Driving My Life Away? Essays examining the impact of commuting on income and well-being

by

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Abstract

Commuting is an important and increasing component of time use. In 1995/97, the average worker in Britain commuted for 48 minutes per day; by 2012 this had increased to 56 minutes, c. 12% of a standard fulltime working week (Department of Transport National Travel Survey (NTS), 2013).

Since commuting is viewed as an economic bad, rational individuals should only undertake longer commutes if they are compensated for doing so. This compensation can be monetary (e.g. higher pay) and non-monetary (e.g. better housing). Because of this compensation, people with longer commutes should not report lower levels of subjective well-being (SWB) - a proxy for utility - than people with shorter commutes. The principle aim of this thesis is to examine commuting behaviour against a number of different outcomes.

Chapter 2 uses data from the Annual Survey of Hours and Earnings (ASHE) to investigate the causal relationship between commuting distance and pay. Specifically, we focus on exogenous shocks to commuting, similar to the papers by Mulalic et al (2010, 2013). We find evidence of a positive and significant relationship between commuting distance and income, suggesting that individuals receive financial compensation for longer commutes.

Chapter 3 considers commuting and social capital, specifically in the presence of congestion charging. Using unique data, we analyse the impact that the Western Extension Zone (WEZ) had on an individual's stock of social capital. Following Putnam (2000), we proxy social capital by the frequency of visiting friends and family. Using difference-in-difference (D-i-D) techniques, we find that the WEZ did lead to lower levels of social capital.

Chapters 4 and 5 then look at the relationship between commuting and well-being using data from the British Household Panel Survey. In chapter 4 we show that there is an insignificant relationship between commuting time and life satisfaction for individuals, albeit there is a relationship between the General Health Questionnaire (GHQ) score and commuting for women. In chapter 5, we then consider the couple as the unit of analysis. Again we find no evidence of a negative relationship between commuting time and SWB. This is robust to including spousal commuting information.

We conclude that commuting further increases individuals' pay. However, we find no evidence of a significant relationship between commuting and SWB, which is a broader measure of individual utility. This may be due to commuting being associated with lower levels of social capital, which cancels out the effect of income on well-being.

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I would like to take this opportunity to express my greatest thanks to my two supervisors, Professor Andy Dickerson and Dr. Arne Risa Hole, for their time, guidance, and unwaivering support at each and every stage of my PhD. Further to this, I would like to express my thanks for everyone else at the Department of Economics at the University of Sheffield for their continual support and friendship throughout my time at Sheffield. In addition I would like to thank Professor Jenny Roberts for her assistance when completing the application form to study a PhD, and also Professor Gregg Marsden and other members of the UK Transport Research Centre, as well as the ESRC for financial support.

I thank my friends and peers, both inside and outside of academia, who have made the whole PhD experience enjoyable, and at times reminded me there is life outside of study.

Finally, and by no means least, I thank my family: my parents, Joan and Kevin, my sister Anna, and my grandmothers Joan and Irene, for their unconditional love and support - not just throughout my studies, but at all times.

Notes and Disclaimers

Chapter 2 is based on data from the *Annual Survey of Hours and Earnings* (ASHE) 1997-2011, produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive. The data are Crown Copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the data in this work does not imply the endorsement of ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research data sets which may not exactly reproduce National Statistics aggregates.

Chapter 3 uses a unique data set, which was kindly provided by Claire Sheffield at Transport for London (TfL). The data was initially collected by the market research company *Accent* on behalf of the TfL. Neither TfL nor Accent are in anyway responsible for the data analysis or interpretation presented in this thesis.

Chapter 4 and 5 uses data from the *British Household Panel Survey* (BHPS). The data (and tabulations) used in these chapters were made available through the ESRC Data Archive. The data were originally collected by the ESRC Research Centre on Micro-social Change at the University of Essex (now incorporated within the Institute for Social and Economic Research). Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here.

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Chapter 1

Introduction

1.1 Motivation and Aims

1.1.1 What is commuting?

In order to be able to live at a given household location, H, and work at a work-place location, W, an employee must travel between H and W (assuming that an individual does not work from home). This journey is known as the *'commute'*. In this sense, commuting can be thought of as the interaction between the housing and labour markets.

Commuting may be viewed as both an economic 'bad' and an economic 'good'. It is a bad in the sense that the opportunity cost of commuting is high - time spent traveling to and from work cannot be used for other purposes (with a number of possible exceptions, such as working on a long train journey, say). Another way in which commuting may be viewed as an economic bad is the fact that longer commutes may have implications for community cohesion and social capital (Putnam, 2000); people who travel further to work are less likely to partake in local area social activities, and hence may feel more socially excluded.

Commuting can also be viewed as an economic good, however, in the sense that possible benefits of longer commutes are compensation in the housing market (such as larger homes, safer neighbourhoods, closer proximity to friends and family etc.) and/or compensation in the labour market (such as higher salaries, greater job security, increased chances of career development etc.). However, since commuting is predominantly viewed as an economic bad, rational individuals should only undertake longer commutes if they are compensated by some of the factors listed in this paragraph.

In an article in The New Yorker magazine (The New Yorker, 2007), the economist Alois Stutzer made the observation that individuals may simultaneously overestimate the perceived benefits associated with longer commutes whilst underestimating the possibly negative implications. When combined, Stutzer argues that this may lead to an overall negative impact of longer commutes on overall well-being.

It is widely assumed that household location decisions are likely to be made at the household level (e.g. Alonso, 1964, Mok, 2007), such that people with young children may partake in longer commutes in order to attempt to gain their child(ren) access to better quality schools, say. Further to this, the household location decision may be made in order to benefit one particular partner, whilst inadvertently making the other worse off. We examine this possibility in chapter 5.

Becker (1965) considered commuting in a model of optimal time allocation, and since then attention to commuting within economics has been dissipated across several areas including transport, labour, urban and regional economics.

Commuting is an important and increasing component of time use in the UK, and we look at the changing patterns of commuting behaviour in Britain in the next subsection.

