$	-0.0488	0.1128
$\delta_{\text{social}}^{WD}$	$\delta_{\text{travel}}^{SAT}$	0.1053	0.0928
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{work}}^{SUN}$	0.3768	0.1025
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{school}}^{SUN}$	-0.2287	0.1218
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.2746	0.1397
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{daily shop}}^{SUN}$	-0.1917	0.0738
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.3650	0.1576
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{social}}^{SUN}$	0.1019	0.0695
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{leisure}}^{SUN}$	-0.0649	0.0482
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{private business}}^{SUN}$	0.1736	0.1052
$\delta_{\text{social}}^{WD}$	$\gamma_{\text{travel}}^{SUN}$	-0.1308	0.0729
$\delta_{\text{social}}^{WD}$	$\delta_{\text{work}}^{SUN}$	-0.2253	0.1361
$\delta_{\text{social}}^{WD}$	$\delta_{\text{school}}^{SUN}$	-0.2104	0.1565
$\delta_{\text{social}}^{WD}$	$\delta_{\text{drop pick}}^{SUN}$	0.4676	0.1165
$\delta_{\text{social}}^{WD}$	$\delta_{\text{daily shop}}^{SUN}$	-0.0830	0.0776

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{social}}^{WD}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.1672	0.0913
$\delta_{\text{social}}^{WD}$	$\delta_{\text{social}}^{SUN}$	0.3254	0.0935
$\delta_{\text{social}}^{WD}$	$\delta_{\text{leisure}}^{SUN}$	-0.0283	0.1076
$\delta_{\text{social}}^{WD}$	$\delta_{\text{private business}}^{SUN}$	0.1759	0.0812
$\delta_{\text{social}}^{WD}$	$\delta_{\text{travel}}^{SUN}$	0.1529	0.0674
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{leisure}}^{WD}$	1.5365	0.2276
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{private business}}^{WD}$	-0.2346	0.1019
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{travel}}^{WD}$	0.1143	0.0758
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{work}}^{SAT}$	-0.2805	0.1361
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{school}}^{SAT}$	0.6460	0.1429
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{drop pick}}^{SAT}$	-0.5575	0.1236
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{daily shop}}^{SAT}$	0.0422	0.0759
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{non daily shop}}^{SAT}$	-0.1255	0.2495
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{social}}^{SAT}$	-0.4032	0.0995
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{leisure}}^{SAT}$	0.0590	0.1473
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{private business}}^{SAT}$	0.3809	0.1241
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{travel}}^{SAT}$	0.1601	0.1001
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{work}}^{SAT}$	-0.1238	0.2029
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{school}}^{SAT}$	0.4996	0.2078
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{drop pick}}^{SAT}$	0.3507	0.1801
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{daily shop}}^{SAT}$	-0.3162	0.1483
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.2120	0.1291
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{social}}^{SAT}$	0.2607	0.1338
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{leisure}}^{SAT}$	0.9009	0.1784
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{private business}}^{SAT}$	-0.1237	0.0891
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{travel}}^{SAT}$	-0.0064	0.1136
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{work}}^{SUN}$	-0.1265	0.2041
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{school}}^{SUN}$	-0.6341	0.1978
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.2505	0.1595
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{daily shop}}^{SUN}$	0.3728	0.1303
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{non daily shop}}^{SUN}$	0.4873	0.2812
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{social}}^{SUN}$	-0.0930	0.1278
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{leisure}}^{SUN}$	-0.2270	0.0869
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{private business}}^{SUN}$	0.4631	0.1201
$\delta_{\text{leisure}}^{WD}$	$\gamma_{\text{travel}}^{SUN}$	-0.0803	0.0651
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{work}}^{SUN}$	0.3479	0.1578
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{school}}^{SUN}$	0.3110	0.1730
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{drop pick}}^{SUN}$	0.5053	0.1828
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{daily shop}}^{SUN}$	-0.1009	0.1423
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{non daily shop}}^{SUN}$	0.1564	0.1048
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{social}}^{SUN}$	-0.1169	0.0823
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{leisure}}^{SUN}$	0.9947	0.1604
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{private business}}^{SUN}$	-0.1261	0.1303
$\delta_{\text{leisure}}^{WD}$	$\delta_{\text{travel}}^{SUN}$	0.2750	0.0973
$\delta_{\text{private business}}^{WD}$	$\delta_{\text{private business}}^{WD}$	0.5706	0.1094
$\delta_{\text{private business}}^{WD}$	$\delta_{\text{travel}}^{WD}$	-0.1548	0.0517
$\delta_{\text{private business}}^{WD}$	$\gamma_{\text{work}}^{SAT}$	0.0071	0.1018
$\delta_{\text{private business}}^{WD}$	$\gamma_{\text{school}}^{SAT}$	-0.1575	0.0890
$\delta_{\text{private business}}^{WD}$	$\gamma_{\text{drop pick}}^{SAT}$	-0.1138	0.0759
$\delta_{\text{private business}}^{WD}$	$\gamma_{\text{daily shop}}^{SAT}$	-0.1205	0.0685

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.0449	0.0693
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	0.0017	0.0613
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.0862	0.0814
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	-0.0723	0.0493
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	-0.2284	0.0679
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{work}^{SAT}}$	0.0132	0.1121
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{school}^{SAT}}$	0.1445	0.1139
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	0.0618	0.0666
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0641	0.0693
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.2243	0.0672
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{social}^{SAT}}$	0.0506	0.0613
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	-0.0664	0.0702
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	0.2438	0.0635
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	0.2626	0.0846
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	0.2279	0.0837
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	0.2046	0.1790
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.3055	0.1197
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.2095	0.0997
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.2270	0.1248
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.0859	0.0485
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0821	0.0453
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	-0.1607	0.1111
$\delta_{\text{private business}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	-0.1244	0.0589
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{work}^{SUN}}$	-0.1570	0.0717
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{school}^{SUN}}$	-0.0790	0.1396
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	0.0275	0.1081
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	0.2391	0.0797
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.2267	0.0647
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{social}^{SUN}}$	-0.0048	0.0627
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0205	0.1005
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.1641	0.0694
$\delta_{\text{private business}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	0.1873	0.0627
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.2225	0.0529
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{SAT}}$	0.2753	0.0758
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{school}^{SAT}}$	-0.1215	0.0527
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.0520	0.0659
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.0740	0.0367
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.1426	0.0724
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{SAT}}$	-0.0676	0.0435
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.0724	0.0554
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{private business}^{SAT}}$	0.1090	0.0404
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{SAT}}$	0.0435	0.0394
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{work}^{SAT}}$	0.2627	0.0850
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{school}^{SAT}}$	0.0246	0.0790
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.0162	0.0736
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{daily shop}^{SAT}}$	-0.1536	0.0604
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{non daily shop}^{SAT}}$	-0.0309	0.0597
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{social}^{SAT}}$	0.1365	0.0454
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{leisure}^{SAT}}$	0.1005	0.0564
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{private business}^{SAT}}$	-0.0985	0.0273

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{SAT}}$	-0.0004	0.0517
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{SUN}}$	-0.0037	0.0501
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{school}^{SUN}}$	-0.0040	0.1317
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.1216	0.0753
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.0023	0.0541
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.0714	0.0750
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{SUN}}$	0.0033	0.0351
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.0506	0.0294
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{private business}^{SUN}}$	0.2291	0.0733
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{SUN}}$	0.0553	0.0499
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{work}^{SUN}}$	0.0204	0.0503
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{school}^{SUN}}$	-0.1870	0.0680
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{SUN}}$	0.2166	0.0620
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.1592	0.0366
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.1658	0.0613
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{social}^{SUN}}$	0.1194	0.0445
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{leisure}^{SUN}}$	0.0147	0.0710
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{private business}^{SUN}}$	0.0188	0.0428
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{SUN}}$	-0.0193	0.0440
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{work}^{SAT}}$	1.1125	0.2394
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{school}^{SAT}}$	-0.5856	0.1096
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.1109	0.1211
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.0680	0.0852
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.2177	0.1141
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{social}^{SAT}}$	0.0137	0.0911
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{leisure}^{SAT}}$	-0.3054	0.1118
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{private business}^{SAT}}$	-0.0701	0.0721
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{travel}^{SAT}}$	-0.0682	0.1109
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{work}^{SAT}}$	1.2452	0.2147
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{school}^{SAT}}$	-0.5584	0.1465
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{drop pick}^{SAT}}$	0.0017	0.0950
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{daily shop}^{SAT}}$	0.0998	0.0942
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.3308	0.1171
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{social}^{SAT}}$	-0.0097	0.0976
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{leisure}^{SAT}}$	0.0099	0.1119
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{private business}^{SAT}}$	-0.0285	0.0929
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{travel}^{SAT}}$	0.1627	0.1065
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{work}^{SUN}}$	-0.2209	0.1594
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{school}^{SUN}}$	0.6583	0.1796
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.4833	0.1554
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.3749	0.1645
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.4405	0.1033
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	0.0420	0.0747
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.0048	0.0621
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	0.2468	0.0916
$\gamma_{\text{work}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	0.1907	0.0645
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	0.0312	0.0970
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	-1.0259	0.1540
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	0.0959	0.1283
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.1727	0.0733

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.2867	0.0928
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	0.1608	0.0878
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	-0.1080	0.0995
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	0.0344	0.0632
$\gamma_{\text{work}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	-0.1286	0.0910
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{school}^{SAT}}$	0.6790	0.1434
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{drop pick}^{SAT}}$	-0.0356	0.0981
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.0309	0.0669
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{non daily shop}^{SAT}}$	-0.2367	0.0814
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{social}^{SAT}}$	-0.0534	0.0852
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{leisure}^{SAT}}$	0.2481	0.1208
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{private business}^{SAT}}$	0.0588	0.0881
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{travel}^{SAT}}$	0.2363	0.1216
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{work}^{SAT}}$	-0.4530	0.1596
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{school}^{SAT}}$	0.0624	0.1356
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.0182	0.0749
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{daily shop}^{SAT}}$	-0.1385	0.0850
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{non daily shop}^{SAT}}$	-0.1642	0.0824
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{social}^{SAT}}$	-0.1084	0.0878
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{leisure}^{SAT}}$	0.2437	0.0887
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{private business}^{SAT}}$	-0.0350	0.0703
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{travel}^{SAT}}$	-0.2910	0.1211
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{work}^{SUN}}$	-0.1054	0.2121
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{school}^{SUN}}$	-0.5055	0.1704
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{drop pick}^{SUN}}$	0.4124	0.1320
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{daily shop}^{SUN}}$	0.2924	0.0811
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.4987	0.1453
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	-0.0922	0.0911
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.0181	0.0511
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	-0.0511	0.0776
$\gamma_{\text{school}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0558	0.0638
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	0.2010	0.1043
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	0.4886	0.1285
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.1878	0.1268
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.0238	0.0808
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.1031	0.0664
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	-0.2157	0.0738
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	0.3185	0.1041
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	-0.2249	0.0975
$\gamma_{\text{school}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	-0.0053	0.0789
$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{drop pick}^{SAT}}$	0.4356	0.1228
$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{daily shop}^{SAT}}$	0.0374	0.0427
$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{non daily shop}^{SAT}}$	0.0017	0.1373
$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{social}^{SAT}}$	0.2409	0.0659
$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{leisure}^{SAT}}$	0.1401	0.0953
$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{private business}^{SAT}}$	-0.1891	0.0756
$\gamma_{\text{drop pick}^{SAT}}$	$\gamma_{\text{travel}^{SAT}}$	0.1285	0.0892
$\gamma_{\text{drop pick}^{SAT}}$	$\delta_{\text{work}^{SAT}}$	-0.1114	0.1452
$\gamma_{\text{drop pick}^{SAT}}$	$\delta_{\text{school}^{SAT}}$	-0.3247	0.1501
$\gamma_{\text{drop pick}^{SAT}}$	$\delta_{\text{drop pick}^{SAT}}$	-0.3025	0.1575

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ drop pick^{SAT}	δ daily shop^{SAT}	0.0503	0.0937
γ drop pick^{SAT}	δ non daily shop^{SAT}	-0.0221	0.0856
γ drop pick^{SAT}	δ social^{SAT}	-0.2178	0.0674
γ drop pick^{SAT}	δ leisure^{SAT}	-0.4414	0.1167
γ drop pick^{SAT}	δ private business^{SAT}	-0.0358	0.0652
γ drop pick^{SAT}	δ travel^{SAT}	-0.2698	0.1394
γ drop pick^{SAT}	γ work^{SUN}	-0.0350	0.0833
γ drop pick^{SAT}	γ school^{SUN}	0.0509	0.1102
γ drop pick^{SAT}	γ drop pick^{SUN}	0.5067	0.1747
γ drop pick^{SAT}	γ daily shop^{SUN}	-0.0127	0.0894
γ drop pick^{SAT}	γ non daily shop^{SUN}	0.0280	0.0894
γ drop pick^{SAT}	γ social^{SUN}	-0.0194	0.0398
γ drop pick^{SAT}	γ leisure^{SUN}	0.1172	0.0645
γ drop pick^{SAT}	γ private business^{SUN}	-0.2150	0.0707
γ drop pick^{SAT}	γ travel^{SUN}	0.0681	0.0466
γ drop pick^{SAT}	δ work^{SUN}	-0.0631	0.0617
γ drop pick^{SAT}	δ school^{SUN}	0.0581	0.1295
γ drop pick^{SAT}	δ drop pick^{SUN}	-0.4208	0.1136
γ drop pick^{SAT}	δ daily shop^{SUN}	-0.0370	0.0631
γ drop pick^{SAT}	δ non daily shop^{SUN}	-0.1497	0.1033
γ drop pick^{SAT}	δ social^{SUN}	-0.0192	0.0519
γ drop pick^{SAT}	δ leisure^{SUN}	-0.5038	0.1251
γ drop pick^{SAT}	δ private business^{SUN}	-0.0934	0.0549
γ drop pick^{SAT}	δ travel^{SUN}	-0.2630	0.0985
γ daily shop^{SAT}	γ daily shop^{SAT}	0.1263	0.0613
γ daily shop^{SAT}	γ non daily shop^{SAT}	0.0520	0.0470
γ daily shop^{SAT}	γ social^{SAT}	0.0251	0.0296
γ daily shop^{SAT}	γ leisure^{SAT}	0.0328	0.0616
γ daily shop^{SAT}	γ private business^{SAT}	-0.0113	0.0344
γ daily shop^{SAT}	γ travel^{SAT}	0.1152	0.0610
γ daily shop^{SAT}	δ work^{SAT}	0.0416	0.0863
γ daily shop^{SAT}	δ school^{SAT}	-0.0614	0.0620
γ daily shop^{SAT}	δ drop pick^{SAT}	-0.0523	0.0418
γ daily shop^{SAT}	δ daily shop^{SAT}	-0.1311	0.0524
γ daily shop^{SAT}	δ non daily shop^{SAT}	0.0303	0.0443
γ daily shop^{SAT}	δ social^{SAT}	-0.0566	0.0421
γ daily shop^{SAT}	δ leisure^{SAT}	-0.0173	0.0485
γ daily shop^{SAT}	δ private business^{SAT}	-0.0330	0.0575
γ daily shop^{SAT}	δ travel^{SAT}	-0.1260	0.0644
γ daily shop^{SAT}	γ work^{SUN}	-0.0366	0.0468
γ daily shop^{SAT}	γ school^{SUN}	0.0102	0.0714
γ daily shop^{SAT}	γ drop pick^{SUN}	0.1218	0.0872
γ daily shop^{SAT}	γ daily shop^{SUN}	0.0550	0.0362
γ daily shop^{SAT}	γ non daily shop^{SUN}	0.0835	0.0914
γ daily shop^{SAT}	γ social^{SUN}	-0.0249	0.0208
γ daily shop^{SAT}	γ leisure^{SUN}	0.0407	0.0314
γ daily shop^{SAT}	γ private business^{SUN}	0.0871	0.0818
γ daily shop^{SAT}	γ travel^{SUN}	0.0492	0.0265
γ daily shop^{SAT}	δ work^{SUN}	0.0713	0.0297
γ daily shop^{SAT}	δ school^{SUN}	-0.0084	0.0916