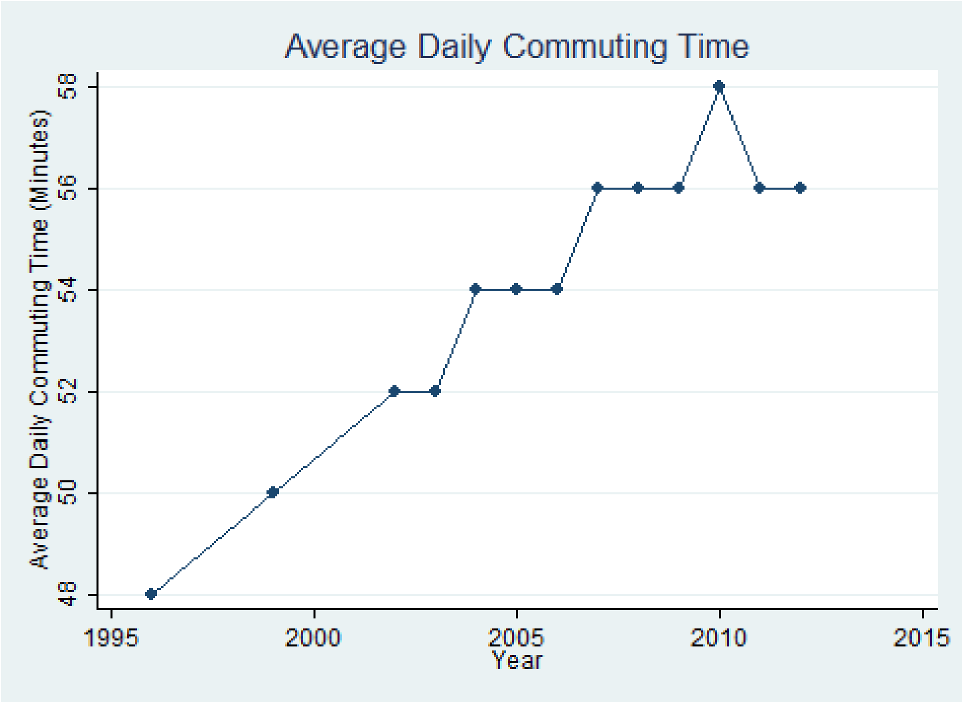
In this thesis we explore the impact that commuting has on a number of outcomes in the UK, outcomes that are both objective (*i.e.* income) and subjective (*i.e.* social capital and subjective well-being).

1.1.2 Commuting in the UK

In 1995-1997, the average worker in Britain commuted for 48 minutes per day; by 2012 this had increased to 56 minutes - around 12% of a standard fulltime working week (Department of Transport (DfT), National Travel Survey (NTS), 2013). According to the NTS, commuting time reached a peak at 58 minutes per day in 2010. These numbers are shown graphically in Figure 1.1.

In terms of commuting distance, the average daily one-way commute of a typical worker has increased from 8.2 miles in 1995/1997 to 9 miles in 2012. Interestingly, in the same time period total annual commuting distance has decreased from 1425 miles per year in 1995/97 to 1318 miles per year in 2012. These figures are depicted in Figure 1.2. One possible explanation for this increase in average distance coupled with a decrease in total annual commuting distance is an increase in the number of

Figure 1.1: The Changes in Commuting Time in Britain: 1996-2012

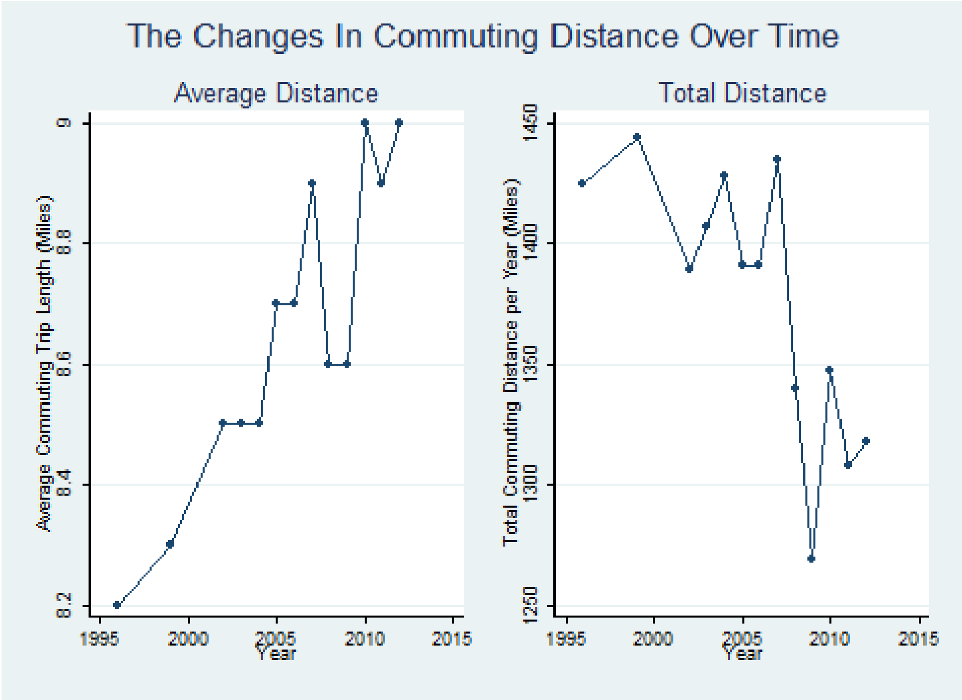


Source: NTS, DfT (2013)

people who now work from home at least one day a week, as documented by the Trades Union Congress (2013).

Using data from the British Household Panel Survey (BHPS) Benito and Oswald (2000) study patterns in commuting in the UK in the 1990s. They find that the average journey time (per-day) to be around 42 minutes for the whole of the UK, but considerably higher for London and the south east (whose daily commutes are 76 minutes and 66 minutes respectively). They go on to show that the length of the commute depends positively on educational attainment, with people who are educated to university degree level or higher typically commuting 50% more than those without degree level qualifications. They further find that homeowners typically commute further than renters. This is to be expected if housing rental markets are centred around places of high employment (e.g. Dodson, 2005).

Figure 1.2: The Changes in Commuting Distance in Britain: 1996-2012



Source: NTS, DfT (2013)

When examining mode choice there is consistent evidence that the most common mode of transport used to travel to work in the UK is driving a car or other private motor vehicle (ONS, 2013a, and NTS, 2013). However, the Office for National Statistics (2013b) do observe that while commuting to work by car is an increasing trend in the majority of the UK, there has in fact been a decrease in the number of people who drive to work in London between the 2001 and 2011 censuses. This is not entirely surprising given the report by the Transport Commons Committee (2012) which found that in 2010-2011 £18bn was spent on public transport in the UK, of which 34% was spent in London, by far the highest percentage of any region, with the North-West the next biggest spender with 13% of the budget. The London Congestion Charge (LCC) was also introduced between the two censuses, which is likely to be a significant factor in changing the mode of travel-to-work for many Londoners.

Until recently, the effect that commuting behaviour has on subjective well-being (SWB) in the UK has been an under-researched area. To our knowledge, Roberts et al. (2011) were the first to look at this relationship using UK data. Using the General Health Questionnaire (GHQ) score as a proxy for SWB they find that women are negatively affected by longer commutes, but men are not.

In a more recent development, the Office for National Statistics (2014) look at a number of SWB proxies with respect to commuting. These are life satisfaction, a feeling of worthwhileness, whether a person was happy yesterday, and whether or not they were anxious the previous day[1]. In the report, the Office for National Statistics (2014) acknowledge that the response to the questions are ordinal, but they use ordinary least squares (OLS) techniques to estimate their models. In the technical appendix they provide robustness checks, and find their results are robust to using the ordered probit model. Due to ease of interpretation they therefore report OLS estimates. They find that commuters (when compared to non-commuters) are less likely to be satisfied with life or have been happy yesterday, and less likely to feel worthwhile. Also they find that commuting does increases the chances of an individual being anxious. When focusing on the effect of commuting time (in minutes) they find the coefficient to be -0.002 on all positive outcomes (life satisfaction, worthwhileness, and happy the previous day), and 0.005 on the anxiety measure. These results are significant at the 5% level, and are robust to controlling

[1] The exact wording of the questions are: (1) Overall, how satisfied with you are your life nowadays? Answers are coded on a 1-10 scale, where 1 is *'not satisfied at all'* and 10 is *'completely satisfied.* (2) Overall, to what extent do you feel the things you do in your life are worthwhile? Answers are coded on a 1-10 scale, with 1 being *'not at all worthwhile'* and 10 being *'completely worthwhile'*. (3) Overall, how happy did you feel yesterday? Here, using the same 1-10 scale, 1 is *'not at all happy'* through to 10 being *'completely happy'*. (4) Overall, how anxious did you feel yesterday? For this question 1 was coded to be *'not at all anxious'* and 10 corresponds to *'completely anxious'*.

for observable socioeconomic factors known to correlated with SWB. These results indicate that longer commutes do lead to lower levels of SWB, and higher levels of anxiety. However, it is worth observing here that these results may not be causal, due to the cross-sectional nature of the data - this may simply be picking up the fact that individuals with low levels of SWB can only find ‘worse’ jobs. Finally, by including commuting time in banded groups, they show that if the one way daily commute is above 60 minutes then the results become larger than if compared to commuters whose daily commute is less than 15 minutes. This would tend to suggest a non-linear relationship between commuting and well-being, although this is not investigated further.

1.1.3 Possible costs and/or benefits of commuting

The fact that there is empirical evidence which implies that people with longer commutes have lower reported levels of SWB would tend to suggest that individuals are not operating as utility maximising agents, as microeconomic theory postulates they should. If the compensations required for partaking in longer commutes were fully met, we would expect the relationship between commuting and well-being to be insignificant. This negative relationship appears not to be constrained to the UK; Stutzer and Frey (2008) find that, using the German Socio-Economic Panel (GSOEP), workers in Germany with longer commutes report lower levels of SWB, as measured by overall life satisfaction. The authors imply their results indicate a *‘Commuting Paradox’* since workers are obviously not receiving sufficient compensation for partaking in longer commutes. We add to this growing body of empirical literature in Chapter 4 for individuals, and Chapter 5 for members of a couple.

Given that people with longer commutes are found to have lower levels of reported SWB according to the available empirical evidence, we postulate that these workers must be somehow receiving compensation through other channels. If there were no benefits at all to compensate for longer commutes, and peoples' well-being was negatively impacted upon by commuting, then rational individuals would not partake in the commutes. The obvious starting position is to consider income; if workers who travel further to work are worse off with respect to well-being, it may be possible that these individuals receive higher levels of financial compensation, in the form of higher pay. However, both Stutzer and Frey (2008) and Roberts et al. (2011) consider income as a compensating variable, yet still find evidence of a negative relationship between commuting and SWB. This may be due to the endogenous relationship between commuting and income, and we attempt to minimise this endogeneity in the first empirical chapter.

Income

Based on the existing literature, workers are apparently not maximising their SWB with respect to commuting. It may therefore be possible that workers are more interested in maximising their income. It was initially assumed by economists that considering either SWB or income as the maximand in a traditional utility maximisation framework should lead to essentially the same outcomes (Graham, 2012). In the late 1960's and early 1970's however, some questions began to emerge regarding the validity of this assumption. Robert Kennedy, in 1968, famously said that:

> *"GDP measures everything except that which is worthwhile."*

If we take the definition of GDP to be the total of all income within an economy, then the above quote implies that money, whilst important, is not the be all and end all for rational individuals.

In a seminal work in the economics of SWB, Easterlin (1974) showed that even though levels of GDP (and hence income) were increasing over time, levels of aggregate well-being in economies appeared to be relatively stable. He did observe, however, that within a given economy people with higher income did report higher well-being scores. His first finding, coupled with the second finding, denoted in the literature as "The Easterlin Paradox", does raise an interesting question: if people do not achieve higher levels of well-being with higher levels of income, should we use income or well-being as a measure of welfare? The Easterlin Paradox returns us the the question above; is the maximand in traditional utility theory monetary wealth? Or levels of well-being?

Subjective well-being

Despite the emergence of the Easterlin Paradox, research into SWB in the economics literature remained relatively low for the next 20 or so years. One possible explanation for this apparent reluctance by economists to use SWB as a valid outcome measure could be the fact that SWB is such a loosely defined term. Its origins lie within psychology and sociology, and it is defined broadly as *"people's cognitive and affective evaluations of their lives"*, (Diener, 2000, p.63). As such it can be thought of a term that encompasses people's emotions and beliefs about their current situation. Initially economists held the belief that due to this definition making inter-personal comparisons would be very difficult.

Clark and Oswald (1994) were the first of a new generation of economists that were prepared to use SWB measures as a proxy for utility. They examine the effects that unemployment has on well-being, and find evidence to reject the hypothesis of voluntary unemployment, finding that the unemployed have substantially lower levels of SWB than those in employment.

Following on from the work of Clark and Oswald (1994) was a paper by Frey and Stutzer (2002b) who deduce that well-being and utility can be directly measured and compared. They use responses to life satisfaction questions to ascertain the effect that income, inflation, and labour market status (amongst other things) have on SWB.