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ daily shop^{SAT}	δ drop pick^{SUN}	-0.0593	0.0782
γ daily shop^{SAT}	δ daily shop^{SUN}	-0.1267	0.0343
γ daily shop^{SAT}	δ non daily shop^{SUN}	-0.0974	0.0355
γ daily shop^{SAT}	δ social^{SUN}	-0.0147	0.0337
γ daily shop^{SAT}	δ leisure^{SUN}	-0.0539	0.0585
γ daily shop^{SAT}	δ private business^{SUN}	-0.0648	0.0354
γ daily shop^{SAT}	δ travel^{SUN}	-0.0910	0.0395
γ non daily shop^{SAT}	γ non daily shop^{SAT}	0.2492	0.0512
γ non daily shop^{SAT}	γ social^{SAT}	-0.0188	0.0935
γ non daily shop^{SAT}	γ leisure^{SAT}	-0.0936	0.0510
γ non daily shop^{SAT}	γ private business^{SAT}	0.0346	0.0993
γ non daily shop^{SAT}	γ travel^{SAT}	-0.0334	0.0485
γ non daily shop^{SAT}	δ work^{SAT}	0.1137	0.1952
γ non daily shop^{SAT}	δ school^{SAT}	0.1317	0.0783
γ non daily shop^{SAT}	δ drop pick^{SAT}	0.0370	0.0488
γ non daily shop^{SAT}	δ daily shop^{SAT}	-0.1038	0.0856
γ non daily shop^{SAT}	δ non daily shop^{SAT}	-0.0105	0.0459
γ non daily shop^{SAT}	δ social^{SAT}	0.1316	0.0858
γ non daily shop^{SAT}	δ leisure^{SAT}	-0.0274	0.1840
γ non daily shop^{SAT}	δ private business^{SAT}	-0.0425	0.0427
γ non daily shop^{SAT}	δ travel^{SAT}	0.0824	0.0766
γ non daily shop^{SAT}	γ work^{SUN}	0.0893	0.0732
γ non daily shop^{SAT}	γ school^{SUN}	0.0717	0.1363
γ non daily shop^{SAT}	γ drop pick^{SUN}	-0.1585	0.1490
γ non daily shop^{SAT}	γ daily shop^{SUN}	-0.0273	0.0561
γ non daily shop^{SAT}	γ non daily shop^{SUN}	-0.0979	0.0679
γ non daily shop^{SAT}	γ social^{SUN}	0.0077	0.0403
γ non daily shop^{SAT}	γ leisure^{SUN}	-0.0014	0.0606
γ non daily shop^{SAT}	γ private business^{SUN}	0.1701	0.1072
γ non daily shop^{SAT}	γ travel^{SUN}	0.0327	0.0383
γ non daily shop^{SAT}	δ work^{SUN}	-0.0678	0.1267
γ non daily shop^{SAT}	δ school^{SUN}	-0.0941	0.1434
γ non daily shop^{SAT}	δ drop pick^{SUN}	0.2338	0.1394
γ non daily shop^{SAT}	δ daily shop^{SUN}	-0.1072	0.0542
γ non daily shop^{SAT}	δ non daily shop^{SUN}	-0.0904	0.0603
γ non daily shop^{SAT}	δ social^{SUN}	0.1292	0.0399
γ non daily shop^{SAT}	δ leisure^{SUN}	-0.1087	0.1796
γ non daily shop^{SAT}	δ private business^{SUN}	0.0829	0.0540
γ non daily shop^{SAT}	δ travel^{SUN}	0.0111	0.0533
γ social^{SAT}	γ social^{SAT}	0.2135	0.0601
γ social^{SAT}	γ leisure^{SAT}	0.0744	0.0399
γ social^{SAT}	γ private business^{SAT}	-0.1896	0.0433
γ social^{SAT}	γ travel^{SAT}	0.0729	0.0545
γ social^{SAT}	δ work^{SAT}	0.0276	0.0931
γ social^{SAT}	δ school^{SAT}	-0.3029	0.1407
γ social^{SAT}	δ drop pick^{SAT}	-0.1593	0.0923
γ social^{SAT}	δ daily shop^{SAT}	0.0863	0.0572
γ social^{SAT}	δ non daily shop^{SAT}	0.0889	0.0425
γ social^{SAT}	δ social^{SAT}	-0.2285	0.0675
γ social^{SAT}	δ leisure^{SAT}	-0.3090	0.0880

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
γ social^{SAT}	δ private business^{SAT}	0.0265	0.0468
γ social^{SAT}	δ travel^{SAT}	-0.1557	0.0907
γ social^{SAT}	γ work^{SUN}	-0.0584	0.0736
γ social^{SAT}	γ school^{SUN}	0.1717	0.0793
γ social^{SAT}	γ drop pick^{SUN}	0.2880	0.1220
γ social^{SAT}	γ daily shop^{SUN}	-0.0346	0.0651
γ social^{SAT}	γ non daily shop^{SUN}	0.0098	0.1033
γ social^{SAT}	γ social^{SUN}	-0.0155	0.0362
γ social^{SAT}	γ leisure^{SUN}	0.1039	0.0433
γ social^{SAT}	γ private business^{SUN}	-0.1634	0.0768
γ social^{SAT}	γ travel^{SUN}	0.0697	0.0312
γ social^{SAT}	δ work^{SUN}	-0.0141	0.0496
γ social^{SAT}	δ school^{SUN}	-0.0341	0.0936
γ social^{SAT}	δ drop pick^{SUN}	-0.3436	0.0993
γ social^{SAT}	δ daily shop^{SUN}	-0.0083	0.0465
γ social^{SAT}	δ non daily shop^{SUN}	-0.0593	0.0626
γ social^{SAT}	δ social^{SUN}	-0.0602	0.0513
γ social^{SAT}	δ leisure^{SUN}	-0.3246	0.0967
γ social^{SAT}	δ private business^{SUN}	-0.0755	0.0451
γ social^{SAT}	δ travel^{SUN}	-0.1810	0.0612
γ leisure^{SAT}	γ leisure^{SAT}	0.2276	0.1011
γ leisure^{SAT}	γ private business^{SAT}	-0.0373	0.0379
γ leisure^{SAT}	γ travel^{SAT}	0.1481	0.0518
γ leisure^{SAT}	δ work^{SAT}	-0.2723	0.1303
γ leisure^{SAT}	δ school^{SAT}	-0.0635	0.1046
γ leisure^{SAT}	δ drop pick^{SAT}	-0.1357	0.0688
γ leisure^{SAT}	δ daily shop^{SAT}	-0.0568	0.0761
γ leisure^{SAT}	δ non daily shop^{SAT}	-0.0779	0.0499
γ leisure^{SAT}	δ social^{SAT}	-0.1150	0.0552
γ leisure^{SAT}	δ leisure^{SAT}	-0.0824	0.0898
γ leisure^{SAT}	δ private business^{SAT}	-0.0326	0.0622
γ leisure^{SAT}	δ travel^{SAT}	-0.2235	0.0703
γ leisure^{SAT}	γ work^{SUN}	-0.0065	0.0804
γ leisure^{SAT}	γ school^{SUN}	-0.2167	0.1107
γ leisure^{SAT}	γ drop pick^{SUN}	0.3765	0.1088
γ leisure^{SAT}	γ daily shop^{SUN}	0.1435	0.0960
γ leisure^{SAT}	γ non daily shop^{SUN}	0.2181	0.1113
γ leisure^{SAT}	γ social^{SUN}	-0.0318	0.0252
γ leisure^{SAT}	γ leisure^{SUN}	0.0476	0.0499
γ leisure^{SAT}	γ private business^{SUN}	-0.0536	0.0576
γ leisure^{SAT}	γ travel^{SUN}	0.0066	0.0298
γ leisure^{SAT}	δ work^{SUN}	0.0722	0.1101
γ leisure^{SAT}	δ school^{SUN}	0.2597	0.1196
γ leisure^{SAT}	δ drop pick^{SUN}	-0.2325	0.0842
γ leisure^{SAT}	δ daily shop^{SUN}	-0.0043	0.0447
γ leisure^{SAT}	δ non daily shop^{SUN}	-0.0151	0.0809
γ leisure^{SAT}	δ social^{SUN}	-0.0830	0.0753
γ leisure^{SAT}	δ leisure^{SUN}	-0.0777	0.1316
γ leisure^{SAT}	δ private business^{SUN}	-0.1128	0.0504
γ leisure^{SAT}	δ travel^{SUN}	-0.0959	0.0735

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{private business}}^{SAT}$	0.2626	0.0682
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{travel}}^{SAT}$	-0.0468	0.0512
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{work}}^{SAT}$	-0.1183	0.0957
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{school}}^{SAT}$	0.3546	0.1316
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	0.0992	0.0615
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	-0.1550	0.1070
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.1569	0.0605
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	0.2818	0.0634
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	0.2688	0.0725
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	-0.0692	0.0458
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.1139	0.0727
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	0.1315	0.0575
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	-0.2801	0.0739
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.2240	0.0759
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	0.0716	0.0524
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.0244	0.1132
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	0.0288	0.0422
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	-0.1137	0.0435
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	0.1826	0.1032
$\gamma_{\text{private business}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	-0.0733	0.0384
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	-0.0136	0.0455
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	0.1049	0.1046
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	0.3751	0.0895
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	-0.0326	0.0614
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.0026	0.0515
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	0.1053	0.0388
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	0.2531	0.0849
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	0.0908	0.0415
$\gamma_{\text{private business}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	0.1677	0.0407
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{travel}}^{SAT}$	0.2896	0.0752
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{work}}^{SAT}$	0.0419	0.0853
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{school}}^{SAT}$	-0.2399	0.1044
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	-0.1521	0.0653
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	-0.1489	0.0827
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.0131	0.0601
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	-0.1539	0.0653
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	-0.0203	0.0653
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	-0.0880	0.0494
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	-0.3387	0.1065
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	-0.1502	0.0695
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	-0.1053	0.0992
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	0.3934	0.1291
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	0.1191	0.0596
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	0.2483	0.0855
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	-0.0730	0.0480
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	0.0445	0.0312
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	0.0595	0.0996
$\gamma_{\text{travel}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	0.0731	0.0407
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	0.1333	0.0680
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	0.0517	0.0757

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	-0.2510	0.1229
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	-0.1684	0.0495
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.1395	0.0830
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	-0.0876	0.0580
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	-0.0634	0.0911
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	-0.1998	0.0754
$\gamma_{\text{travel}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	-0.1913	0.0715
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{work}}^{SAT}$	1.8191	0.2728
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{school}}^{SAT}$	-1.0284	0.1778
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	-0.1414	0.1183
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	0.1334	0.1718
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	0.4151	0.1872
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	-0.1119	0.1259
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	0.1191	0.1567
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	-0.0386	0.1568
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.0214	0.1094
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	-0.4193	0.1550
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	0.6589	0.2342
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.3933	0.1466
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	-0.5253	0.2288
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.4241	0.1394
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	0.0158	0.0971
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	-0.0130	0.0751
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	0.2108	0.1249
$\delta_{\text{work}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	0.2294	0.0930
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	0.1317	0.1252
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	-1.4473	0.2010
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	-0.1369	0.1882
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	-0.2200	0.1548
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	-0.3854	0.1292
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	0.1204	0.1051
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	-0.0402	0.1398
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	-0.1348	0.0897
$\delta_{\text{work}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	-0.2439	0.1005
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{school}}^{SAT}$	1.3431	0.2944
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	0.4025	0.1294
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	-0.3062	0.1087
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.2691	0.0936
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	0.5269	0.1597
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	0.3380	0.1880
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	0.0606	0.1285
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.3963	0.1586
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	0.5148	0.1034
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	-0.4764	0.1727
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.4665	0.2044
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	0.2991	0.2041
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	0.0846	0.1252
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	0.0428	0.0830
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	-0.1314	0.0709
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	0.2529	0.1205

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{school}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	-0.2434	0.0936
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	-0.1323	0.0850
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	0.8436	0.1968
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	0.8291	0.1754
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	0.1469	0.1334
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	0.3625	0.1628
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	0.1004	0.0708
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	0.4369	0.1936
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	0.3449	0.1043
$\delta_{\text{school}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	0.4934	0.1275
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{drop pick}}^{SAT}$	0.4038	0.1404
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	0.0679	0.0753
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	-0.0014	0.0693
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	0.1196	0.0644
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	0.2893	0.1531
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	0.0371	0.0509
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.2928	0.1007
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	-0.0004	0.0641
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	0.0250	0.1119
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.4305	0.1267
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	0.0989	0.0787
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	0.0550	0.0922
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	-0.0063	0.0396
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	-0.0947	0.0512
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	0.1527	0.1049
$\delta_{\text{drop pick}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	-0.0379	0.0614
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{work}}^{SUN}$	0.0460	0.0538
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{school}}^{SUN}$	0.1408	0.0996
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{drop pick}}^{SUN}$	0.3570	0.1045
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{daily shop}}^{SUN}$	0.0833	0.0851
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{non daily shop}}^{SUN}$	0.2254	0.0764
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{social}}^{SUN}$	-0.0439	0.0494
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{leisure}}^{SUN}$	0.4012	0.1457
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{private business}}^{SUN}$	0.1103	0.0603
$\delta_{\text{drop pick}}^{SAT}$	$\delta_{\text{travel}}^{SUN}$	0.2358	0.0945
$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{daily shop}}^{SAT}$	0.4804	0.1860
$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{non daily shop}}^{SAT}$	0.0483	0.0588
$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{social}}^{SAT}$	-0.1788	0.0819
$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{leisure}}^{SAT}$	-0.1394	0.0943
$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{private business}}^{SAT}$	0.0194	0.0971
$\delta_{\text{daily shop}}^{SAT}$	$\delta_{\text{travel}}^{SAT}$	0.1393	0.0931
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{work}}^{SUN}$	-0.1832	0.0619
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{school}}^{SUN}$	0.2791	0.1191
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{drop pick}}^{SUN}$	-0.0638	0.1161
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{daily shop}}^{SUN}$	-0.1253	0.0817
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{non daily shop}}^{SUN}$	-0.1222	0.0828
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{social}}^{SUN}$	0.0185	0.0552
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{leisure}}^{SUN}$	-0.0137	0.0484
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{private business}}^{SUN}$	-0.2142	0.0967
$\delta_{\text{daily shop}}^{SAT}$	$\gamma_{\text{travel}}^{SUN}$	0.0373	0.0450

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	-0.0310	0.0626
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	-0.1661	0.1460
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.1966	0.1265
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	0.1791	0.0873
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.0891	0.0683
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	-0.0429	0.0614
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0650	0.0982
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	0.0079	0.0515
$\delta_{\text{daily shop}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	-0.0282	0.0624
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{non daily shop}^{SAT}}$	0.3400	0.0685
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{social}^{SAT}}$	-0.1723	0.0657
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{leisure}^{SAT}}$	-0.0996	0.0767
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{private business}^{SAT}}$	0.1440	0.0625
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{travel}^{SAT}}$	0.0339	0.0594
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{work}^{SUN}}$	-0.0804	0.1119
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{school}^{SUN}}$	0.4011	0.1033
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.0988	0.0984
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.1792	0.0504
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.0982	0.1438
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	0.0177	0.0487
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	0.1015	0.0460
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	-0.0319	0.1195
$\delta_{\text{non daily shop}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	0.0512	0.0557
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	0.0414	0.0907
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	-0.3391	0.0978
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.2104	0.0917
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	0.0137	0.0656
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.0053	0.0619
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	-0.0765	0.0436
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0895	0.0923
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	-0.0151	0.0611
$\delta_{\text{non daily shop}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	-0.0614	0.0767
$\delta_{\text{social}^{SAT}}$	$\delta_{\text{social}^{SAT}}$	0.4574	0.1035
$\delta_{\text{social}^{SAT}}$	$\delta_{\text{leisure}^{SAT}}$	0.2585	0.1054
$\delta_{\text{social}^{SAT}}$	$\delta_{\text{private business}^{SAT}}$	-0.0458	0.0720
$\delta_{\text{social}^{SAT}}$	$\delta_{\text{travel}^{SAT}}$	0.2464	0.1056
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{work}^{SUN}}$	0.2840	0.0695
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{school}^{SUN}}$	-0.2540	0.1079
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.4052	0.1336
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.0173	0.0618
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.1824	0.1557
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	0.0651	0.0416
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.1231	0.0410
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	0.2114	0.1332
$\delta_{\text{social}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	-0.1235	0.0383

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{social}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	0.2107	0.0486
$\delta_{\text{social}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	0.2109	0.1131
$\delta_{\text{social}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	0.2041	0.0599
$\delta_{\text{social}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	0.2594	0.0597
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{leisure}^{SAT}}$	0.6428	0.1833
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{private business}^{SAT}}$	-0.0592	0.0524
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{travel}^{SAT}}$	0.1588	0.1043
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{work}^{SUN}}$	-0.0581	0.1227
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{school}^{SUN}}$	-0.3025	0.1172
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.4102	0.1427
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{daily shop}^{SUN}}$	0.1202	0.0687
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	0.1478	0.1891
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	-0.0312	0.0749
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.1773	0.0657
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	0.3139	0.1265
$\delta_{\text{leisure}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0646	0.0507
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	0.1646	0.0713
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	-0.0027	0.1255
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	0.4604	0.1513
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	-0.0395	0.0902
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.1079	0.0870
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	-0.0052	0.0536
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	0.6748	0.1604
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	0.0005	0.0714
$\delta_{\text{leisure}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	0.2424	0.0860
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{private business}^{SAT}}$	0.1836	0.0683
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{travel}^{SAT}}$	0.0949	0.0523
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{work}^{SUN}}$	0.0763	0.1001
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{school}^{SUN}}$	0.1309	0.0941
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.0915	0.0927
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.0786	0.0690
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.0464	0.0926
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	0.0221	0.0398
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0599	0.0364
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	-0.1149	0.0770
$\delta_{\text{private business}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0423	0.0606
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	-0.0165	0.0636
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	0.0078	0.0961
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.0567	0.0864
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	0.1063	0.0542
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.1226	0.0425
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	-0.0649	0.0390
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	0.0056	0.0633
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	0.0535	0.0670
$\delta_{\text{private business}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	0.0601	0.0654