In a later attempt to verify the measures of SWB as a suitable proxy for utility, Oswald and Wu (2010) use data from the US to elicit the correlation between subjective and objective measures of well-being. Their subjective measures are responses to life-satisfaction style questions and their objective measures are characteristics of certain locations (such as sunshine and scenery as pleasant factors, and land prices and traffic fumes as negative factors). They find a statistically significant correlation, which the authors claim *"...has some potential to help unify disciplines"*, since this can be taken as evidence that there is a relationship between objective and subjective well-being measures.

Clark et al. (2008) revisit the Easterlin paradox, and add further evidence to the argument that it is relative income that is important to an individual - and not absolute income. Individuals will usually compare themselves to friends and peers, and as such their relative income levels (to a pre-determined reference group) is more important in determining their levels of SWB than their absolute income.

Based on this expanding body of literature, from an economic perspective it is now regarded that statements about SWB can be used as suitable proxies for an individual's level of utility (Frey and Stutzer, 2002b, Shields and Price, 2005, Gardner and Oswald, 2006, Kahneman and Krueger, 2006, Clark et al., 2008, Oswald and Wu, 2010). These SWB measures are viewed as a more representative measure of people's life as a whole, when compared to income.

The use of SWB at an aggregate level has received increasing attention in recent time. Many politicians now argue that GDP alone is not a suitable measure to capture the economic performance of a country. For example, in 2008 Nicolas Sarkozy (the then President of France) commissioned a report on measuring SWB at the national level. This report team was led by the noted economist Joseph Stiglitz, and included other notable economists such as Amartya Sen, Jean-Paul Fitoussi and Andrew Oswald. One of the main recommendations (Recommendation 10) to come out of the comprehensive report of Stiglitz et al. (2010) is given below:

> *"Measures of subjective well-being provide key information about people's quality of life. Statistical offices should incorporate questions to capture people's life evaluations, hedonic experiences and priorities in their own surveys."*

Stiglitz et al. (2010); p16[2]

[2] Also quoted on page 58 and page 216.

In the UK, Prime Minister David Cameron followed suit, and in 2010 commissioned the Office for National Statistics (ONS) to collect information relating to a number of national well-being indicators, such as happiness levels, life satisfaction scores and anxiety measures. The first ONS report on well-being in the UK was published in 2011 (Office for National Statistics, 2011) with a subsequent report published in 2013 (Office for National Statistics, 2013c).

Social capital

Another possible outcome of interest to an individual that may be affected by commuting is social capital. Alongside SWB, social capital is a term whose origins lie within the disciplines of psychology and sociology. Woolcock (1998) defined social capital as:

> *"...a broad term encompassing the norms and networks facilitating collective action for mutual benefit."*

Woolcock (1998); p.155

One of the main contributions to the social capital literature was the seminal book of Putnam (2000): Bowling Alone: The Collapse and Revival of American Community. In this book Putnam attempts to uncover why there has been a marked decline in social activities in America, and see if there are any policies that may be able to reverse this trend. To our knowledge there has been no detailed replication of Putnam (2000) using data from the UK. We aim to replicate a small piece of the comprehensive analysis of Putnam by looking at the relationship between social capital and travel behaviour in the presence of congestion charging.

Due to no precise definition of social capital existing, it is often difficult to choose suitable proxies for empirical analysis. Some of these proxies are outlined in chapter 3 of this thesis.

Social capital is different from SWB in the sense that social capital is more concerned with social cohesion, and encouraging participation in mutually beneficial activities at the local level. In this sense, social capital may in fact be a determinant of SWB.

Choice of methodology

Given that there are a number of alternative proxies available to attempt to quantify utility in the literature, it is important to understand the similarities and differences between these outcome measures of interest. For example, analysing SWB outcomes may be similar to analysing social capital outcomes if the proxies for social capital and SWB are similar. These outcomes are more likely to be ordinal in nature. When analysing income however, it is important to note that the outcome of interest is a cardinal measure. This number of available outcome measures implies that it is important to chose the right econometric methodology when analysing the commuting/utility relationship depending on whether the outcome is cardinal or ordinal.

Cardinality implies that two outcomes (levels of utility, say) may be directly compared, whereas ordinality implies that only the relative rankings of the two outcomes may be compared. As an example, cardinality allows us to assert that £200 is twice as ‘good’ than £100 (assuming rationality and non-satiation). However, an ordinal satisfaction score of 6 may not be twice as good as a reported score of 3. For an overview of the cardinality vs ordinality discussion, see Mandler (2006).

1.1.4 Aims of the Thesis

As we have demonstrated, commuting is an important part of the working week for the majority of working individuals. Commuting appears to be increasing at a steady rate, and as such it is important to see what impact longer commutes have on individuals, when measured against a number of different proxies for utility. We therefore aim to look at the relationship between commuting behaviour and utility, when using the three proxies for utility listed above, namely income, social capital and SWB, respectively.

Because of the methodological differences between the proxies for utility, we aim to utilise a number of econometric techniques to examine this relationship. We will, where appropriate, look to expand the current methodologies, and advocate the use of the theoretically correct technique when analysing ordinal data.

1.2 Structure and Content of Thesis

This thesis is broken down into four stand-alone empirical studies. Chapters 2, 3, 4 and 5 present these empirical analyses. Chapter 6 concludes. A brief summary of each of the empirical chapters is given below.

1.2.1 Brief Overview of Chapter 2

The first empirical chapter explores the relationship between commuting distance and income using data from the Annual Survey of Hours and Earnings. In the labour economics field there is a strong body of empirical literature that argues that there is likely to exist causality in the relationship between commuting and income, and that this causality is bidirectional; it is difficult to infer whether workers with longer commutes are compensated by higher wages, or whether workers enjoy higher wages as they are prepared to partake in longer commutes. Due to the potential reverse causal nature of the relationship, we focus on a subset of employees who experience an exogenous shock to their commuting distance. This shock is brought about by a change in workplace location, given the employee lives in the same household location and does the same job.

Chapter 2 closely follows the work of Mulalic et al. (2010, 2013), who focus on a similar sub-sample of individuals using Danish data. However, we use individual fixed-effects techniques to control for individual heterogeneity, whereas they use first differencing methods. We find evidence of strong serial correlation in the error terms when we implemented first differencing, so the majority of our analysis is based on individual worker fixed effects.

Our results indicate that there is a positive and statistically significant *causal* relationship between commuting distance and income. We find a one percent increase in one way commuting distance is compensated by a 0.0055% increase in annual (pre-tax) gross pay, and a 0.0077% increase in basic weekly pay. When we evaluate these figures at the sample means, they imply a 15km increase in commuting distance is compensated by a £7,558.43 increase in annual gross pay, and a £184.82 increase in basic weekly pay. These results are robust to the inclusion of a number of controls, such as if an employee has managerial status and the sector in which the firm operates.