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{travel}^{SAT}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.2723	0.0901
$\delta_{\text{travel}^{SAT}}$	$\gamma_{\text{social}^{SUN}}$	0.0783	0.0554
$\delta_{\text{travel}^{SAT}}$	$\gamma_{\text{leisure}^{SUN}}$	-0.0891	0.0397
$\delta_{\text{travel}^{SAT}}$	$\gamma_{\text{private business}^{SUN}}$	0.0652	0.1238
$\delta_{\text{travel}^{SAT}}$	$\gamma_{\text{travel}^{SUN}}$	-0.0820	0.0449
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{work}^{SUN}}$	-0.1178	0.0697
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{school}^{SUN}}$	-0.0859	0.1019
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{drop pick}^{SUN}}$	0.4456	0.1766
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{daily shop}^{SUN}}$	0.1810	0.0904
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.1927	0.1017
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{social}^{SUN}}$	0.1089	0.0742
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{leisure}^{SUN}}$	0.2202	0.1195
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{private business}^{SUN}}$	0.2636	0.0942
$\delta_{\text{travel}^{SAT}}$	$\delta_{\text{travel}^{SUN}}$	0.2884	0.1100
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{work}^{SUN}}$	0.4580	0.1214
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{school}^{SUN}}$	-0.1698	0.1785
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.1680	0.1440
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.0147	0.1231
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.1834	0.1279
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{social}^{SUN}}$	0.0887	0.0437
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0162	0.0434
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{private business}^{SUN}}$	-0.0096	0.0650
$\gamma_{\text{work}^{SUN}}$	$\gamma_{\text{travel}^{SUN}}$	-0.1522	0.0407
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{work}^{SUN}}$	-0.2098	0.0920
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{school}^{SUN}}$	0.2580	0.1563
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{drop pick}^{SUN}}$	0.2978	0.0935
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{daily shop}^{SUN}}$	0.0794	0.0684
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{non daily shop}^{SUN}}$	0.0864	0.0697
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{social}^{SUN}}$	0.1477	0.0604
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{leisure}^{SUN}}$	-0.0796	0.1421
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{private business}^{SUN}}$	0.2207	0.0927
$\gamma_{\text{work}^{SUN}}$	$\delta_{\text{travel}^{SUN}}$	0.1991	0.0592
$\gamma_{\text{school}^{SUN}}$	$\gamma_{\text{school}^{SUN}}$	0.8463	0.1963
$\gamma_{\text{school}^{SUN}}$	$\gamma_{\text{drop pick}^{SUN}}$	-0.2357	0.1087
$\gamma_{\text{school}^{SUN}}$	$\gamma_{\text{daily shop}^{SUN}}$	-0.3190	0.0886
$\gamma_{\text{school}^{SUN}}$	$\gamma_{\text{non daily shop}^{SUN}}$	-0.3429	0.2180
$\gamma_{\text{school}^{SUN}}$	$\gamma_{\text{social}^{SUN}}$	0.0394	0.1072
$\gamma_{\text{school}^{SUN}}$	$\gamma_{\text{leisure}^{SUN}}$	0.0970	0.0751
$\gamma_{\text{school}^{SUN}}$	$\gamma_{\text{private business}^{SUN}}$	-0.0896	0.2318
$\gamma_{\text{school}^{SUN}}$	$\gamma_{\text{travel}^{SUN}}$	0.1384	0.0844
$\gamma_{\text{school}^{SUN}}$	$\delta_{\text{work}^{SUN}}$	-0.0311	0.0781
$\gamma_{\text{school}^{SUN}}$	$\delta_{\text{school}^{SUN}}$	-0.6291	0.2093
$\gamma_{\text{school}^{SUN}}$	$\delta_{\text{drop pick}^{SUN}}$	-0.2337	0.2206
$\gamma_{\text{school}^{SUN}}$	$\delta_{\text{daily shop}^{SUN}}$	0.0360	0.0700
$\gamma_{\text{school}^{SUN}}$	$\delta_{\text{non daily shop}^{SUN}}$	-0.0262	0.0801

Table B.3: Covariance matrix for the Concepción dataset - base model

Covariance matrix for the Concepción dataset - base model

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{drop pick}}^{WD}$	0.033726	0.016874
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{family}}^{WD}$	0.013779	0.011486
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{HH obligations}}^{WD}$	0.037434	0.032591
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{OH recreation}}^{WD}$	-0.02025	0.012264
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{IH recreation}}^{WD}$	-0.00364	0.013641
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{services}}^{WD}$	-0.00083	0.008375
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{social}}^{WD}$	-0.00789	0.011811
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{shopping}}^{WD}$	-0.00424	0.011911
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{study}}^{WD}$	-0.01495	0.014688
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{travel}}^{WD}$	-0.00406	0.017859
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{work}}^{WD}$	0.019314	0.01483
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{drop pick}}^{WE}$	0.00424	0.012182
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{family}}^{WE}$	-0.00127	0.010423
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{HH obligations}}^{WE}$	0.032023	0.024244
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{OH recreation}}^{WE}$	-0.0161	0.014551
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{IH recreation}}^{WE}$	-0.00684	0.013673
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{services}}^{WE}$	-0.00375	0.00935
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{social}}^{WE}$	-0.00973	0.010214
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{shopping}}^{WE}$	0.012678	0.009818
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{study}}^{WE}$	-0.02009	0.02007
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{travel}}^{WE}$	-0.00243	0.012586
$\delta_{\text{drop pick}}^{WD}$	$\delta_{\text{work}}^{WE}$	0.003175	0.01156
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{drop pick}}^{WD}$	-0.00925	0.012274
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{family}}^{WD}$	0.003008	0.013037
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{HH obligations}}^{WD}$	0.000706	0.014087
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{OH recreation}}^{WD}$	-0.00999	0.012178
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{IH recreation}}^{WD}$	0.010409	0.014058
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{services}}^{WD}$	0.002012	0.016007
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{social}}^{WD}$	0.001706	0.013292
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{shopping}}^{WD}$	-0.00394	0.017512
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{study}}^{WD}$	-0.00208	0.010686
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	-0.00098	0.00969
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{work}}^{WD}$	0.014128	0.019253
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{drop pick}}^{WE}$	0.000694	0.014679
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{family}}^{WE}$	0.016568	0.017817
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	-0.01306	0.018874
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	0.000672	0.016011
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{IH recreation}}^{WE}$	0.001742	0.013496
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{services}}^{WE}$	-0.00786	0.018905
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{social}}^{WE}$	0.004128	0.012161
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{shopping}}^{WE}$	-0.00632	0.020964
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{study}}^{WE}$	-0.01238	0.020287
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{travel}}^{WE}$	-0.00951	0.013782
$\delta_{\text{drop pick}}^{WD}$	$\gamma_{\text{work}}^{WE}$	0.001148	0.017128
$\delta_{\text{family}}^{WD}$	$\delta_{\text{family}}^{WD}$	0.030715	0.017183
$\delta_{\text{family}}^{WD}$	$\delta_{\text{HH obligations}}^{WD}$	0.020158	0.02625
$\delta_{\text{family}}^{WD}$	$\delta_{\text{OH recreation}}^{WD}$	-0.01772	0.012577
$\delta_{\text{family}}^{WD}$	$\delta_{\text{IH recreation}}^{WD}$	-0.00902	0.012912
$\delta_{\text{family}}^{WD}$	$\delta_{\text{services}}^{WD}$	1.73E-05	0.008442
$\delta_{\text{family}}^{WD}$	$\delta_{\text{social}}^{WD}$	-0.01123	0.012946
$\delta_{\text{family}}^{WD}$	$\delta_{\text{shopping}}^{WD}$	-0.00542	0.010699
$\delta_{\text{family}}^{WD}$	$\delta_{\text{study}}^{WD}$	-0.01438	0.014072
$\delta_{\text{family}}^{WD}$	$\delta_{\text{travel}}^{WD}$	-0.00272	0.013144
$\delta_{\text{family}}^{WD}$	$\delta_{\text{work}}^{WD}$	0.020114	0.014314
$\delta_{\text{family}}^{WD}$	$\delta_{\text{drop pick}}^{WE}$	0.007648	0.013258
$\delta_{\text{family}}^{WD}$	$\delta_{\text{family}}^{WE}$	0.000509	0.01156
$\delta_{\text{family}}^{WD}$	$\delta_{\text{HH obligations}}^{WE}$	0.02068	0.018681
$\delta_{\text{family}}^{WD}$	$\delta_{\text{OH recreation}}^{WE}$	-0.01357	0.012629
$\delta_{\text{family}}^{WD}$	$\delta_{\text{IH recreation}}^{WE}$	-0.01221	0.015735
$\delta_{\text{family}}^{WD}$	$\delta_{\text{services}}^{WE}$	-0.00233	0.010627
$\delta_{\text{family}}^{WD}$	$\delta_{\text{social}}^{WE}$	-0.00801	0.010061
$\delta_{\text{family}}^{WD}$	$\delta_{\text{shopping}}^{WE}$	0.010452	0.011171
$\delta_{\text{family}}^{WD}$	$\delta_{\text{study}}^{WE}$	-0.01732	0.015519
$\delta_{\text{family}}^{WD}$	$\delta_{\text{travel}}^{WE}$	0.004376	0.015644
$\delta_{\text{family}}^{WD}$	$\delta_{\text{work}}^{WE}$	0.00829	0.013022
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{drop pick}}^{WD}$	-0.00731	0.012763
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{family}}^{WD}$	0.001042	0.013591
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{HH obligations}}^{WD}$	-0.00073	0.011697
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{OH recreation}}^{WD}$	-0.00909	0.013396
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{IH recreation}}^{WD}$	0.01243	0.01295
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{services}}^{WD}$	0.003495	0.012041
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{social}}^{WD}$	0.001588	0.011766
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{shopping}}^{WD}$	-0.00204	0.014628
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{study}}^{WD}$	0.001776	0.020495
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	-0.00247	0.012698
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{work}}^{WD}$	0.008351	0.016544
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{drop pick}}^{WE}$	-0.00149	0.018643
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{family}}^{WE}$	0.009979	0.017108
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	-0.00332	0.018789
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	0.002403	0.014889
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{IH recreation}}^{WE}$	-0.00225	0.013767
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{services}}^{WE}$	-0.00394	0.018444
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{social}}^{WE}$	0.004803	0.010738
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{shopping}}^{WE}$	-0.00831	0.01748
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{study}}^{WE}$	-0.01038	0.012757
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{travel}}^{WE}$	-0.00614	0.011995
$\delta_{\text{family}}^{WD}$	$\gamma_{\text{work}}^{WE}$	0.00335	0.015981
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{HH obligations}}^{WD}$	0.227342	0.100677
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{OH recreation}}^{WD}$	-0.05986	0.039974
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{IH recreation}}^{WD}$	0.006233	0.047644
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{services}}^{WD}$	0.00193	0.026779
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{social}}^{WD}$	0.002568	0.026766
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{shopping}}^{WD}$	-0.02233	0.027512
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{study}}^{WD}$	-0.05448	0.041999
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{travel}}^{WD}$	-0.00489	0.044546
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{work}}^{WD}$	0.051269	0.030095
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{drop pick}}^{WE}$	-0.03743	0.037378
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{family}}^{WE}$	-0.0174	0.029671
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{HH obligations}}^{WE}$	0.147496	0.055871
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{OH recreation}}^{WE}$	-0.07482	0.051122
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{IH recreation}}^{WE}$	0.024028	0.036958
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{services}}^{WE}$	-0.02336	0.028553
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{social}}^{WE}$	-0.03912	0.025634
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{shopping}}^{WE}$	0.019708	0.026253
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{study}}^{WE}$	-0.04881	0.053039
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{travel}}^{WE}$	-0.05807	0.043529
$\delta_{\text{HH obligations}}^{WD}$	$\delta_{\text{work}}^{WE}$	0.028187	0.032499
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{drop pick}}^{WD}$	-0.05186	0.049706
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{family}}^{WD}$	0.033041	0.046606
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{HH obligations}}^{WD}$	0.022232	0.046854
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{OH recreation}}^{WD}$	-0.03861	0.057108
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{IH recreation}}^{WD}$	0.037723	0.047969
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{services}}^{WD}$	-0.00658	0.056614
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{social}}^{WD}$	0.030072	0.052646
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{shopping}}^{WD}$	-0.00368	0.052845
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{study}}^{WD}$	-0.0017	0.029761
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	0.007929	0.033561
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{work}}^{WD}$	0.063985	0.07141
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{drop pick}}^{WE}$	-0.00378	0.048193
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{family}}^{WE}$	0.091406	0.051036
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	-0.05745	0.063768
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	0.000234	0.044737
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{IH recreation}}^{WE}$	0.027812	0.055277
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{services}}^{WE}$	-0.07486	0.078803
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{social}}^{WE}$	0.039033	0.055212
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{shopping}}^{WE}$	-0.01871	0.044773
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{study}}^{WE}$	-0.04909	0.063278
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{travel}}^{WE}$	-0.06438	0.037926
$\delta_{\text{HH obligations}}^{WD}$	$\gamma_{\text{work}}^{WE}$	-0.00972	0.055113
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{OH recreation}}^{WD}$	0.054375	0.026071
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{IH recreation}}^{WD}$	0.017902	0.01724
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{services}}^{WD}$	-0.00062	0.012428
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{social}}^{WD}$	0.017853	0.013299
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{shopping}}^{WD}$	0.010064	0.012315
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{study}}^{WD}$	0.030732	0.016054
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{travel}}^{WD}$	0.007199	0.019713
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{work}}^{WD}$	-0.03468	0.016777
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{drop pick}}^{WE}$	0.000567	0.017458
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{family}}^{WE}$	0.010461	0.016742
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{HH obligations}}^{WE}$	-0.05352	0.032917
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{OH recreation}}^{WE}$	0.031361	0.022388
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{IH recreation}}^{WE}$	0.015939	0.019645
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{services}}^{WE}$	0.007959	0.01338
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{social}}^{WE}$	0.015683	0.014152
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{shopping}}^{WE}$	-0.0144	0.012319
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{study}}^{WE}$	0.032776	0.019781
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{travel}}^{WE}$	0.003478	0.019656
$\delta_{\text{OH recreation}}^{WD}$	$\delta_{\text{work}}^{WE}$	-0.01757	0.01519
$\delta_{\text{OH recreation}}^{WD}$	$\gamma_{\text{drop pick}}^{WD}$	0.021171	0.018306
$\delta_{\text{OH recreation}}^{WD}$	$\gamma_{\text{family}}^{WD}$	-0.00747	0.019173

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ OH recreation^{WD}	γ HH obligations^{WD}	-0.00197	0.022592
δ OH recreation^{WD}	γ OH recreation^{WD}	0.014119	0.016867
δ OH recreation^{WD}	γ IH recreation^{WD}	-0.02354	0.025045
δ OH recreation^{WD}	γ services^{WD}	-0.00393	0.024409
δ OH recreation^{WD}	γ social^{WD}	-0.00451	0.022118
δ OH recreation^{WD}	γ shopping^{WD}	-0.00095	0.02282
δ OH recreation^{WD}	γ study^{WD}	-0.00134	0.022876
δ OH recreation^{WD}	γ travel^{WD}	-0.00036	0.013767
δ OH recreation^{WD}	γ work^{WD}	-0.02586	0.034971
δ OH recreation^{WD}	γ drop pick^{WE}	0.003656	0.026528
δ OH recreation^{WD}	γ family^{WE}	-0.02681	0.023987
δ OH recreation^{WD}	γ HH obligations^{WE}	0.008952	0.018666
δ OH recreation^{WD}	γ OH recreation^{WE}	0.002472	0.018379
δ OH recreation^{WD}	γ IH recreation^{WE}	-0.0029	0.026754
δ OH recreation^{WD}	γ services^{WE}	0.017554	0.041005
δ OH recreation^{WD}	γ social^{WE}	-0.01769	0.020434
δ OH recreation^{WD}	γ shopping^{WE}	0.009726	0.027155
δ OH recreation^{WD}	γ study^{WE}	0.016363	0.019492
δ OH recreation^{WD}	γ travel^{WE}	0.018206	0.02306
δ OH recreation^{WD}	γ work^{WE}	0.000747	0.020814
δ IH recreation^{WD}	δ IH recreation^{WD}	0.043034	0.032084
δ IH recreation^{WD}	δ services^{WD}	0.000409	0.013225
δ IH recreation^{WD}	δ social^{WD}	0.018141	0.016668
δ IH recreation^{WD}	δ shopping^{WD}	0.005063	0.013978
δ IH recreation^{WD}	δ study^{WD}	0.012201	0.013931
δ IH recreation^{WD}	δ travel^{WD}	0.006061	0.017748
δ IH recreation^{WD}	δ work^{WD}	-0.01308	0.018677
δ IH recreation^{WD}	δ drop pick^{WE}	-0.00722	0.016094
δ IH recreation^{WD}	δ family^{WE}	0.007443	0.013253
δ IH recreation^{WD}	δ HH obligations^{WE}	-0.0049	0.028621
δ IH recreation^{WD}	δ OH recreation^{WE}	0.00722	0.017197
δ IH recreation^{WD}	δ IH recreation^{WE}	0.027517	0.031944
δ IH recreation^{WD}	δ services^{WE}	-0.00213	0.012902
δ IH recreation^{WD}	δ social^{WE}	-0.0009	0.013204
δ IH recreation^{WD}	δ shopping^{WE}	-0.00593	0.012232
δ IH recreation^{WD}	δ study^{WE}	0.018391	0.019804
δ IH recreation^{WD}	δ travel^{WE}	-0.01881	0.027373
δ IH recreation^{WD}	δ work^{WE}	-0.00679	0.014594
δ IH recreation^{WD}	γ drop pick^{WD}	0.004833	0.017088
δ IH recreation^{WD}	γ family^{WD}	0.002164	0.013541
δ IH recreation^{WD}	γ HH obligations^{WD}	7.83E-05	0.016432
δ IH recreation^{WD}	γ OH recreation^{WD}	0.007393	0.017829
δ IH recreation^{WD}	γ IH recreation^{WD}	-0.00955	0.015875
δ IH recreation^{WD}	γ services^{WD}	-0.00641	0.019912
δ IH recreation^{WD}	γ social^{WD}	0.004348	0.015428
δ IH recreation^{WD}	γ shopping^{WD}	-0.00505	0.015556
δ IH recreation^{WD}	γ study^{WD}	0.000608	0.018449
δ IH recreation^{WD}	γ travel^{WD}	0.004445	0.013137
δ IH recreation^{WD}	γ work^{WD}	0.005264	0.033604
δ IH recreation^{WD}	γ drop pick^{WE}	0.001857	0.016622
δ IH recreation^{WD}	γ family^{WE}	0.004285	0.034749
δ IH recreation^{WD}	γ HH obligations^{WE}	-0.01103	0.023188
δ IH recreation^{WD}	γ OH recreation^{WE}	0.002706	0.017566
δ IH recreation^{WD}	γ IH recreation^{WE}	0.010535	0.02489
δ IH recreation^{WD}	γ services^{WE}	-0.00757	0.027405
δ IH recreation^{WD}	γ social^{WE}	-0.004	0.019268
δ IH recreation^{WD}	γ shopping^{WE}	-0.00091	0.016202
δ IH recreation^{WD}	γ study^{WE}	0.00326	0.014463
δ IH recreation^{WD}	γ travel^{WE}	-0.00712	0.022926
δ IH recreation^{WD}	γ work^{WE}	-0.00837	0.021196
δ services^{WD}	δ services^{WD}	0.016849	0.006851
δ services^{WD}	δ social^{WD}	0.000353	0.010363
δ services^{WD}	δ shopping^{WD}	-0.00152	0.007501
δ services^{WD}	δ study^{WD}	0.000366	0.011813
δ services^{WD}	δ travel^{WD}	-0.00107	0.008429
δ services^{WD}	δ work^{WD}	0.002424	0.012691
δ services^{WD}	δ drop pick^{WE}	-0.00017	0.008846
δ services^{WD}	δ family^{WE}	2.82E-05	0.007818
δ services^{WD}	δ HH obligations^{WE}	0.001387	0.018238
δ services^{WD}	δ OH recreation^{WE}	-0.00088	0.010682
δ services^{WD}	δ IH recreation^{WE}	0.001642	0.01335
δ services^{WD}	δ services^{WE}	-0.00013	0.006769
δ services^{WD}	δ social^{WE}	-3.3E-05	0.008026
δ services^{WD}	δ shopping^{WE}	-0.00027	0.006897
δ services^{WD}	δ study^{WE}	0.000472	0.013479
δ services^{WD}	δ travel^{WE}	-1.6E-05	0.012213
δ services^{WD}	δ work^{WE}	0.000494	0.008572
δ services^{WD}	γ drop pick^{WD}	-0.00065	0.010178
δ services^{WD}	γ family^{WD}	-0.00047	0.009681
δ services^{WD}	γ HH obligations^{WD}	-0.00195	0.009486
δ services^{WD}	γ OH recreation^{WD}	0.002171	0.010804
δ services^{WD}	γ IH recreation^{WD}	-0.0036	0.0112
δ services^{WD}	γ services^{WD}	0.002528	0.011874
δ services^{WD}	γ social^{WD}	-0.00083	0.01004
δ services^{WD}	γ shopping^{WD}	0.000477	0.007278
δ services^{WD}	γ study^{WD}	0.000857	0.009513
δ services^{WD}	γ travel^{WD}	-0.00147	0.006712
δ services^{WD}	γ work^{WD}	-0.00087	0.017276
δ services^{WD}	γ drop pick^{WE}	-0.00054	0.010949
δ services^{WD}	γ family^{WE}	-0.00081	0.013898
δ services^{WD}	γ HH obligations^{WE}	-0.00146	0.011164
δ services^{WD}	γ OH recreation^{WE}	-0.00106	0.010093
δ services^{WD}	γ IH recreation^{WE}	-0.00016	0.009504
δ services^{WD}	γ services^{WE}	0.002011	0.012018
δ services^{WD}	γ social^{WE}	-0.00044	0.008609
δ services^{WD}	γ shopping^{WE}	0.00023	0.008827
δ services^{WD}	γ study^{WE}	3E-05	0.010106
δ services^{WD}	γ travel^{WE}	0.002969	0.013144
δ services^{WD}	γ work^{WE}	0.000554	0.010222
δ social^{WD}	δ social^{WD}	0.030997	0.014943
δ social^{WD}	δ shopping^{WD}	0.002704	0.0099
δ social^{WD}	δ study^{WD}	0.011638	0.011939
δ social^{WD}	δ travel^{WD}	0.002701	0.013128
δ social^{WD}	δ work^{WD}	-0.01669	0.015788
δ social^{WD}	δ drop pick^{WE}	-0.00888	0.012313
δ social^{WD}	δ family^{WE}	0.002181	0.012321
δ social^{WD}	δ HH obligations^{WE}	-0.00776	0.018632
δ social^{WD}	δ OH recreation^{WE}	0.007183	0.012284
δ social^{WD}	δ IH recreation^{WE}	0.020905	0.018296
δ social^{WD}	δ services^{WE}	-0.00145	0.01001
δ social^{WD}	δ social^{WE}	0.003313	0.009889
δ social^{WD}	δ shopping^{WE}	-0.00787	0.011872
δ social^{WD}	δ study^{WE}	0.013557	0.015215
δ social^{WD}	δ travel^{WE}	-0.01429	0.016439
δ social^{WD}	δ work^{WE}	-0.00693	0.011938
δ social^{WD}	γ drop pick^{WD}	0.003742	0.011864
δ social^{WD}	γ family^{WD}	0.003411	0.012712
δ social^{WD}	γ HH obligations^{WD}	0.003583	0.012959
δ social^{WD}	γ OH recreation^{WD}	0.004484	0.014478
δ social^{WD}	γ IH recreation^{WD}	-0.00819	0.013889
δ social^{WD}	γ services^{WD}	-0.00389	0.013066
δ social^{WD}	γ social^{WD}	0.005459	0.011456
δ social^{WD}	γ shopping^{WD}	-0.0019	0.013651
δ social^{WD}	γ study^{WD}	-0.00154	0.016516
δ social^{WD}	γ travel^{WD}	0.002624	0.01104
δ social^{WD}	γ work^{WD}	-0.00516	0.020678
δ social^{WD}	γ drop pick^{WE}	0.002853	0.014145
δ social^{WD}	γ family^{WE}	-0.00134	0.019358
δ social^{WD}	γ HH obligations^{WE}	-0.00488	0.015504
δ social^{WD}	γ OH recreation^{WE}	-0.0029	0.014446
δ social^{WD}	γ IH recreation^{WE}	0.005276	0.014706
δ social^{WD}	γ services^{WE}	-0.00392	0.018326
δ social^{WD}	γ social^{WE}	-0.00091	0.011745
δ social^{WD}	γ shopping^{WE}	0.003984	0.015762
δ social^{WD}	γ study^{WE}	0.005452	0.014866
δ social^{WD}	γ travel^{WE}	-0.00213	0.014072
δ social^{WD}	γ work^{WE}	-0.00576	0.015249
δ shopping^{WD}	δ shopping^{WD}	0.024182	0.012345
δ shopping^{WD}	δ study^{WD}	0.008184	0.012851
δ shopping^{WD}	δ travel^{WD}	0.001117	0.013284
δ shopping^{WD}	δ work^{WD}	-0.01025	0.014455
δ shopping^{WD}	δ drop pick^{WE}	0.003389	0.011779
δ shopping^{WD}	δ family^{WE}	0.005203	0.010084
δ shopping^{WD}	δ HH obligations^{WE}	-0.01799	0.0196
δ shopping^{WD}	δ OH recreation^{WE}	0.008091	0.013108
δ shopping^{WD}	δ IH recreation^{WE}	0.001162	0.014767
δ shopping^{WD}	δ services^{WE}	0.002754	0.007806
δ shopping^{WD}	δ social^{WE}	0.004867	0.009213
δ shopping^{WD}	δ shopping^{WE}	0.000553	0.011339
δ shopping^{WD}	δ study^{WE}	0.008735	0.017193

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{travel}^{WE}}$	0.00389	0.014767
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{work}^{WE}}$	-0.00763	0.010999
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.005657	0.011935
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{family}^{WD}}$	-0.00217	0.011725
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00222	0.011715
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.00571	0.013625
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.00447	0.012184
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.001354	0.012378
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{social}^{WD}}$	-0.00239	0.010445
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0013	0.012665
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.003054	0.008919
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.00313	0.010007
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.00558	0.014201
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	0.000514	0.011845
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.00993	0.015033
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.004186	0.014187
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0022	0.012144
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0027	0.011015
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{services}^{WE}}$	0.006434	0.016072
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.00774	0.011741
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.00061	0.012178
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{study}^{WE}}$	0.004519	0.015732
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	0.008009	0.013268
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.00145	0.012162
$\delta_{\text{study}^{WD}}$	$\delta_{\text{study}^{WD}}$	0.047614	0.02477
$\delta_{\text{study}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.003589	0.015292
$\delta_{\text{study}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.03094	0.017007
$\delta_{\text{study}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	0.001597	0.015883
$\delta_{\text{study}^{WD}}$	$\delta_{\text{family}^{WE}}$	0.011015	0.012996
$\delta_{\text{study}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.04269	0.026593
$\delta_{\text{study}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	0.027867	0.023368
$\delta_{\text{study}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	0.013442	0.018131
$\delta_{\text{study}^{WD}}$	$\delta_{\text{services}^{WE}}$	0.006569	0.013937
$\delta_{\text{study}^{WD}}$	$\delta_{\text{social}^{WE}}$	0.012073	0.014773
$\delta_{\text{study}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	-0.0112	0.012576
$\delta_{\text{study}^{WD}}$	$\delta_{\text{study}^{WE}}$	0.037539	0.026564
$\delta_{\text{study}^{WD}}$	$\delta_{\text{travel}^{WE}}$	0.00385	0.01955
$\delta_{\text{study}^{WD}}$	$\delta_{\text{work}^{WE}}$	-0.01631	0.013819
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.018023	0.01663
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{family}^{WD}}$	-0.01092	0.020963
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00242	0.020764
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.015953	0.023884
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0219	0.022578
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{services}^{WD}}$	-0.00453	0.024224
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{social}^{WD}}$	-0.00951	0.021938
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.00131	0.02176
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.00068	0.016999
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.00153	0.013717
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.02292	0.02715
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0023	0.019099

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.02347	0.020006
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.009734	0.020576
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.003569	0.022759
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.00034	0.021349
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{services}^{WE}}$	0.014887	0.029194
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.01678	0.016462
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.010285	0.022971
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{study}^{WE}}$	0.016654	0.024932
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	0.016043	0.019399
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{work}^{WE}}$	-0.00061	0.018593
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.029827	0.01857
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.00535	0.018767
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	-0.00249	0.015964
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{family}^{WE}}$	-0.00091	0.011578
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.00351	0.034381
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	0.004711	0.015974
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	0.004031	0.019346
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{services}^{WE}}$	-0.00156	0.011176
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{social}^{WE}}$	-0.00111	0.012468
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	-0.00458	0.014173
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{study}^{WE}}$	0.010244	0.02195
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{WE}}$	-0.00351	0.018054
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{work}^{WE}}$	0.001223	0.01234
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.00344	0.014124
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{family}^{WD}}$	0.000589	0.011802
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00303	0.012243
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-7.8E-06	0.01436
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.00054	0.016815
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.00153	0.014982
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{WD}}$	-0.00031	0.013215
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.00236	0.015712
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.003019	0.012268
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.003969	0.01117
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.00327	0.021655
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.00326	0.014479
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.00182	0.02075
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.00021	0.021033
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.006339	0.012332
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.003206	0.011664
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.00739	0.0189
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.00173	0.013323
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.000298	0.013663
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.00693	0.017272
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.00182	0.01646
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.003601	0.016141
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{WD}}$	0.056792	0.027943
$\delta_{\text{work}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	0.001961	0.01461
$\delta_{\text{work}^{WD}}$	$\delta_{\text{family}^{WE}}$	-0.0098	0.018014
$\delta_{\text{work}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	0.047558	0.028788
$\delta_{\text{work}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	-0.02506	0.014532

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{work}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	-0.01636	0.021304
$\delta_{\text{work}^{WD}}$	$\delta_{\text{services}^{WE}}$	-0.00638	0.016526
$\delta_{\text{work}^{WD}}$	$\delta_{\text{social}^{WE}}$	-0.01523	0.015391
$\delta_{\text{work}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	0.015231	0.012377
$\delta_{\text{work}^{WD}}$	$\delta_{\text{study}^{WE}}$	-0.03572	0.020636
$\delta_{\text{work}^{WD}}$	$\delta_{\text{travel}^{WE}}$	0.002665	0.016902
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{WE}}$	0.019768	0.017476
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.01719	0.0199
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{family}^{WD}}$	0.008923	0.021726
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00133	0.019705
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.01343	0.016707
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.017239	0.020611
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.000437	0.020449
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.003605	0.020687
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.00506	0.024984
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.002823	0.02413
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.00302	0.0174
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{work}^{WD}}$	0.028846	0.034964
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0025	0.025759
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.02499	0.024818
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.01429	0.025335
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	7.89E-05	0.021099
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.000237	0.021252
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.01426	0.028815
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{social}^{WE}}$	0.012366	0.015189
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	-0.00833	0.02746
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.01919	0.026402
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.01312	0.017741
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.001981	0.022282
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{drop pick}^{WE}}$	0.03474	0.018423
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{family}^{WE}}$	0.007112	0.012243
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.02254	0.026838
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{OH recreation}^{WE}}$	0.008422	0.01848
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{IH recreation}^{WE}}$	-0.01526	0.014862
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{services}^{WE}}$	0.006566	0.013071
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{social}^{WE}}$	0.002681	0.011494
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	0.006446	0.012573
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{study}^{WE}}$	-0.00522	0.017471
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.018029	0.014899
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.0044	0.012987
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	0.006255	0.01723
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.00942	0.013269
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00401	0.012034
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.00437	0.013822
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.00084	0.017501
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.002633	0.016676
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{social}^{WD}}$	-0.00721	0.013697
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.000418	0.015116
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.000344	0.015047
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.00428	0.01136

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ drop pick^{WE}	γ work^{WD}	-0.00533	0.018596
δ drop pick^{WE}	γ drop pick^{WE}	-0.00066	0.0141
δ drop pick^{WE}	γ family^{WE}	-0.01206	0.018391
δ drop pick^{WE}	γ HH obligations^{WE}	0.010724	0.018789
δ drop pick^{WE}	γ OH recreation^{WE}	0.002179	0.016445
δ drop pick^{WE}	γ IH recreation^{WE}	-0.00587	0.015105
δ drop pick^{WE}	γ services^{WE}	0.015288	0.023739
δ drop pick^{WE}	γ social^{WE}	-0.0071	0.021259
δ drop pick^{WE}	γ shopping^{WE}	-0.00293	0.012488
δ drop pick^{WE}	γ study^{WE}	0.006767	0.015762
δ drop pick^{WE}	γ travel^{WE}	0.012899	0.014941
δ drop pick^{WE}	γ work^{WE}	0.004782	0.017002
δ family^{WE}	δ family^{WE}	0.025616	0.020578
δ family^{WE}	δ HH obligations^{WE}	-0.01426	0.022959
δ family^{WE}	δ OH recreation^{WE}	0.008166	0.014695
δ family^{WE}	δ IH recreation^{WE}	0.006987	0.01885
δ family^{WE}	δ services^{WE}	0.004654	0.009678
δ family^{WE}	δ social^{WE}	0.003111	0.011403
δ family^{WE}	δ shopping^{WE}	0.000689	0.010046
δ family^{WE}	δ study^{WE}	0.011772	0.016343
δ family^{WE}	δ travel^{WE}	0.000898	0.01217
δ family^{WE}	δ work^{WE}	-0.00646	0.013363
δ family^{WE}	γ drop pick^{WD}	0.008788	0.016579
δ family^{WE}	γ family^{WD}	-0.00542	0.010668
δ family^{WE}	γ HH obligations^{WD}	-0.00306	0.011504
δ family^{WE}	γ OH recreation^{WD}	0.007372	0.016477
δ family^{WE}	γ IH recreation^{WD}	-0.00658	0.012667
δ family^{WE}	γ services^{WD}	-0.00265	0.011813
δ family^{WE}	γ social^{WD}	-0.00097	0.0119
δ family^{WE}	γ shopping^{WD}	0.002114	0.013457
δ family^{WE}	γ study^{WD}	0.003332	0.011898
δ family^{WE}	γ travel^{WD}	-0.00053	0.00988
δ family^{WE}	γ work^{WD}	-0.00636	0.015828
δ family^{WE}	γ drop pick^{WE}	-0.00202	0.011223
δ family^{WE}	γ family^{WE}	-0.00263	0.014338
δ family^{WE}	γ HH obligations^{WE}	0.005071	0.013346
δ family^{WE}	γ OH recreation^{WE}	0.004208	0.012556
δ family^{WE}	γ IH recreation^{WE}	-0.00039	0.01139
δ family^{WE}	γ services^{WE}	0.005585	0.01566
δ family^{WE}	γ social^{WE}	-0.00628	0.010486
δ family^{WE}	γ shopping^{WE}	0.000385	0.013662
δ family^{WE}	γ study^{WE}	0.004786	0.014964
δ family^{WE}	γ travel^{WE}	0.004317	0.013718
δ family^{WE}	γ work^{WE}	0.005361	0.011279
δ HH obligations^{WE}	δ HH obligations^{WE}	0.128821	0.052861
δ HH obligations^{WE}	δ OH recreation^{WE}	-0.05213	0.025682
δ HH obligations^{WE}	δ IH recreation^{WE}	0.006105	0.026427
δ HH obligations^{WE}	δ services^{WE}	-0.01976	0.024104
δ HH obligations^{WE}	δ social^{WE}	-0.0281	0.018379
δ HH obligations^{WE}	δ shopping^{WE}	0.018125	0.018454