The results for basic weekly pay and annual gross pay differ here, as basic weekly pay is likely to include overtime and the pay of workers who are not on a fixed salary. Annual gross pay, however, is the pay of individuals who have a salaried position, and as such may have greater job security. Due to these potential differences between the two types of pay, we deduce that it will be beneficial to examine them both separately.

When breaking our results down by observable demographics, we find that non-managers achieve higher percentage increases in pay (although lower monetary increases) and that employees in the public and private sectors do better than employees in local authorities, central government and the charitable/voluntary sectors.

There is evidence to suggest that workers who benefit from a reduction in commuting distance following exogenous workplace relocation also benefit from increases in pay. However, the effects are generally larger for employees whose commute increases.

1.2.2 Brief Overview of Chapter 3

The second empirical chapter looks at the effect that congestion charging policies have on levels of social capital. By focusing on the western extension to the London congestion charge, and exploiting unique data, we investigate what impact the western extension zone (WEZ) had on the number of visits to friends and family made by London residents.

By employing difference-in-difference (D-i-D) techniques, and a number of econometric methodologies, we determine that the frequency of visits made fell by a statistically significant amount after the implementation of the WEZ. However, when we look at the difference-in-difference coefficients, we find that they are rarely significant. We attribute this insignificance to a possible violation of the D-i-D assumptions.

We further observe a reduction in the number of visits made as a volunteer and/or carer. This reduction is likely to increase social exclusion, as the person that was visited before the WEZ may now no longer be visited, and hence may become socially excluded from their network of friends and family.

As we focus on such a small time frame, we deduce that the WEZ was the main factor for this reduction in social visits to friends and family. In the period we analyse, there were few other confounding factors reported in London that could have influenced people's decisions to make visits. We further find that these results are not driven by changes in income, and determine that congestion charging affects social capital through channels other than income.

1.2.3 Brief Overview of Chapter 4[3]

Chapter 4 aims to build on the research of Roberts et al. (2011) and Stutzer and Frey (2008) by using the BHPS to examine the impact that commuting time has on SWB. Using a number of proxies (including satisfaction with life overall, GHQ and satisfaction with leisure time) we investigate the impact that commuting time has on SWB.

We also add to the literature on the choice of methodology when analysing ordinal data with fixed effects. We find that there is very little difference between assuming ordinality or cardinality, but advocate the use of the fixed effects ordered logit model as we document a straightforward application of the results to make them more interpretable, which is analogous to the 'life satisfaction approach'. Whilst assuming cardinality appears to be empirically robust, there is no formal econometric proof to say that this should always be the case. As such we conclude that the fixed-effects ordered logit model should be utilised.

Unlike Stutzer and Frey (2008), we find no evidence of a negative relationship between commuting and SWB when considering life satisfaction. This is robust to looking at differences by gender, differences in the time period considered, differences by mode of travel, and including the self-employed. We deduce that their results may be German specific, and that further cross-country comparisons may be needed before a general consensus is agreed upon.

[3] **Disclaimer:** Chapter 4 is joint work with my two supervisors, Prof. Andy Dickerson and Dr. Arne Risa Hole. A condensed version of chapter 4 has been submitted to a spatial health econometric edition of Regional Science and Urban Economics and is currently under the revise and resubmit process.

We are able to replicate the results of Roberts et al. (2011) when our dependent variable is the same as theirs, namely GHQ. Commuting time, as expected, is always negatively associated with satisfaction with leisure time, which we take as a validation of our results. By definition, any increase in commuting time will lead to a decrease in time to be allocated between other activities, including leisure time. Therefore we postulate that the relationship between commuting and satisfaction with leisure time will be negative, and this is what we do find evidence of.

By considering a subset of individuals who experience an exogenous shock to commuting (individuals who live in the same home address and work for the same firm, but whose commuting time changes), we find further evidence to support our main finding; that there is no significant relationship between commuting and well-being. If there was an effect, this subset of the population are more likely to feel it. Conversely, we show there is a positive relationship between commuting and well-being for people who move house and/or job. However this relationship is likely to be endogenous as people who become so dissatisfied with their commutes are more likely to relocate closer to their place of work, and/or change employer. Finally, the type of job an individual has is an insignificant factor in the commuting/well-being relationship in this analysis.

1.2.4 Brief Overview of Chapter 5

Chapter 5 is a natural progression of chapter 4 in that we now turn our attention to studying couples (which we interchangeably define as households) instead of individuals. There is a small body of literature in urban economics that argues that household location decisions are made at the household level (see, for example Alonso, 1964, Mok, 2007). Despite this, there has been little or no empirical investigation into commuting and well-being at the household (or couple) level.

We consider three outcome measures in the analysis in this chapter: (i) the aggregated satisfaction score of the couple; (ii) the satisfaction score of the male; and (iii) the satisfaction score of the female. We then examine what impact male and female commuting times have on all three outcome measures. Actually defining outcome (i) takes some consideration here. Because this is a relatively new area of research, there is no widely accepted way of aggregating household level satisfaction scores. As we use fixed effects ordered logit (FE-OL) models we require our dependent variable to be ordinal, and as such we merely sum up the two member's life satisfaction scores to obtain the household score. By considering male and female satisfaction scores as functions of both own and spousal covariates allows us to consider household bargaining models, as proposed by Manser and Brown (1980), McElroy (1990), Lundberg and Pollak (1996), and Akerlof and Kranton (2000), amongst others.

For completeness we initially assume that only one member of the couple must be in employment, but later strengthen this to the restriction that both members must be working. This latter restriction does not appear to influence the results, from which we conclude that single and dual worker household are essentially similar in the context under consideration here.

Our results indicate that there is generally no significant relationship between male and female commuting times and aggregated couple life satisfaction. One exception in for dual worker couples between 2002 and 2008, where we do observe a significant negative relationship between female commuting time and couple satisfaction.

When we consider own life satisfaction as a function of both own and spousal characteristics, such that we allow bargaining models to operate at the household level i.e. members of a couple may bargain with each other when deciding on household location decisions, we again mostly observe statistical insignificance between commuting variables and well-being. From this we conclude that household bargaining must be efficient and equitable, as neither partner is worse off as a result of the other's commuting decisions. We further infer that household location decisions must have been made at the household level, consistent with the urban economics literature (e.g. Alonso, 1964, Mills, 1967).