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ HH obligations^{WE}	δ study^{WE}	-0.04129	0.03106
δ HH obligations^{WE}	δ travel^{WE}	-0.03215	0.022907
δ HH obligations^{WE}	δ work^{WE}	0.024648	0.023433
δ HH obligations^{WE}	γ drop pick^{WD}	-0.0371	0.032626
δ HH obligations^{WE}	γ family^{WD}	0.018312	0.032247
δ HH obligations^{WE}	γ HH obligations^{WD}	0.009202	0.033239
δ HH obligations^{WE}	γ OH recreation^{WD}	-0.02632	0.028358
δ HH obligations^{WE}	γ IH recreation^{WD}	0.035009	0.04173
δ HH obligations^{WE}	γ services^{WD}	-0.00592	0.044573
δ HH obligations^{WE}	γ social^{WD}	0.016203	0.036479
δ HH obligations^{WE}	γ shopping^{WD}	-0.00591	0.042648
δ HH obligations^{WE}	γ study^{WD}	-0.00025	0.026204
δ HH obligations^{WE}	γ travel^{WD}	0.006328	0.025001
δ HH obligations^{WE}	γ work^{WD}	0.057329	0.065894
δ HH obligations^{WE}	γ drop pick^{WE}	-0.00503	0.037574
δ HH obligations^{WE}	γ family^{WE}	0.064565	0.037212
δ HH obligations^{WE}	γ HH obligations^{WE}	-0.03879	0.045458
δ HH obligations^{WE}	γ OH recreation^{WE}	3.9E-05	0.035038
δ HH obligations^{WE}	γ IH recreation^{WE}	0.012984	0.036545
δ HH obligations^{WE}	γ services^{WE}	-0.05284	0.057429
δ HH obligations^{WE}	γ social^{WE}	0.028489	0.044753
δ HH obligations^{WE}	γ shopping^{WE}	-0.01395	0.040435
δ HH obligations^{WE}	γ study^{WE}	-0.0333	0.044028
δ HH obligations^{WE}	γ travel^{WE}	-0.04802	0.032729
δ HH obligations^{WE}	γ work^{WE}	-0.00494	0.038965
δ OH recreation^{WE}	δ OH recreation^{WE}	0.049116	0.031377
δ OH recreation^{WE}	δ IH recreation^{WE}	0.001345	0.018201
δ OH recreation^{WE}	δ services^{WE}	0.008528	0.011918
δ OH recreation^{WE}	δ social^{WE}	0.015794	0.01505
δ OH recreation^{WE}	δ shopping^{WE}	-0.01206	0.010926
δ OH recreation^{WE}	δ study^{WE}	0.027178	0.025769
δ OH recreation^{WE}	δ travel^{WE}	0.014547	0.020194
δ OH recreation^{WE}	δ work^{WE}	-0.01268	0.013737
δ OH recreation^{WE}	γ drop pick^{WD}	0.020834	0.021646
δ OH recreation^{WE}	γ family^{WD}	-0.01287	0.02201
δ OH recreation^{WE}	γ HH obligations^{WD}	-0.00829	0.020656
δ OH recreation^{WE}	γ OH recreation^{WD}	0.015319	0.026676
δ OH recreation^{WE}	γ IH recreation^{WD}	-0.02082	0.022478
δ OH recreation^{WE}	γ services^{WD}	-0.00225	0.020706
δ OH recreation^{WE}	γ social^{WD}	-0.01005	0.022769
δ OH recreation^{WE}	γ shopping^{WD}	-0.00102	0.020709
δ OH recreation^{WE}	γ study^{WD}	-0.00074	0.015941
δ OH recreation^{WE}	γ travel^{WD}	-0.00211	0.012804
δ OH recreation^{WE}	γ work^{WD}	-0.02321	0.027778
δ OH recreation^{WE}	γ drop pick^{WE}	-0.00099	0.019152
δ OH recreation^{WE}	γ family^{WE}	-0.03164	0.022345
δ OH recreation^{WE}	γ HH obligations^{WE}	0.016323	0.018554
δ OH recreation^{WE}	γ OH recreation^{WE}	0.001784	0.016002
δ OH recreation^{WE}	γ IH recreation^{WE}	-0.00802	0.027057
δ OH recreation^{WE}	γ services^{WE}	0.024884	0.039332

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ OH recreation^{WE}	γ social^{WE}	-0.01656	0.017491
δ OH recreation^{WE}	γ shopping^{WE}	0.009995	0.02227
δ OH recreation^{WE}	γ study^{WE}	0.020365	0.026953
δ OH recreation^{WE}	γ travel^{WE}	0.021243	0.020193
δ OH recreation^{WE}	γ work^{WE}	0.004143	0.018446
δ IH recreation^{WE}	δ IH recreation^{WE}	0.051386	0.039634
δ IH recreation^{WE}	δ services^{WE}	-0.00318	0.013149
δ IH recreation^{WE}	δ social^{WE}	-0.00168	0.016752
δ IH recreation^{WE}	δ shopping^{WE}	-0.01082	0.014213
δ IH recreation^{WE}	δ study^{WE}	0.019005	0.019133
δ IH recreation^{WE}	δ travel^{WE}	-0.02523	0.02477
δ IH recreation^{WE}	δ work^{WE}	-0.00399	0.017935
δ IH recreation^{WE}	γ drop pick^{WD}	-0.00043	0.019458
δ IH recreation^{WE}	γ family^{WD}	0.00564	0.017196
δ IH recreation^{WE}	γ HH obligations^{WD}	0.002442	0.014526
δ IH recreation^{WE}	γ OH recreation^{WD}	0.005158	0.023366
δ IH recreation^{WE}	γ IH recreation^{WD}	-0.00863	0.01712
δ IH recreation^{WE}	γ services^{WD}	-0.00806	0.024438
δ IH recreation^{WE}	γ social^{WD}	0.01066	0.014675
δ IH recreation^{WE}	γ shopping^{WD}	-0.00046	0.021352
δ IH recreation^{WE}	γ study^{WD}	-0.00061	0.020555
δ IH recreation^{WE}	γ travel^{WD}	0.004551	0.014018
δ IH recreation^{WE}	γ work^{WD}	0.002647	0.03098
δ IH recreation^{WE}	γ drop pick^{WE}	-0.00048	0.015659
δ IH recreation^{WE}	γ family^{WE}	0.011728	0.031729
δ IH recreation^{WE}	γ HH obligations^{WE}	-0.01071	0.024161
δ IH recreation^{WE}	γ OH recreation^{WE}	-0.00423	0.02318
δ IH recreation^{WE}	γ IH recreation^{WE}	0.01365	0.023378
δ IH recreation^{WE}	γ services^{WE}	-0.01268	0.023682
δ IH recreation^{WE}	γ social^{WE}	0.000358	0.015821
δ IH recreation^{WE}	γ shopping^{WE}	0.00235	0.017781
δ IH recreation^{WE}	γ study^{WE}	0.003696	0.019321
δ IH recreation^{WE}	γ travel^{WE}	-0.01113	0.018903
δ IH recreation^{WE}	γ work^{WE}	-0.01157	0.026053
δ services^{WE}	δ services^{WE}	0.022988	0.012322
δ services^{WE}	δ social^{WE}	0.006097	0.010048
δ services^{WE}	δ shopping^{WE}	-1.7E-05	0.008275
δ services^{WE}	δ study^{WE}	0.004106	0.012992
δ services^{WE}	δ travel^{WE}	0.009158	0.012592
δ services^{WE}	δ work^{WE}	-0.00354	0.011572
δ services^{WE}	γ drop pick^{WD}	0.004631	0.013585
δ services^{WE}	γ family^{WD}	-0.0025	0.010311
δ services^{WE}	γ HH obligations^{WD}	-0.00277	0.009873
δ services^{WE}	γ OH recreation^{WD}	0.002012	0.010698
δ services^{WE}	γ IH recreation^{WD}	-0.00519	0.013069
δ services^{WE}	γ services^{WD}	-0.00038	0.013445
δ services^{WE}	γ social^{WD}	-0.00245	0.010285
δ services^{WE}	γ shopping^{WD}	0.003208	0.012671
δ services^{WE}	γ study^{WD}	-0.00016	0.011567
δ services^{WE}	γ travel^{WD}	-0.00407	0.009613

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.011	0.020135
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.00331	0.011246
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.00752	0.014281
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.008953	0.016627
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.00143	0.01027
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.00225	0.011909
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{services}^{WE}}$	0.008509	0.018099
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.00643	0.017625
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.001353	0.010571
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.007311	0.012477
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.009184	0.013456
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.002155	0.012287
$\delta_{\text{social}^{WE}}$	$\delta_{\text{social}^{WE}}$	0.028956	0.014237
$\delta_{\text{social}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	-0.00428	0.010033
$\delta_{\text{social}^{WE}}$	$\delta_{\text{study}^{WE}}$	0.009513	0.015918
$\delta_{\text{social}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.012802	0.013366
$\delta_{\text{social}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.01155	0.01072
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	0.010699	0.014107
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.00719	0.012995
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00142	0.01102
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.007735	0.01526
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.00885	0.011894
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.000356	0.013033
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{social}^{WD}}$	-0.00594	0.011012
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.003481	0.017915
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{study}^{WD}}$	-0.0006	0.01099
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.0057	0.010591
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.01383	0.018806
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.00075	0.013277
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.01654	0.014342
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.013046	0.017582
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-1.7E-05	0.009963
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0059	0.01564
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{services}^{WE}}$	0.009154	0.020102
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.00694	0.011199
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.002714	0.013171
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.013917	0.017498
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.014028	0.011714
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.001577	0.012575
$\delta_{\text{shopping}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	0.027245	0.016118
$\delta_{\text{shopping}^{WE}}$	$\delta_{\text{study}^{WE}}$	-0.01719	0.017958
$\delta_{\text{shopping}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.00494	0.01129
$\delta_{\text{shopping}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.00013	0.015029
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.00483	0.011986
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{family}^{WD}}$	0.001755	0.011763
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.000349	0.011902
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.00557	0.014135
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.008181	0.013668
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.001403	0.010978
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{social}^{WD}}$	-0.00098	0.011466

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	-0.00221	0.011045
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.001246	0.015609
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.00299	0.010028
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{work}^{WD}}$	0.008176	0.017778
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	0.001334	0.014636
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{family}^{WE}}$	0.010293	0.015848
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.00774	0.016035
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.002736	0.013135
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.00083	0.01157
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.00385	0.01601
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{social}^{WE}}$	0.001508	0.010142
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	-0.00576	0.015175
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{study}^{WE}}$	-0.00791	0.014766
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	-0.0012	0.011418
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.005319	0.011875
$\delta_{\text{study}^{WE}}$	$\delta_{\text{study}^{WE}}$	0.064001	0.038493
$\delta_{\text{study}^{WE}}$	$\delta_{\text{travel}^{WE}}$	-0.00455	0.021465
$\delta_{\text{study}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.01379	0.015713
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	0.020863	0.019052
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.00942	0.021959
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00363	0.025335
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.01735	0.02965
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.02425	0.026267
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{services}^{WD}}$	-0.00312	0.025938
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{social}^{WD}}$	-0.00699	0.030088
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.003694	0.023259
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.003634	0.018598
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	0.005461	0.015038
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.02305	0.032746
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.00251	0.022002
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.02194	0.026009
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.011739	0.022763
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.006082	0.024983
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.004126	0.023059
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{services}^{WE}}$	0.006646	0.029209
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.01396	0.015943
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.010334	0.029424
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.014191	0.027127
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.01174	0.022378
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.000887	0.019733
$\delta_{\text{travel}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.044675	0.027393
$\delta_{\text{travel}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.0039	0.015137
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	0.010479	0.018355
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.00982	0.016346
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00663	0.018643
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.00385	0.021823
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.00496	0.016238
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.004762	0.024039
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{social}^{WD}}$	-0.01151	0.014386
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	-0.00027	0.020904

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{study}^{WD}}$	-0.00074	0.015372
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.00866	0.014757
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.0144	0.026013
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.00029	0.016514
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.02327	0.028758
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.018475	0.030747
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.000144	0.019763
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0131	0.022052
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{services}^{WE}}$	0.022991	0.031263
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.00964	0.02338
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.001944	0.0135
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.009801	0.021179
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.022744	0.017966
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.009754	0.019369
$\delta_{\text{work}^{WE}}$	$\delta_{\text{work}^{WE}}$	0.03241	0.017418
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.00978	0.01557
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{family}^{WD}}$	0.0051	0.014395
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00135	0.013038
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.00983	0.019108
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.011169	0.014084
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.002065	0.018021
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.007158	0.01388
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.002515	0.013426
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.005617	0.016343
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	0.000316	0.012277
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{work}^{WD}}$	0.012675	0.025898
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0043	0.019205
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{family}^{WE}}$	0.012129	0.021533
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.00025	0.017176
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.00242	0.012632
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.00022	0.016598
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.00956	0.021381
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{social}^{WE}}$	0.009087	0.014743
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	-0.00639	0.015943
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{study}^{WE}}$	-0.00832	0.016011
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	-0.01158	0.015181
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{work}^{WE}}$	-0.00092	0.016699
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.036706	0.024026
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{family}^{WD}}$	-0.00995	0.015611
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.00605	0.016636
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.011412	0.018692
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.01516	0.016786
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.002346	0.019937
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{social}^{WD}}$	-0.00661	0.017394
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	0.001526	0.018749
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.002481	0.014713
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.00079	0.010768
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.02298	0.03254
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	0.003551	0.017919
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.02446	0.023079

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.009678	0.022234
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.003122	0.013607
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.00725	0.019887
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{services}^{WE}}$	0.01877	0.034497
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.01509	0.017149
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.00736	0.016535
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{study}^{WE}}$	0.011478	0.020481
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	0.017267	0.020721
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.007355	0.021504
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{family}^{WD}}$	0.02943	0.019177
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.003783	0.014396
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.00936	0.019935
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.004631	0.017379
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{services}^{WD}}$	-0.00182	0.017782
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.011479	0.018903
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.00306	0.014332
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.004	0.011236
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.001419	0.011081
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{work}^{WD}}$	0.006362	0.017522
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	0.000755	0.014637
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.013471	0.020802
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.01056	0.018911
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.00388	0.014927
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.002802	0.015906
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.00881	0.019535
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{social}^{WE}}$	0.007	0.012038
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	-0.00083	0.014011
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.01357	0.024959
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.00914	0.016653
$\gamma_{\text{family}^{WD}}$	$\gamma_{\text{work}^{WE}}$	-0.00241	0.015166

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.03725	0.033968
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.01085	0.01774
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{services}^{WD}}$	-0.00405	0.019237
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{social}^{WD}}$	-0.01096	0.02533
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	0.002154	0.013133
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.003084	0.011364
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.000137	0.010622
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.0065	0.016347
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	0.001507	0.014591
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.01187	0.026735
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.0061	0.016784
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.002245	0.014917
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.003584	0.018711
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{services}^{WE}}$	0.006909	0.015982
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.0056	0.015299
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.00537	0.016139
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{study}^{WE}}$	0.015397	0.028295
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	0.009164	0.019182
$\gamma_{\text{OH recreation}^{WD}}$	$\gamma_{\text{work}^{WE}}$	-0.00196	0.013704
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0408	0.029722
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{services}^{WD}}$	-0.00244	0.021704
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.00493	0.01916
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.00023	0.01659
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.00236	0.01663
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.001242	0.012059
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{work}^{WD}}$	0.023006	0.042534
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.00635	0.021301
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.019132	0.028087
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.00168	0.01789
$\gamma_{\text{IH recreation}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.00251	0.017997

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{services}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.004372	0.014758
$\gamma_{\text{services}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.0003	0.017323
$\gamma_{\text{services}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	0.008228	0.029067
$\gamma_{\text{services}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.004693	0.019602
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.031966	0.025438
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.00013	0.013311
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.00036	0.012945
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.00068	0.009882
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{work}^{WD}}$	0.004846	0.018074
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.00348	0.016063
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.010458	0.019937
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.00414	0.01764
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.00634	0.016914
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.001539	0.016438
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.00845	0.018532
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{social}^{WE}}$	0.008342	0.012532
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0039	0.012965
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.0042	0.021537
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.01287	0.016402
$\gamma_{\text{social}^{WD}}$	$\gamma_{\text{work}^{WE}}$	-0.00175	0.013568
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	0.032631	0.018606
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.005311	0.012848
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.00257	0.014256
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.00708	0.026387
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.00478	0.01463
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.00083	0.024016
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.012058	0.022811
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.00173	0.015957
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.00278	0.014467
$\gamma_{\text{shopping}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.00037	0.027991

Table B.4: Covariance matrix for the Concepción dataset - model with basic socio-demographic

Covariance matrix for the Concepción dataset - model with basic socio-demographic characteristics

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ drop pick^{WD}	δ drop pick^{WD}	0.0446	0.0256
δ drop pick^{WD}	δ family^{WD}	0.0217	0.0166
δ drop pick^{WD}	δ HH obligations^{WD}	0.0359	0.0237
δ drop pick^{WD}	δ OH recreation^{WD}	-0.0314	0.0209
δ drop pick^{WD}	δ IH recreation^{WD}	-0.0095	0.0196
δ drop pick^{WD}	δ services^{WD}	-0.0031	0.0097
δ drop pick^{WD}	δ social^{WD}	-0.0126	0.0109
δ drop pick^{WD}	δ shopping^{WD}	-0.0017	0.0123
δ drop pick^{WD}	δ study^{WD}	-0.0228	0.0155
δ drop pick^{WD}	δ travel^{WD}	-0.0057	0.0157
δ drop pick^{WD}	δ work^{WD}	0.0368	0.0235
δ drop pick^{WD}	δ drop pick^{WE}	0.0181	0.0170
δ drop pick^{WD}	δ family^{WE}	-0.0018	0.0169
δ drop pick^{WD}	δ HH obligations^{WE}	0.0298	0.0190
δ drop pick^{WD}	δ OH recreation^{WE}	-0.0189	0.0144
δ drop pick^{WD}	δ IH recreation^{WE}	-0.0185	0.0214
δ drop pick^{WD}	δ services^{WE}	-0.0021	0.0132
δ drop pick^{WD}	δ social^{WE}	-0.0094	0.0103
δ drop pick^{WD}	δ shopping^{WE}	0.0173	0.0146
δ drop pick^{WD}	δ study^{WE}	-0.0245	0.0178
δ drop pick^{WD}	δ travel^{WE}	0.0157	0.0246
δ drop pick^{WD}	δ work^{WE}	0.0088	0.0174
δ drop pick^{WD}	γ drop pick^{WD}	-0.0079	0.0222
δ drop pick^{WD}	γ family^{WD}	0.0014	0.0148
δ drop pick^{WD}	γ HH obligations^{WD}	0.0092	0.0195
δ drop pick^{WD}	γ OH recreation^{WD}	0.0184	0.0212
δ drop pick^{WD}	γ IH recreation^{WD}	-0.0196	0.0239
δ drop pick^{WD}	γ services^{WD}	-0.0051	0.0239
δ drop pick^{WD}	γ social^{WD}	0.0000	0.0143
δ drop pick^{WD}	γ shopping^{WD}	0.0118	0.0166
δ drop pick^{WD}	γ study^{WD}	0.0219	0.0167
δ drop pick^{WD}	γ travel^{WD}	-0.0132	0.0168
δ drop pick^{WD}	γ work^{WD}	0.0243	0.0214
δ drop pick^{WD}	γ drop pick^{WE}	0.0166	0.0194
δ drop pick^{WD}	γ family^{WE}	-0.0018	0.0173
δ drop pick^{WD}	γ HH obligations^{WE}	0.0087	0.0183
δ drop pick^{WD}	γ OH recreation^{WE}	-0.0131	0.0196
δ drop pick^{WD}	γ IH recreation^{WE}	0.0037	0.0199
δ drop pick^{WD}	γ services^{WE}	0.0029	0.0176
δ drop pick^{WD}	γ social^{WE}	0.0077	0.0137
δ drop pick^{WD}	γ shopping^{WE}	0.0128	0.0228
δ drop pick^{WD}	γ study^{WE}	0.0093	0.0259
δ drop pick^{WD}	γ travel^{WE}	0.0111	0.0192
δ drop pick^{WD}	γ work^{WE}	-0.0205	0.0215
δ family^{WD}	δ family^{WD}	0.0390	0.0293
δ family^{WD}	δ HH obligations^{WD}	0.0232	0.0283
δ family^{WD}	δ OH recreation^{WD}	-0.0238	0.0205
δ family^{WD}	δ IH recreation^{WD}	-0.0074	0.0228
δ family^{WD}	δ services^{WD}	-0.0022	0.0089
δ family^{WD}	δ social^{WD}	-0.0113	0.0121

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ family^{WD}	δ shopping^{WD}	-0.0059	0.0134
δ family^{WD}	δ study^{WD}	-0.0189	0.0185
δ family^{WD}	δ travel^{WD}	-0.0070	0.0152
δ family^{WD}	δ work^{WD}	0.0309	0.0248
δ family^{WD}	δ drop pick^{WE}	0.0156	0.0129
δ family^{WD}	δ family^{WE}	0.0013	0.0149
δ family^{WD}	δ HH obligations^{WE}	0.0191	0.0217
δ family^{WD}	δ OH recreation^{WE}	-0.0124	0.0154
δ family^{WD}	δ IH recreation^{WE}	-0.0178	0.0205
δ family^{WD}	δ services^{WE}	-0.0021	0.0145
δ family^{WD}	δ social^{WE}	-0.0043	0.0113
δ family^{WD}	δ shopping^{WE}	0.0100	0.0160
δ family^{WD}	δ study^{WE}	-0.0178	0.0155
δ family^{WD}	δ travel^{WE}	0.0137	0.0268
δ family^{WD}	δ work^{WE}	0.0085	0.0126
δ family^{WD}	γ drop pick^{WD}	-0.0136	0.0227
δ family^{WD}	γ family^{WD}	-0.0041	0.0188
δ family^{WD}	γ HH obligations^{WD}	0.0096	0.0156
δ family^{WD}	γ OH recreation^{WD}	0.0144	0.0184
δ family^{WD}	γ IH recreation^{WD}	-0.0171	0.0201
δ family^{WD}	γ services^{WD}	-0.0102	0.0229
δ family^{WD}	γ social^{WD}	0.0007	0.0121
δ family^{WD}	γ shopping^{WD}	0.0083	0.0145
δ family^{WD}	γ study^{WD}	0.0135	0.0180
δ family^{WD}	γ travel^{WD}	-0.0090	0.0133
δ family^{WD}	γ work^{WD}	0.0164	0.0194
δ family^{WD}	γ drop pick^{WE}	0.0127	0.0169
δ family^{WD}	γ family^{WE}	0.0012	0.0189
δ family^{WD}	γ HH obligations^{WE}	0.0004	0.0192
δ family^{WD}	γ OH recreation^{WE}	-0.0120	0.0155
δ family^{WD}	γ IH recreation^{WE}	0.0000	0.0159
δ family^{WD}	γ services^{WE}	0.0039	0.0144
δ family^{WD}	γ social^{WE}	0.0072	0.0132
δ family^{WD}	γ shopping^{WE}	0.0094	0.0189
δ family^{WD}	γ study^{WE}	0.0055	0.0250
δ family^{WD}	γ travel^{WE}	0.0067	0.0195
δ family^{WD}	γ work^{WE}	-0.0167	0.0210
δ HH obligations^{WD}	δ HH obligations^{WD}	0.1415	0.0518
δ HH obligations^{WD}	δ OH recreation^{WD}	-0.0678	0.0262
δ HH obligations^{WD}	δ IH recreation^{WD}	0.0355	0.0329
δ HH obligations^{WD}	δ services^{WD}	0.0067	0.0184
δ HH obligations^{WD}	δ social^{WD}	-0.0114	0.0178
δ HH obligations^{WD}	δ shopping^{WD}	-0.0260	0.0192
δ HH obligations^{WD}	δ study^{WD}	-0.0388	0.0304
δ HH obligations^{WD}	δ travel^{WD}	-0.0237	0.0327
δ HH obligations^{WD}	δ work^{WD}	0.0596	0.0305
δ HH obligations^{WD}	δ drop pick^{WE}	-0.0088	0.0349
δ HH obligations^{WD}	δ family^{WE}	-0.0043	0.0302
δ HH obligations^{WD}	δ HH obligations^{WE}	0.0976	0.0415
δ HH obligations^{WD}	δ OH recreation^{WE}	-0.0505	0.0281

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
δ HH obligations^{WD}	δ IH recreation^{WE}	0.0228	0.0322
δ HH obligations^{WD}	δ services^{WE}	-0.0322	0.0272
δ HH obligations^{WD}	δ social^{WE}	-0.0394	0.0194
δ HH obligations^{WD}	δ shopping^{WE}	0.0035	0.0209
δ HH obligations^{WD}	δ study^{WE}	-0.0304	0.0264
δ HH obligations^{WD}	δ travel^{WE}	-0.0551	0.0428
δ HH obligations^{WD}	δ work^{WE}	0.0221	0.0231
δ HH obligations^{WD}	γ drop pick^{WD}	-0.0133	0.0405
δ HH obligations^{WD}	γ family^{WD}	0.0027	0.0538
δ HH obligations^{WD}	γ HH obligations^{WD}	0.0003	0.0423
δ HH obligations^{WD}	γ OH recreation^{WD}	0.0415	0.0372
δ HH obligations^{WD}	γ IH recreation^{WD}	-0.0220	0.0381
δ HH obligations^{WD}	γ services^{WD}	-0.0254	0.0448
δ HH obligations^{WD}	γ social^{WD}	-0.0063	0.0242
δ HH obligations^{WD}	γ shopping^{WD}	0.0020	0.0337
δ HH obligations^{WD}	γ study^{WD}	0.0390	0.0464
δ HH obligations^{WD}	γ travel^{WD}	-0.0235	0.0326
δ HH obligations^{WD}	γ work^{WD}	0.0578	0.0380
δ HH obligations^{WD}	γ drop pick^{WE}	0.0225	0.0514
δ HH obligations^{WD}	γ family^{WE}	-0.0172	0.0339
δ HH obligations^{WD}	γ HH obligations^{WE}	0.0355	0.0322
δ HH obligations^{WD}	γ OH recreation^{WE}	-0.0207	0.0333
δ HH obligations^{WD}	γ IH recreation^{WE}	-0.0044	0.0382
δ HH obligations^{WD}	γ services^{WE}	0.0158	0.0300
δ HH obligations^{WD}	γ social^{WE}	0.0251	0.0324
δ HH obligations^{WD}	γ shopping^{WE}	-0.0037	0.0443
δ HH obligations^{WD}	γ study^{WE}	-0.0119	0.0539
δ HH obligations^{WD}	γ travel^{WE}	-0.0187	0.0290
δ HH obligations^{WD}	γ work^{WE}	-0.0284	0.0365
δ OH recreation^{WD}	δ OH recreation^{WD}	0.0647	0.0283
δ OH recreation^{WD}	δ IH recreation^{WD}	-0.0009	0.0234
δ OH recreation^{WD}	δ services^{WD}	-0.0022	0.0124
δ OH recreation^{WD}	δ social^{WD}	0.0153	0.0119
δ OH recreation^{WD}	δ shopping^{WD}	0.0133	0.0140
δ OH recreation^{WD}	δ study^{WD}	0.0289	0.0176
δ OH recreation^{WD}	δ travel^{WD}	0.0115	0.0182
δ OH recreation^{WD}	δ work^{WD}	-0.0501	0.0239
δ OH recreation^{WD}	δ drop pick^{WE}	-0.0044	0.0238
δ OH recreation^{WD}	δ family^{WE}	0.0078	0.0204
δ OH recreation^{WD}	δ HH obligations^{WE}	-0.0534	0.0247
δ OH recreation^{WD}	δ OH recreation^{WE}	0.0291	0.0170
δ OH recreation^{WD}	δ IH recreation^{WE}	0.0086	0.0230
δ OH recreation^{WD}	δ services^{WE}	0.0113	0.0167
δ OH recreation^{WD}	δ social^{WE}	0.0188	0.0177
δ OH recreation^{WD}	δ shopping^{WE}	-0.0112	0.0195
δ OH recreation^{WD}	δ study^{WE}	0.0261	0.0195
δ OH recreation^{WD}	δ travel^{WE}	0.0055	0.0340
δ OH recreation^{WD}	δ work^{WE}	-0.0190	0.0179
δ OH recreation^{WD}	γ drop pick^{WD}	0.0111	0.0259
δ OH recreation^{WD}	γ family^{WD}	-0.0004	0.0240

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0048	0.0221
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0286	0.0230
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0222	0.0300
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.0106	0.0288
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.0042	0.0169
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0108	0.0188
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.0319	0.0235
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0164	0.0212
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.0369	0.0266
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0207	0.0304
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.0083	0.0216
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0195	0.0270
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0176	0.0245
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0019	0.0236
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.0066	0.0213
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.0113	0.0169
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0088	0.0274
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.0029	0.0349
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.0027	0.0215
$\delta_{\text{OH recreation}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.0292	0.0257
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{IH recreation}^{WD}}$	0.0793	0.0446
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{services}^{WD}}$	0.0055	0.0141
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{social}^{WD}}$	0.0133	0.0141
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{shopping}^{WD}}$	-0.0109	0.0156
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{study}^{WD}}$	0.0131	0.0250
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{travel}^{WD}}$	-0.0110	0.0267
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.0172	0.0251
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	-0.0222	0.0193
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{family}^{WE}}$	0.0148	0.0173
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	0.0186	0.0266
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	-0.0067	0.0167
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	0.0571	0.0326
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{services}^{WE}}$	-0.0221	0.0246
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{social}^{WE}}$	-0.0211	0.0227
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	-0.0239	0.0190
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{study}^{WE}}$	0.0174	0.0235
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{travel}^{WE}}$	-0.0794	0.0499
$\delta_{\text{IH recreation}^{WD}}$	$\delta_{\text{work}^{WE}}$	-0.0043	0.0236
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0005	0.0266
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{family}^{WD}}$	-0.0059	0.0277
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0064	0.0429
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.0005	0.0257
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0132	0.0287
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{services}^{WD}}$	-0.0175	0.0297
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{social}^{WD}}$	-0.0057	0.0303
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0241	0.0283
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.0179	0.0282
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0021	0.0156
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{work}^{WD}}$	0.0051	0.0537
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0004	0.0502

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.0029	0.0232
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.0143	0.0422
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0057	0.0441
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0210	0.0364
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{services}^{WE}}$	0.0082	0.0266
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{social}^{WE}}$	0.0138	0.0270
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0182	0.0193
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.0508	0.0572
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.0322	0.0250
$\delta_{\text{IH recreation}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.0245	0.0384
$\delta_{\text{services}^{WD}}$	$\delta_{\text{services}^{WD}}$	0.0180	0.0095
$\delta_{\text{services}^{WD}}$	$\delta_{\text{social}^{WD}}$	0.0008	0.0072
$\delta_{\text{services}^{WD}}$	$\delta_{\text{shopping}^{WD}}$	-0.0054	0.0098
$\delta_{\text{services}^{WD}}$	$\delta_{\text{study}^{WD}}$	0.0020	0.0116
$\delta_{\text{services}^{WD}}$	$\delta_{\text{travel}^{WD}}$	-0.0014	0.0104
$\delta_{\text{services}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.0045	0.0135
$\delta_{\text{services}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	-0.0053	0.0101
$\delta_{\text{services}^{WD}}$	$\delta_{\text{family}^{WE}}$	-0.0006	0.0073
$\delta_{\text{services}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	0.0048	0.0149
$\delta_{\text{services}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	-0.0036	0.0097
$\delta_{\text{services}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	0.0073	0.0132
$\delta_{\text{services}^{WD}}$	$\delta_{\text{services}^{WE}}$	-0.0057	0.0107
$\delta_{\text{services}^{WD}}$	$\delta_{\text{social}^{WE}}$	-0.0007	0.0081
$\delta_{\text{services}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	-0.0032	0.0098
$\delta_{\text{services}^{WD}}$	$\delta_{\text{study}^{WE}}$	0.0017	0.0106
$\delta_{\text{services}^{WD}}$	$\delta_{\text{travel}^{WE}}$	-0.0102	0.0178
$\delta_{\text{services}^{WD}}$	$\delta_{\text{work}^{WE}}$	-0.0020	0.0090
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0003	0.0104
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{family}^{WD}}$	0.0010	0.0093
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0015	0.0106
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.0025	0.0102
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0009	0.0127
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{services}^{WD}}$	-0.0034	0.0091
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.0008	0.0087
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0029	0.0095
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.0001	0.0114
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.0018	0.0077
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{work}^{WD}}$	0.0004	0.0136
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0049	0.0151
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.0017	0.0091
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0010	0.0110
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0012	0.0139
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0026	0.0090
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{services}^{WE}}$	0.0018	0.0082
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{social}^{WE}}$	0.0041	0.0091
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0039	0.0095
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.0037	0.0144
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.0071	0.0129
$\delta_{\text{services}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.0008	0.0102
$\delta_{\text{social}^{WD}}$	$\delta_{\text{social}^{WD}}$	0.0237	0.0105