The results of this chapter again confirm the finding that the choice between assuming ordinality or cardinality leads to essentially the same conclusions when analysing SWB scores.

Chapter 2

Is Income the Main Driver of Commuting Distance? Evidence from a quasi-natural experiment using data from ASHE

2.1 Introduction

There has long been a debate in the labour economics and urban economics literature as to the actual *causal* effect of commuting distance (and or/time) on wages. The labour economics literature focuses predominantly on the wage bargaining hypothesis which argues that longer commutes should, in theory, be compensated by higher wages - assuming the housing market is in equilibrium, that is people chose their place of residence based on a number of factors such as price, location, space, etc, see for example Zenou (2009). On the other hand, the urban economics literature assumes the labour market is in equilibrium (in the sense that individuals chose their place of work, subject to factors such as pay, prospects, satisfaction, etc, e.g. Manning (2003) and Zenou (2009)) and then workers try to minimise their daily commute subject to a number of constraints, such as quality and price of housing, the quality of neighbourhood etc.

However, both schools of thought are fraught with the possible endogeneity of commuting distance and wages. The relationship is endogenous in that fact that it is hard to determine whether workers tolerate longer commutes for higher wages, or workers have higher wages because they are prepared to tolerate longer commutes - that is to say it is hard to determine what influences what in this context. Gibbons and Machin (2006) and Manning (2003) both note that despite the vast number of studies that attempt the ascertain the relationship between commuting distance and income, there is virtually no direct conclusive empirical evidence of the causal relationship between the two. The literature argues that this lack of evidence is due to the fact that it is almost impossible to find suitable instruments for commuting distance to overcome the problems of endogeneity in an instrumental variable framework.

This study aims to elicit this *causal* relationship by bypassing instrumental variable analysis and building on the earlier work of Mulalic et al. (2010) (later published as Mulalic et al., 2013) by considering a sub-set of employees who experience an exogenous shock to their commuting distance. This exogenous shock is brought about by a change in work place location, given that the employee does not move house **and** they do the same job for the same company (*i.e.* they are not promoted/demoted, nor do they take a sideways step in employment). Therefore the change to commuting distance is exogenous in the sense that the employee has no direct say over it. This will be outlined further in the data section.

We focus predominantly on the labour economics side of the debate and assume that the location of the household is endogenously chosen depending on income. It is argued that compensation in terms of higher wages does not occur when commuters are fully compensated by lower housing prices (as argued by Zenou, 2009). However, as we stipulate that an individual is only in our sample if they do not move house, this issue is negated here as housing location is constant, and hence will drop out of any fixed-effects specification.

In a double logarithmic specification evaluated at the mean levels of commuting distance and income, with both worker and firm fixed effects, we find that a 50% increase in one-way daily commuting distance leads to a £7,558.43 increase in pre-tax annual gross pay. If we take the average daily commute for the whole period under consideration (31km), then an increase of (approximately) 15km to 46km leads to a seven and a half thousand pound increase in annual pay. This is a sizable sum. For basic weekly pay, a 50% increase on commuting distance (from 31km to 46km) leads to an increase of around £184.82 per week - again a sizable sum. In a linear specification we can deduce that commuting distance is inverse - U shaped with respect to wages, but the peak of the curve is well beyond any reasonable level of commuting distance ($>$ 350km, one way, per day).

When looking at different subgroups we find that non-managers gain more in percentage terms from an increase in commuting distance, but less in actual monetary terms. With respect to the sector in which the firm operates, we find that employees in the public sector do the best out of changes in commuting distance, followed by the private sector. Those employed in local authority also benefit, but central government employees do not. Finally, when considering increases in commuting distance against decreases, we find that it is not the direction of the change in commute that matters, merely that there has been a change. This result is consistent with the literature on wages following 'bad' and 'good' shocks, but inconsistent with economic theory.

This chapter proceeds as follows: Section 2 will discuss some of the existing literature on commuting and wages; Section 3 will outline the data and the methodology employed in this study; Section 4 will present the results and provide a discussion of these results. Finally, Section 5 will conclude.

2.2 Literature Review

The causal relationship between commuting and income has long been a source of frustration for economists. The relationship is so endogenous there is a debate as to which way round the regression models should actually be run. For example, Benito and Oswald (2000) and Gutirrez-i Puigarnau and van Ommeren (2013) argue that commuting distance should be a function of income, whereas as *inter alios* Manning (2003), van Ommeren and Rietveld (2005), and Mulalic et al. (2010, 2013) argue that in fact income should be a function of commuting distance. The lack of valid instruments to use in an instrumental variable set up has long been an issue of concern. These problems with endogeneity imply that no real understanding has been established in the literature of the true causal effect that commuting distance has on income.

We start by examining the literature on equilibrium job search models with bargaining power.

Whilst Marimon and Zilibotti (1999) are not interested in commuting *per-se*, they do build an equilibrium job search-matching model. Their primary focus lies in examining the effect that differing types of unemployment benefit have on an individual's job-search behaviour. To examine differing unemployment benefit systems they focus on the US and make comparisons to continental Europe. They assume risk neutral agents, such that employees and employers are both risk neutral. Their theoretical model is mathematically motivated, and as such technical detail is omitted here. Their main conclusion is that two (quasi-)common economies may well react completely differently following a technological shock depending on the unemployment benefit regime of the country. Their outcomes of interest include unemployment rates and wage inequality of those employees who do not become unemployed. They then use their model to attempt to ascertain why there are such marked differences between the US and Europe, when certain common factors are held constant between the two economies.

Despite the fact that the main aim of Marimon and Zilibotti (1999) is not to examine commuting behaviour, they do acknowledge that their model may be of interest to researchers interested in the effects on firms and workers following firm relocations. However, as their main policy variable of interest is unemployment (and job-search behaviour) and we focus on people who are employed, we are not able to test their theoretical model here. The model of Marimon and Zilibotti (1999) has been built upon in the literature, and we discuss some of those extensions in what follows.

van Ommeren and Rietveld (2005) aim to add to the literature on job search models by examining a subset of workers with endogenously chosen commuting costs[1]. They assume a uniformly distributed continuum of identical firms and places of residence over a homogenous two-dimensional space, in a closed economy. Further all individuals are identical, except that some are employed and some are not. By the definitions and assumptions of their model, only those individuals who are unemployed search for employment. Those who are employed face commuting (time) costs, t, proportional to the commuting distance between their home and place of work, d. The authors then impose further restrictions on their model and work through a number of possible scenarios, both for the employed and the unemployed. Their proposition that is of the most relevance to this chapter is their Proposition 1, which states that:

> *"Given the presence of bargaining power, $\beta < 1$, the wage w depends positively on the commuting costs t. The effect of the commuting costs on the wage is a negative function of the strength of the worker's bargaining position, measured by β."*

van Ommeren and Rietveld (2005); p443

[1] Their analysis is concerned with commuting time, whereas what we study here is commuting distance. It is argued that commuting time often best captures the opportunity cost of commuting (Stutzer and Frey, 2008), although in the absence of data on commuting time, we have to focus on distance in our analysis.

Therefore, they deduce that an employer-induced increase in commuting cost (which in our case will be commuting distance) should be met with compensation in the form of higher wages, assuming that there is bargaining power within the firm.

van Ommeren and Rietveld (2005) further go on to show that within their model there is a maximum commuting cost - a cost after which it no longer becomes beneficial for the employee to embark upon such a long commute. We can directly test this in our analysis by including a commuting distance squared term.

Whilst van Ommeren and Rietveld (2005) is a theoretical paper, their results (to our knowledge) have not been tested using real empirical data. We therefore aim to test their main hypotheses using actual observational data, based on an exogenous shock to commuting distance.

Further to the above, Pissarides (2000) notes that the share of commuting costs reimbursed through higher wages depends on the characteristics of the firm. For example, the firm must have market power, and the degree of market power the firm has can determine the level of reimbursement. Mulalic et al. (2010) note that if the labour market is perfectly competitive and the firm has no market power then the share is zero. Alternatively if the firm has full market power (*i.e.* is a true monopolist), then the share is one - such that an employee receives a wage which makes them indifferent between working and being unemployed, assuming suitable unemployment benefit. In most firms however, the share is likely to be in the interval $(0, 1)$.

In an influential paper Manning (2003) formulates a model that examines what happens when labour markets are 'thin'. He defines thin as a situation where there are few perspective employers within a reasonable[2] distance of workers, so that from the worker's perspective the labour market appears thin - due to the perceived lack of options. Another form of 'thin' labour markets is brought about by a number of large firms operating as an oligopsonist, and hence there appearing to be a lack of alternatives due to the interaction of the firms. Manning notes that there are two types of modern monopsony models: (i) models that assume full information on the part of the worker, and no mobility costs but jobs are in some way differentiated[3]; and (ii) search models that assume all jobs are identical, but there are search costs (in terms of time and money) associated with finding and moving to these new jobs[4]. Manning (2003) proposes the introduction of a third model of monopsony, which is outlined below.

Manning (2003) argues that a model should be characterised by both wages and location, but that new jobs arrive only occasionally. He then constructs a utility function, which is dependent on wages (positive effect) and travel time (negative effect). For simplicity he assumes that wages are distributed independently of employer location. The arrival rate of new jobs is independent of whether a person is employed or not. A key assumption is that the arrival rate of offers, at a given sensible level of commute, is considered finite. The main proposition of interest is Proposition 1 (a), which states that:

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[2] He places reasonable in quotation marks, and does not allude to the ranges of distances which may or may not be considered reasonable.

[3] For more information, see *inter alios*, Brueckner et al. (2002) and Hamilton et al. (2000).

[4] See, for example Albrecht and Axell (1984) and Burdett and Mortensen (1998).

The wage distribution across workers is increasing in the commute (...) if the wage offer distribution satisfies the condition that $ln[1 - F(w)]$ is concave in w.

Manning (2003);p110

where w is wages and $F(w)$ is the wage offer distribution. In part (b) of Proposition 1, Manning states that utility is decreasing in the commute; that is to say as an individual's commute increases their overall utility will fall. Whilst this is an interesting proposition, our data does not allow us to test for it here - however, we return to this debate later in the thesis in chapters 4 and 5. Further he argues that, together, Proposition 1 (a) and (b) imply that workers trade off wages and commuting time in a way such that it results in a compensating wage differential.

Manning (2003) then uses the Labour Force Survey (LFS), 1993 - 2001, and the British Household Panel Survey (BHPS), 1991 - 2000, to test his theories. For a sample of people who move job (the main focus of his analysis) he finds that the coefficient on commuting time in an earnings function to be 0.056 for the LFS sample and 0.058 for the BHPS sample. These results are robust to fixed effects specifications and controlling for education and occupation.

The paper that this current study is most closely related to is the work of Mulalic et al. (2010). Similar to what we do here, they analyse an exogenous shock in commuting brought about by workplace relocation. Their study utilises rich data from Denmark in order to elicit the magnitude of the share of commuting distance reimbursed through higher wage income in Denmark. They overcome the reverse causation problem by using a quasi-natural experiment based on workplace relocation[5], and to overcome the problem of unobserved variables (such as a worker's underlying level of skill) they used worker fixed-effects. They use data taken from 2003 - 2005 from Statistics Denmark. They have information on the location of an individual's home and their place of work. Income data is annual net wages (derived from worker's pay slips, as observed by the Danish Tax Authority). Following a number of selection criteria, some of which we employ in our study, they are left with a sample of 6,165 workers from 1,144 firms. However, they control for worker promotion, whereas we stipulate that an employee must have the same job pre- and post-workplace relocation. As expected their promotion variable (denoted change of worker function) has a positive and significant effect on wages.

Denmark offers tax relief for commuters with a commuting distance of over 12.5 km each way, and a further break for people whose commute exceeds 50km. Hence Mulalic et al. (2010) controls for individuals who fall into these categories. Their main result is that there is a positive relationship between commuting distance and income, independent of the length of commute. They find that a one kilometre increase in commuting distance leads to an increase in pay of about 0.42%. They conclude by stating that their results imply the wage bargaining parameter is approximately 0.5, for both commuters who are eligible for tax relief, and for those who are not.

In related work, Fujita et al. (1997) assume perfectly competitive labour markets and use this assumption to derive a theoretical model that seeks to determine what

[5] Which is essentially identical to the data selection process we use here (outlined in the next section).

happens when firms open new premises (mainly to encourage the formation of secondary employment centres) that are located far away from areas of high residency. Assuming a homogeneous labour force, they deduce that a *spatial wage gradient* will ensue - that is firms who locate far away from residential locations will have to compensate their workforce with higher wages. In an empirical test of this hypothesis, Timothy and Wheaton (2001) use data for two large metropolitan areas of the US, taken from the 1990 census, to estimate wage equations based upon the zone of employment of an individual. They show that the average commute of a worker in a given zone is highly correlated with the variation in the wages of equivalently similar workers (where 'equivalently similar' is based on observable characteristics such as age and gender etc.). That is, two workers who have (approximately) the same socioeconomic covariates, with the exception of commuting time, can have different levels of wages. They attribute the difference in wages to the difference in commuting time - hence validating the spatial wage gradient model of Fujita et al. (1997).