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{social}^{WD}}$	$\delta_{\text{shopping}^{WD}}$	-0.0003	0.0080
$\delta_{\text{social}^{WD}}$	$\delta_{\text{study}^{WD}}$	0.0115	0.0127
$\delta_{\text{social}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.0008	0.0106
$\delta_{\text{social}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.0217	0.0145
$\delta_{\text{social}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	-0.0075	0.0118
$\delta_{\text{social}^{WD}}$	$\delta_{\text{family}^{WE}}$	0.0035	0.0089
$\delta_{\text{social}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.0136	0.0156
$\delta_{\text{social}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	0.0095	0.0099
$\delta_{\text{social}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	0.0168	0.0141
$\delta_{\text{social}^{WD}}$	$\delta_{\text{services}^{WE}}$	-0.0033	0.0091
$\delta_{\text{social}^{WD}}$	$\delta_{\text{social}^{WE}}$	0.0033	0.0096
$\delta_{\text{social}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	-0.0105	0.0100
$\delta_{\text{social}^{WD}}$	$\delta_{\text{study}^{WE}}$	0.0123	0.0115
$\delta_{\text{social}^{WD}}$	$\delta_{\text{travel}^{WE}}$	-0.0159	0.0184
$\delta_{\text{social}^{WD}}$	$\delta_{\text{work}^{WE}}$	-0.0049	0.0097
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0058	0.0124
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{family}^{WD}}$	-0.0013	0.0116
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0010	0.0133
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0102	0.0156
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0090	0.0132
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{services}^{WD}}$	-0.0019	0.0124
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{social}^{WD}}$	-0.0004	0.0120
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0076	0.0108
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.0152	0.0135
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0041	0.0091
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.0106	0.0176
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0081	0.0147
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.0004	0.0133
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0019	0.0154
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0077	0.0148
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0061	0.0101
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.0016	0.0098
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.0009	0.0090
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0055	0.0137
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.0140	0.0197
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.0084	0.0119
$\delta_{\text{social}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.0137	0.0142
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{shopping}^{WD}}$	0.0305	0.0189
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{study}^{WD}}$	0.0028	0.0119
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.0075	0.0152
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.0087	0.0166
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	0.0076	0.0107
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{family}^{WE}}$	0.0034	0.0105
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.0184	0.0162
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	0.0084	0.0130
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	-0.0124	0.0190
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{services}^{WE}}$	0.0124	0.0164
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{social}^{WE}}$	0.0108	0.0125
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	0.0102	0.0115
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{study}^{WE}}$	0.0015	0.0126

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{travel}^{WE}}$	0.0219	0.0224
$\delta_{\text{shopping}^{WD}}$	$\delta_{\text{work}^{WE}}$	-0.0096	0.0151
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0005	0.0137
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{family}^{WD}}$	0.0044	0.0187
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.0001	0.0159
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0060	0.0121
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0030	0.0136
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.0053	0.0129
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.0028	0.0112
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	0.0056	0.0173
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.0067	0.0157
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0024	0.0120
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.0087	0.0136
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0015	0.0226
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.0032	0.0149
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0084	0.0154
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0035	0.0152
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0027	0.0146
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.0004	0.0108
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.0062	0.0126
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.0033	0.0148
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{study}^{WE}}$	0.0134	0.0197
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	0.0119	0.0154
$\delta_{\text{shopping}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.0039	0.0139
$\delta_{\text{study}^{WD}}$	$\delta_{\text{study}^{WD}}$	0.0500	0.0262
$\delta_{\text{study}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.0057	0.0171
$\delta_{\text{study}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.0452	0.0217
$\delta_{\text{study}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	-0.0158	0.0168
$\delta_{\text{study}^{WD}}$	$\delta_{\text{family}^{WE}}$	0.0046	0.0149
$\delta_{\text{study}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.0305	0.0210
$\delta_{\text{study}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	0.0192	0.0185
$\delta_{\text{study}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	0.0196	0.0191
$\delta_{\text{study}^{WD}}$	$\delta_{\text{services}^{WE}}$	0.0021	0.0172
$\delta_{\text{study}^{WD}}$	$\delta_{\text{social}^{WE}}$	0.0086	0.0114
$\delta_{\text{study}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	-0.0151	0.0153
$\delta_{\text{study}^{WD}}$	$\delta_{\text{study}^{WE}}$	0.0317	0.0188
$\delta_{\text{study}^{WD}}$	$\delta_{\text{travel}^{WE}}$	-0.0171	0.0255
$\delta_{\text{study}^{WD}}$	$\delta_{\text{work}^{WE}}$	-0.0174	0.0144
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0141	0.0192
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{family}^{WD}}$	0.0028	0.0223
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0077	0.0169
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0199	0.0192
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0184	0.0241
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.0066	0.0241
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.0029	0.0162
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0110	0.0199
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.0286	0.0248
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0167	0.0188
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.0352	0.0261
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0225	0.0203

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.0041	0.0166
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0134	0.0213
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0216	0.0259
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0046	0.0217
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.0073	0.0172
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.0052	0.0164
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0127	0.0277
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{study}^{WE}}$	-0.0124	0.0386
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	-0.0119	0.0202
$\delta_{\text{study}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.0196	0.0235
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{WD}}$	0.0332	0.0260
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{work}^{WD}}$	-0.0109	0.0182
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	0.0019	0.0211
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{family}^{WE}}$	-0.0032	0.0122
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.0157	0.0267
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	0.0081	0.0139
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	-0.0086	0.0241
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{services}^{WE}}$	0.0092	0.0137
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{social}^{WE}}$	0.0102	0.0136
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	0.0015	0.0178
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{study}^{WE}}$	0.0041	0.0166
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{travel}^{WE}}$	0.0187	0.0396
$\delta_{\text{travel}^{WD}}$	$\delta_{\text{work}^{WE}}$	-0.0032	0.0156
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0053	0.0166
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{family}^{WD}}$	0.0027	0.0176
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0024	0.0160
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0037	0.0163
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0108	0.0192
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.0095	0.0169
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{WD}}$	-0.0016	0.0146
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	0.0027	0.0176
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.0080	0.0176
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0055	0.0123
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.0077	0.0218
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0034	0.0254
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{family}^{WE}}$	0.0032	0.0149
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0028	0.0176
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0013	0.0256
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0024	0.0176
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{services}^{WE}}$	-0.0070	0.0147
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{social}^{WE}}$	-0.0096	0.0120
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.0043	0.0147
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{study}^{WE}}$	0.0136	0.0251
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	0.0079	0.0240
$\delta_{\text{travel}^{WD}}$	$\gamma_{\text{work}^{WE}}$	0.0050	0.0213
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{WD}}$	0.0841	0.0368
$\delta_{\text{work}^{WD}}$	$\delta_{\text{drop pick}^{WE}}$	0.0201	0.0247
$\delta_{\text{work}^{WD}}$	$\delta_{\text{family}^{WE}}$	-0.0109	0.0240
$\delta_{\text{work}^{WD}}$	$\delta_{\text{HH obligations}^{WE}}$	0.0519	0.0272
$\delta_{\text{work}^{WD}}$	$\delta_{\text{OH recreation}^{WE}}$	-0.0264	0.0189

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{work}^{WD}}$	$\delta_{\text{IH recreation}^{WE}}$	-0.0328	0.0256
$\delta_{\text{work}^{WD}}$	$\delta_{\text{services}^{WE}}$	-0.0042	0.0195
$\delta_{\text{work}^{WD}}$	$\delta_{\text{social}^{WE}}$	-0.0166	0.0147
$\delta_{\text{work}^{WD}}$	$\delta_{\text{shopping}^{WE}}$	0.0196	0.0191
$\delta_{\text{work}^{WD}}$	$\delta_{\text{study}^{WE}}$	-0.0414	0.0222
$\delta_{\text{work}^{WD}}$	$\delta_{\text{travel}^{WE}}$	0.0209	0.0288
$\delta_{\text{work}^{WD}}$	$\delta_{\text{work}^{WE}}$	0.0268	0.0221
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.0168	0.0283
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{family}^{WD}}$	-0.0023	0.0256
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.0105	0.0250
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.0305	0.0267
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0288	0.0325
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{services}^{WD}}$	-0.0075	0.0297
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.0002	0.0199
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	0.0201	0.0258
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{study}^{WD}}$	0.0446	0.0281
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	-0.0191	0.0225
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{work}^{WD}}$	0.0450	0.0285
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0307	0.0299
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.0041	0.0238
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.0176	0.0301
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.0225	0.0325
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0064	0.0245
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{services}^{WE}}$	0.0078	0.0252
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{social}^{WE}}$	0.0086	0.0185
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{shopping}^{WE}}$	0.0207	0.0346
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{study}^{WE}}$	0.0119	0.0451
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{travel}^{WE}}$	0.0127	0.0236
$\delta_{\text{work}^{WD}}$	$\gamma_{\text{work}^{WE}}$	-0.0387	0.0282
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{drop pick}^{WE}}$	0.0408	0.0207
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{family}^{WE}}$	0.0024	0.0121
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.0046	0.0297
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{OH recreation}^{WE}}$	-0.0006	0.0147
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{IH recreation}^{WE}}$	-0.0285	0.0188
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{services}^{WE}}$	0.0091	0.0164
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{social}^{WE}}$	0.0047	0.0124
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	0.0176	0.0134
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{study}^{WE}}$	-0.0178	0.0210
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.0375	0.0245
$\delta_{\text{drop pick}^{WE}}$	$\delta_{\text{work}^{WE}}$	0.0034	0.0161
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.0080	0.0173
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.0023	0.0187
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.0086	0.0196
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.0048	0.0247
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0141	0.0246
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{services}^{WD}}$	-0.0029	0.0158
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.0039	0.0161
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.0121	0.0188
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.0084	0.0216
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.0071	0.0158

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{work}^{WD}}$	0.0084	0.0225
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0102	0.0223
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{family}^{WE}}$	0.0028	0.0163
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0052	0.0184
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.0071	0.0189
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0033	0.0160
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.0005	0.0160
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.0011	0.0158
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.0162	0.0212
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.0156	0.0277
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.0182	0.0193
$\delta_{\text{drop pick}^{WE}}$	$\gamma_{\text{work}^{WE}}$	-0.0105	0.0245
$\delta_{\text{family}^{WE}}$	$\delta_{\text{family}^{WE}}$	0.0266	0.0148
$\delta_{\text{family}^{WE}}$	$\delta_{\text{HH obligations}^{WE}}$	-0.0073	0.0232
$\delta_{\text{family}^{WE}}$	$\delta_{\text{OH recreation}^{WE}}$	0.0012	0.0126
$\delta_{\text{family}^{WE}}$	$\delta_{\text{IH recreation}^{WE}}$	0.0129	0.0177
$\delta_{\text{family}^{WE}}$	$\delta_{\text{services}^{WE}}$	-0.0022	0.0109
$\delta_{\text{family}^{WE}}$	$\delta_{\text{social}^{WE}}$	-0.0013	0.0109
$\delta_{\text{family}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	-0.0023	0.0103
$\delta_{\text{family}^{WE}}$	$\delta_{\text{study}^{WE}}$	0.0056	0.0172
$\delta_{\text{family}^{WE}}$	$\delta_{\text{travel}^{WE}}$	-0.0131	0.0239
$\delta_{\text{family}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.0092	0.0140
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.0035	0.0145
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.0018	0.0111
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0014	0.0137
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0011	0.0150
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0012	0.0143
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{services}^{WD}}$	-0.0073	0.0147
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.0010	0.0118
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0060	0.0155
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{study}^{WD}}$	-0.0105	0.0176
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	0.0012	0.0105
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.0037	0.0219
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0050	0.0220
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{family}^{WE}}$	0.0007	0.0113
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0043	0.0184
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0022	0.0207
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0069	0.0132
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{services}^{WE}}$	0.0027	0.0103
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{social}^{WE}}$	0.0021	0.0139
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0040	0.0133
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{study}^{WE}}$	-0.0062	0.0232
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	-0.0046	0.0127
$\delta_{\text{family}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.0100	0.0158
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{HH obligations}^{WE}}$	0.0927	0.0495
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{OH recreation}^{WE}}$	-0.0402	0.0225
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{IH recreation}^{WE}}$	0.0082	0.0267
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{services}^{WE}}$	-0.0188	0.0176
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{social}^{WE}}$	-0.0270	0.0170
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	0.0079	0.0162

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{study}^{WE}}$	-0.0266	0.0203
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{travel}^{WE}}$	-0.0285	0.0319
$\delta_{\text{HH obligations}^{WE}}$	$\delta_{\text{work}^{WE}}$	0.0147	0.0194
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.0149	0.0359
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{family}^{WD}}$	0.0022	0.0367
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0073	0.0320
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.0379	0.0341
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0221	0.0290
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{services}^{WD}}$	-0.0178	0.0358
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{social}^{WD}}$	-0.0022	0.0213
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.0074	0.0232
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.0387	0.0302
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.0186	0.0232
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{work}^{WD}}$	0.0409	0.0293
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0171	0.0426
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.0123	0.0263
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.0271	0.0277
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.0164	0.0265
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0059	0.0233
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{services}^{WE}}$	0.0124	0.0232
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{social}^{WE}}$	0.0159	0.0227
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0007	0.0321
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.0002	0.0419
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	-0.0087	0.0227
$\delta_{\text{HH obligations}^{WE}}$	$\gamma_{\text{work}^{WE}}$	-0.0309	0.0230
$\delta_{\text{OH recreation}^{WE}}$	$\delta_{\text{OH recreation}^{WE}}$	0.0403	0.0203
$\delta_{\text{OH recreation}^{WE}}$	$\delta_{\text{IH recreation}^{WE}}$	-0.0046	0.0165
$\delta_{\text{OH recreation}^{WE}}$	$\delta_{\text{services}^{WE}}$	0.0117	0.0160
$\delta_{\text{OH recreation}^{WE}}$	$\delta_{\text{social}^{WE}}$	0.0131	0.0112
$\delta_{\text{OH recreation}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	-0.0084	0.0115
$\delta_{\text{OH recreation}^{WE}}$	$\delta_{\text{study}^{WE}}$	0.0144	0.0140
$\delta_{\text{OH recreation}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.0114	0.0186
$\delta_{\text{OH recreation}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.0053	0.0131
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0080	0.0196
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.0059	0.0223
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.0005	0.0165
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0184	0.0200
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0134	0.0163
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.0078	0.0188
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.0015	0.0135
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0030	0.0158
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{study}^{WD}}$	-0.0223	0.0238
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	0.0130	0.0159
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.0262	0.0244
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0078	0.0230
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{family}^{WE}}$	0.0070	0.0158
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0095	0.0171
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0108	0.0150
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0024	0.0196
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.0082	0.0116

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.0094	0.0148
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0007	0.0201
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{study}^{WE}}$	-0.0050	0.0258
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.0017	0.0157
$\delta_{\text{OH recreation}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.0144	0.0165
$\delta_{\text{IH recreation}^{WE}}$	$\delta_{\text{IH recreation}^{WE}}$	0.0766	0.0376
$\delta_{\text{IH recreation}^{WE}}$	$\delta_{\text{services}^{WE}}$	-0.0233	0.0306
$\delta_{\text{IH recreation}^{WE}}$	$\delta_{\text{social}^{WE}}$	-0.0171	0.0209
$\delta_{\text{IH recreation}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	-0.0247	0.0164
$\delta_{\text{IH recreation}^{WE}}$	$\delta_{\text{study}^{WE}}$	0.0260	0.0218
$\delta_{\text{IH recreation}^{WE}}$	$\delta_{\text{travel}^{WE}}$	-0.0776	0.0407
$\delta_{\text{IH recreation}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.0086	0.0212
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0061	0.0252
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{family}^{WD}}$	0.0002	0.0272
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0095	0.0408
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0054	0.0200
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0194	0.0295
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{services}^{WD}}$	-0.0116	0.0200
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{social}^{WD}}$	-0.0087	0.0258
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0279	0.0271
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{study}^{WD}}$	-0.0204	0.0291
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	0.0061	0.0167
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.0026	0.0354
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0139	0.0446
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.0053	0.0246
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.0077	0.0408
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0084	0.0329
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0157	0.0260
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{services}^{WE}}$	0.0046	0.0225
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{social}^{WE}}$	0.0073	0.0186
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0248	0.0237
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{study}^{WE}}$	-0.0398	0.0488
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	-0.0323	0.0240
$\delta_{\text{IH recreation}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.0304	0.0312
$\delta_{\text{services}^{WE}}$	$\delta_{\text{services}^{WE}}$	0.0383	0.0310
$\delta_{\text{services}^{WE}}$	$\delta_{\text{social}^{WE}}$	0.0155	0.0158
$\delta_{\text{services}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	0.0096	0.0148
$\delta_{\text{services}^{WE}}$	$\delta_{\text{study}^{WE}}$	-0.0025	0.0183
$\delta_{\text{services}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.0377	0.0423
$\delta_{\text{services}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.0053	0.0125
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.0044	0.0229
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.0007	0.0226
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0069	0.0176
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0053	0.0130
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0012	0.0189
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.0123	0.0169
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.0044	0.0186
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.0097	0.0176
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.0003	0.0224
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	0.0028	0.0120

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.0130	0.0261
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0052	0.0339
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.0004	0.0168
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0031	0.0163
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.0002	0.0226
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0102	0.0214
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.0029	0.0163
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.0112	0.0148
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.0087	0.0180
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.0242	0.0286
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.0179	0.0233
$\delta_{\text{services}^{WE}}$	$\gamma_{\text{work}^{WE}}$	-0.0040	0.0233
$\delta_{\text{social}^{WE}}$	$\delta_{\text{social}^{WE}}$	0.0347	0.0166
$\delta_{\text{social}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	0.0030	0.0123
$\delta_{\text{social}^{WE}}$	$\delta_{\text{study}^{WE}}$	0.0051	0.0134
$\delta_{\text{social}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.0340	0.0266
$\delta_{\text{social}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.0107	0.0132
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0022	0.0170
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{family}^{WD}}$	0.0019	0.0241
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0025	0.0196
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0112	0.0161
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0012	0.0171
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.0073	0.0167
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.0073	0.0119
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.0064	0.0192
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{study}^{WD}}$	-0.0091	0.0184
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	0.0048	0.0106
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.0208	0.0202
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0101	0.0252
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{family}^{WE}}$	0.0054	0.0148
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0133	0.0155
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0057	0.0194
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0050	0.0190
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.0046	0.0132
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.0072	0.0147
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.0036	0.0145
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.0174	0.0334
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.0119	0.0142
$\delta_{\text{social}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.0000	0.0191
$\delta_{\text{shopping}^{WE}}$	$\delta_{\text{shopping}^{WE}}$	0.0366	0.0199
$\delta_{\text{shopping}^{WE}}$	$\delta_{\text{study}^{WE}}$	-0.0188	0.0164
$\delta_{\text{shopping}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.0372	0.0248
$\delta_{\text{shopping}^{WE}}$	$\delta_{\text{work}^{WE}}$	0.0014	0.0165
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.0081	0.0175
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{family}^{WD}}$	0.0033	0.0165
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.0038	0.0176
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.0084	0.0205
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0145	0.0222
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.0015	0.0216
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.0013	0.0185

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.0148	0.0178
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.0150	0.0149
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.0083	0.0126
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{work}^{WD}}$	0.0100	0.0271
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0096	0.0238
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.0024	0.0151
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0021	0.0216
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.0100	0.0218
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0105	0.0173
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{services}^{WE}}$	0.0020	0.0126
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.0021	0.0145
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.0082	0.0157
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.0276	0.0282
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.0194	0.0182
$\delta_{\text{shopping}^{WE}}$	$\gamma_{\text{work}^{WE}}$	-0.0153	0.0220
$\delta_{\text{study}^{WE}}$	$\delta_{\text{study}^{WE}}$	0.0475	0.0233
$\delta_{\text{study}^{WE}}$	$\delta_{\text{travel}^{WE}}$	-0.0249	0.0292
$\delta_{\text{study}^{WE}}$	$\delta_{\text{work}^{WE}}$	-0.0141	0.0199
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0140	0.0202
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{family}^{WD}}$	0.0023	0.0137
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	-0.0037	0.0179
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0193	0.0230
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0236	0.0259
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.0045	0.0215
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.0019	0.0182
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0152	0.0209
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{study}^{WD}}$	-0.0265	0.0210
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	0.0147	0.0166
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.0298	0.0251
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0246	0.0226
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{family}^{WE}}$	0.0012	0.0155
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0132	0.0213
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	0.0191	0.0285
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0077	0.0199
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.0033	0.0165
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.0063	0.0146
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	-0.0136	0.0262
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{study}^{WE}}$	-0.0153	0.0368
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	-0.0141	0.0211
$\delta_{\text{study}^{WE}}$	$\gamma_{\text{work}^{WE}}$	0.0213	0.0220
$\delta_{\text{travel}^{WE}}$	$\delta_{\text{travel}^{WE}}$	0.1291	0.0713
$\delta_{\text{travel}^{WE}}$	$\delta_{\text{work}^{WE}}$	0.0016	0.0303
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.0075	0.0383
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{family}^{WD}}$	0.0004	0.0407
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.0053	0.0521
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0019	0.0300
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0210	0.0432
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.0214	0.0388
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{social}^{WD}}$	0.0125	0.0400
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.0351	0.0386

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.0208	0.0404
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.0069	0.0197
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{work}^{WD}}$	-0.0126	0.0673
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0046	0.0696
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{family}^{WE}}$	0.0048	0.0321
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	-0.0180	0.0453
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.0095	0.0526
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	0.0276	0.0502
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.0091	0.0353
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{social}^{WE}}$	-0.0182	0.0359
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.0280	0.0284
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{study}^{WE}}$	0.0664	0.0774
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.0518	0.0377
$\delta_{\text{travel}^{WE}}$	$\gamma_{\text{work}^{WE}}$	-0.0333	0.0554
$\delta_{\text{work}^{WE}}$	$\delta_{\text{work}^{WE}}$	0.0356	0.0221
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{drop pick}^{WD}}$	-0.0009	0.0146
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{family}^{WD}}$	-0.0083	0.0205
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.0061	0.0161
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{OH recreation}^{WD}}$	0.0079	0.0165
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{IH recreation}^{WD}}$	-0.0049	0.0185
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{services}^{WD}}$	0.0005	0.0131
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{social}^{WD}}$	-0.0060	0.0157
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{shopping}^{WD}}$	0.0015	0.0267
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{study}^{WD}}$	0.0140	0.0206
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{travel}^{WD}}$	-0.0058	0.0132
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{work}^{WD}}$	0.0221	0.0190
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{drop pick}^{WE}}$	0.0156	0.0188
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{family}^{WE}}$	-0.0030	0.0157
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{HH obligations}^{WE}}$	0.0118	0.0170
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{OH recreation}^{WE}}$	-0.0129	0.0227
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{IH recreation}^{WE}}$	-0.0031	0.0212
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{services}^{WE}}$	-0.0017	0.0153
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{social}^{WE}}$	0.0032	0.0141
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{shopping}^{WE}}$	0.0080	0.0180
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{study}^{WE}}$	-0.0083	0.0372
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{travel}^{WE}}$	0.0014	0.0210
$\delta_{\text{work}^{WE}}$	$\gamma_{\text{work}^{WE}}$	-0.0080	0.0245
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{drop pick}^{WD}}$	0.0381	0.0182
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{family}^{WD}}$	0.0075	0.0137
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{HH obligations}^{WD}}$	0.0041	0.0175
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{OH recreation}^{WD}}$	-0.0127	0.0204
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{IH recreation}^{WD}}$	0.0144	0.0187
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{services}^{WD}}$	0.0149	0.0251
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{social}^{WD}}$	0.0032	0.0164
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{shopping}^{WD}}$	-0.0030	0.0164
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{study}^{WD}}$	-0.0103	0.0209
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{travel}^{WD}}$	0.0101	0.0137
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{work}^{WD}}$	-0.0142	0.0219
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{drop pick}^{WE}}$	-0.0178	0.0252
$\gamma_{\text{drop pick}^{WD}}$	$\gamma_{\text{family}^{WE}}$	-0.0008	0.0149

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	-0.0021	0.0201
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	0.0184	0.0169
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{IH recreation}}^{WE}$	-0.0034	0.0166
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{services}}^{WE}$	-0.0096	0.0125
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{social}}^{WE}$	-0.0052	0.0176
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{shopping}}^{WE}$	0.0009	0.0174
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{study}}^{WE}$	-0.0034	0.0312
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{travel}}^{WE}$	-0.0064	0.0217
$\gamma_{\text{drop pick}}^{WD}$	$\gamma_{\text{work}}^{WE}$	0.0089	0.0205
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{family}}^{WD}$	0.0389	0.0297
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{HH obligations}}^{WD}$	-0.0003	0.0219
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{OH recreation}}^{WD}$	-0.0022	0.0172
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{IH recreation}}^{WD}$	-0.0004	0.0141
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{services}}^{WD}$	0.0056	0.0180
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{social}}^{WD}$	0.0007	0.0116
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{shopping}}^{WD}$	0.0046	0.0251
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{study}}^{WD}$	0.0015	0.0256
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	-0.0010	0.0150
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{work}}^{WD}$	-0.0015	0.0285
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{drop pick}}^{WE}$	-0.0146	0.0247
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{family}}^{WE}$	0.0008	0.0175
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	-0.0066	0.0178
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	0.0078	0.0202
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{IH recreation}}^{WE}$	0.0006	0.0190
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{services}}^{WE}$	-0.0023	0.0113
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{social}}^{WE}$	-0.0033	0.0141
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{shopping}}^{WE}$	0.0019	0.0184
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{study}}^{WE}$	0.0154	0.0329
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{travel}}^{WE}$	-0.0017	0.0243
$\gamma_{\text{family}}^{WD}$	$\gamma_{\text{work}}^{WE}$	-0.0041	0.0187

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{OH recreation}}^{WD}$	0.0460	0.0289
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{IH recreation}}^{WD}$	-0.0132	0.0242
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{services}}^{WD}$	-0.0098	0.0213
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{social}}^{WD}$	-0.0024	0.0159
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{shopping}}^{WD}$	0.0054	0.0158
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{study}}^{WD}$	0.0225	0.0251
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	-0.0093	0.0163
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{work}}^{WD}$	0.0206	0.0323
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{drop pick}}^{WE}$	0.0092	0.0266
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{family}}^{WE}$	-0.0057	0.0214
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	0.0126	0.0219
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	-0.0139	0.0253
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{IH recreation}}^{WE}$	0.0047	0.0199
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{services}}^{WE}$	0.0039	0.0125
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{social}}^{WE}$	0.0078	0.0187
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{shopping}}^{WE}$	0.0004	0.0225
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{study}}^{WE}$	0.0065	0.0375
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{travel}}^{WE}$	0.0004	0.0212
$\gamma_{\text{OH recreation}}^{WD}$	$\gamma_{\text{work}}^{WE}$	-0.0160	0.0224
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{IH recreation}}^{WD}$	0.0467	0.0287
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{services}}^{WD}$	0.0089	0.0234
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{social}}^{WD}$	-0.0031	0.0154
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{shopping}}^{WD}$	-0.0140	0.0205
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{study}}^{WD}$	-0.0207	0.0217
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	0.0149	0.0187
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{work}}^{WD}$	-0.0149	0.0319
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{drop pick}}^{WE}$	-0.0077	0.0304
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{family}}^{WE}$	-0.0004	0.0176
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	0.0012	0.0208
$\gamma_{\text{IH recreation}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	0.0103	0.0275

Parameter 1	Parameter 2	Post mean of cov	Post sd of cov
$\gamma_{\text{services}}^{WD}$	$\gamma_{\text{shopping}}^{WE}$	0.0053	0.0187
$\gamma_{\text{services}}^{WD}$	$\gamma_{\text{study}}^{WE}$	0.0170	0.0292
$\gamma_{\text{services}}^{WD}$	$\gamma_{\text{travel}}^{WE}$	0.0105	0.0179
$\gamma_{\text{services}}^{WD}$	$\gamma_{\text{work}}^{WE}$	-0.0008	0.0242
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{social}}^{WD}$	0.0296	0.0189
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{shopping}}^{WD}$	0.0075	0.0144
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{study}}^{WD}$	0.0029	0.0211
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	0.0009	0.0114
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{work}}^{WD}$	-0.0134	0.0263
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{drop pick}}^{WE}$	-0.0124	0.0244
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{family}}^{WE}$	-0.0002	0.0132
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	-0.0096	0.0161
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	0.0119	0.0214
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{IH recreation}}^{WE}$	0.0042	0.0225
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{services}}^{WE}$	0.0007	0.0139
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{social}}^{WE}$	-0.0004	0.0129
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{shopping}}^{WE}$	0.0054	0.0120
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{study}}^{WE}$	0.0111	0.0354
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{travel}}^{WE}$	0.0028	0.0208
$\gamma_{\text{social}}^{WD}$	$\gamma_{\text{work}}^{WE}$	-0.0098	0.0191
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{shopping}}^{WD}$	0.0405	0.0291
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{study}}^{WD}$	0.0182	0.0223
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{travel}}^{WD}$	-0.0067	0.0145
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{work}}^{WD}$	0.0001	0.0309
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{drop pick}}^{WE}$	-0.0003	0.0304
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{family}}^{WE}$	0.0011	0.0163
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{HH obligations}}^{WE}$	-0.0033	0.0266
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{OH recreation}}^{WE}$	0.0037	0.0198
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{IH recreation}}^{WE}$	0.0083	0.0243
$\gamma_{\text{shopping}}^{WD}$	$\gamma_{\text{services}}^{WE}$	-0.0011	0.0131

Appendix C

Appendix to Chapter 7

As described in Section 4 of Chapter 7, we have prepared two additional versions of Table 7.3 and one additional version of Tables 7.4 and 7.5. Table 7.3 refers to the life-course calendar (LCC), and in the paper the descriptive statistics for this part of the survey are only shown for the group of participants who have completed the background survey (BS) and the LCC, for a sample size equal to 1, 290.

Table C.1 below reports the LCC statistics for the respondents who have completed the BS, the LCC and the name generator (NG), i.e. they have completed the online survey, while Table C.2 only includes those who have also used the smartphone app for two weeks.

	Share	**Still living with parents**		**N. of relocations while living with parents**		**N. of long-term partners**		**N. of children**		**N. of homes**		**N. of jobs**		**N. of cars**	
Age		*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*
18 - 24	19.57%	47%	0.50	1.65	1.81	0.35	0.64	0.15	1.13	1.87	1.68	1.53	1.89	1.92	1.87
25 - 29	11.63%	14%	0.35	2.23	2.39	1.01	1.28	0.18	0.54	3.28	2.37	3.68	2.65	3.39	2.23
30 - 39	26.33%	5%	0.21	1.87	2.31	1.37	1.75	0.91	1.07	3.88	2.71	4.65	2.84	4.74	3.84
40 - 49	20.47%	2%	0.13	1.84	2.12	1.55	1.05	1.38	1.34	4.04	2.85	4.95	2.91	4.62	3.47
50 - 59	14.25%	1%	0.11	1.75	1.74	1.59	1.36	1.54	1.15	4.16	2.91	5.09	2.95	5.26	3.52
60 - 65	4.60%	2%	0.14	2.33	2.22	1.33	0.84	1.41	1.19	4.12	2.98	5.02	3.04	4.65	2.98
66 and above	3.16%	0.00	0.00	2.09	2.03	1.63	0.84	1.74	1.17	4.03	2.99	5.03	2.99	5.80	4.38
Men	43.82%	0.13	0.33	1.93	2.08	1.26	1.71	0.98	1.33	3.63	2.81	4.03	3.04	4.15	3.75
Women	56.18%	0.13	0.33	1.83	2.13	1.16	0.97	0.86	1.17	3.71	2.71	4.12	2.97	4.08	3.17
All	.	0.13	0.33	1.87	2.11	1.20	1.35	0.91	1.25	3.67	2.75	4.08	3.00	4.11	3.43

Table C.1: LCC descriptive statistics - online survey completed

Using the same logic, we report the statistics about gender homophily and age homophily calculated using the NG data for respondents who completed the entire survey (including using rMove for two weeks) in Tables C.3 and C.4, respectively.

Comments on these results are provided in the paper.

	Share	Still living with parents		N. of relocations while living with parents		N. of long-term partners		N. of children		N. of homes		N. of jobs		N. of cars	
Age		*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*	*Mean*	*Sd*
18 - 24	19.57%	43%	0.50	1.72	2.12	0.31	0.53	0.06	0.24	1.74	1.50	1.55	1.77	1.99	2.00
25 - 29	11.63%	9%	0.29	2.00	2.28	0.98	1.58	0.14	0.41	3.63	2.43	4.20	2.67	3.61	2.25
30 - 39	26.33%	4%	0.19	1.58	2.16	1.47	2.41	0.99	1.11	3.81	2.74	4.63	2.84	4.39	2.43
40 - 49	20.47%	3%	0.18	1.91	2.11	1.45	0.97	1.28	1.15	4.20	2.64	5.03	2.76	4.55	2.81
50 - 59	14.25%	2%	0.16	1.63	1.73	1.55	1.07	1.60	1.05	4.05	2.80	4.93	2.88	5.11	3.67
60 - 65	4.60%	0%	0.00	2.32	1.80	1.26	0.45	1.26	1.10	3.47	2.27	4.47	2.27	4.26	2.08
66 and above	3.16%	0.00	0.00	2.46	2.57	1.23	0.60	1.85	1.07	4.77	3.09	5.77	3.09	7.23	6.10
Men	43.82%	0.09	0.29	1.66	1.83	1.32	2.17	1.07	1.16	3.63	2.69	4.22	2.89	4.24	3.37
Women	56.18%	0.10	0.30	1.86	2.25	1.19	1.02	0.90	1.07	3.83	2.67	4.35	2.92	4.16	2.77
All	.	0.10	0.29	1.78	2.08	1.25	1.61	0.98	1.11	3.75	2.68	4.30	2.90	4.20	3.03

Table C.2: LCC descriptive statistics - entire survey completed

		Alter	
	Gender	Female	Male
Ego	Female	7.89	3.82
	Male	4.17	5.81

Table C.3: NG gender homophily descriptives - entire survey completed

		Alter							
	Age	Under 18	18 - 24	25 - 29	30 - 39	40 - 49	50 - 59	60 - 69	70 and above
	18 - 24	0.48	6.25	1.06	0.31	0.60	1.09	0.31	0.28
	25 - 29	0.34	1.48	5.34	2.77	0.61	1.09	0.77	0.39
	30 - 39	0.22	0.17	0.82	5.17	1.49	0.72	1.24	0.32
Ego	40 - 49	0.54	0.24	0.32	1.56	4.39	1.55	0.92	1.22
	50 - 59	0.30	0.49	0.50	0.91	2.06	4.79	1.46	1.23
	60 - 65	0.26	0.16	0.58	1.74	1.21	3.05	3.53	1.26
	66 and above	0.69	0.31	0.23	1.38	1.08	1.69	4.15	2.54

Table C.4: NG age homophily descriptives - entire survey completed