Another area of the labour economics literature that has exploited exogenous shocks to commuting behaviour is labour supply. Gutirrez-i Puigarnau and van Ommeren (2010) use employer induced changes to workplace location in attempt to tease out the causal effects on labour supply, measured in a number of different ways.[6] Their analysis is focused on German data taken from the German Socio-Economic Panel (SOEP), for 1997 - 2007. They impose a number of restrictions to ensure they only have employees with a positive commute, who are aged between 20 and 60. Similar to Mulalic et al. (2010) they employ first-difference wage equations. As they are

[6] They use weekly labour supply, number of workdays per week, and daily labour supply as measures.

concerned with labour supply, they include instruments for the wage rate. They find that, as an example, if an individual's daily one way commute increased from 20km to 40km then their labour supply would increase by, approximately, 15 minutes per week. This seems a rather small increase in labour supply for a 100% increase in commuting distance.

Such is the problem with the direction of the causation between income and commuting distance that Gutirrez-i Puigarnau and van Ommeren (2013) estimate an equation that has commuting distance as a function of labour market income. They use the reverse logic to that employed here; that is they consider a sub sample of people who keep the same job location but move house. They show that the elasticity of commuting distance to be 0.18 in the long run. They further show that the results differ depending on whether the household is a single wage-earner or not, with single wage earner households having a higher elasticity. Further, the elasticity is higher for males than it is for females. Whilst their results are informative, we are of the opinion that income should be a function of commuting distance, and not the other way around as they have it. Although they do attempt to account for possible confounding factors, it is our opinion that there is too much 'noise' associated with a household relocation decision, such as family size, age of children, occupation of spouse etc, and as such we focus on income being a function of commuting distance given no change in household location.

In an earlier study Benito and Oswald (2000), construct a theoretical model to examine the relationship between commuting and wages. They also estimate a model that stipulates commuting time should be a function of the wage rate of an individual. Using data from the BHPS, 1991 - 1997, they use instrumental variable techniques to attempt to elicit the relationship between the two variables of interest. They instrument the wage rate by trade union membership indicators, and public sector variables. They find that there is an inverse relationship between (instrumented) wage income and commuting time, which is not in line with the other studies in the literature. However, Manning (2003) shows that the results of Benito and Oswald (2000) are sensitive to the choice of instrument. This adds further weight to the argument that the IV approach may not be the most suitable method for dealing with the endogeneity of commuting and wages, as mentioned in Gibbons and Machin (2006).

To summarise, the general consensus is that there is a positive, albeit small, effect on income of changes in commuting distance.

2.3 Data and Methodology

2.3.1 Data

This chapter uses detailed wage data taken from the Annual Survey of Hours and Earnings (ASHE) from the period 1997 - 2012. The ASHE contains information on the distribution and make-up of earnings and hours worked for employees in the UK. It collects information from all industries and occupations. The ASHE is based on a random one per cent sample of employees. The sample is selected from HM Revenue & Customs (HMRC) PAYE records. Information on earnings and hours is obtained from employers, and as such the information regarding pay and wages is very detailed and accurate.

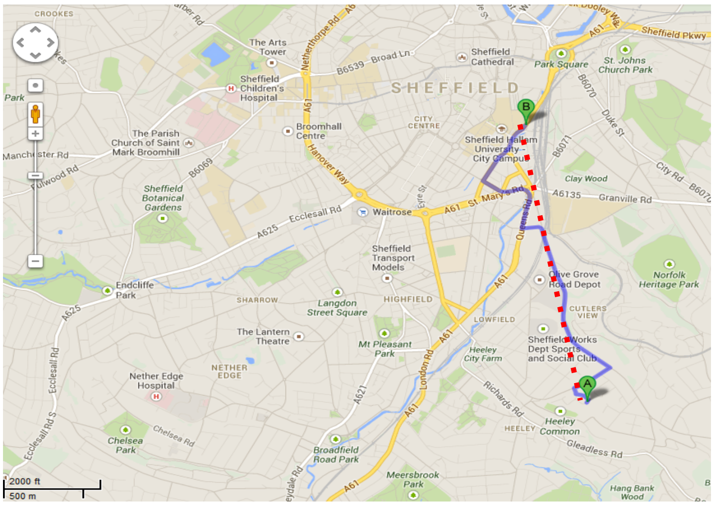
The ASHE does not collect information on those individuals who are self-employed, nor does it cover employees not paid during the reference period. Therefore our sample consists of people who are employed by other people/firms, and have a (from work) income that is greater than zero.

The main commuting distance variable of interest to us here is an approximation. ASHE collects information on an individual's home postcode and their work postcode, but not detailed infirmation on their daily commute. We therefore use a rather crude approximation - we take the Euclidian distance as an approximation. That is we take distance of the straight line (in kilometres) connecting the two points. Certain software packages allow you to calculate the actual road distance between two points, which would give a more precise definition of the actual commuting distance. However, the 'postcodes' given in the ASHE are not the real postcodes given by the firms (due to disclosure reasons), they are ' VML simulated postcodes'. By definition, and construction however, the distance between any two simulated postcodes is identically equal to the distance between the real postcodes, and as such we use this Euclidean distance as an approximation to the actual commuting distance.

A disadvantage of using Euclidian distance is that it will almost always produce an underestimate of the actual travel distance. For example, in Figure 2.1 the dotted line shows the Euclidian distance between points A and B whereas the actual travel distance, as predicted by Google Maps, is shown by the solid line. It is clear that the solid line is longer than the dotted line.

In the transportation research literature several studies have attempted to ascertain

Figure 2.1: Euclidian Distance as an Approximation to Actual Travel Distance



Source: https://maps.google.co.uk/. Dotted line added in Inkscape.

the relationship between actual commuting distance along road networks and the Euclidean approximation. Newell (1980) was first to examine the relationship, and found that 'real' network distance was approximately 1.2 times larger than the Euclidean approximation. O'Sullivan and Morrall (1996) then focused specifically on journey made from home to light rail transit stations on foot in Calgary, Canada, and estimated the scale factor of real network:Euclidean distance to be between 1.21 and 1.23 for journeys to and from the light rail stations. Levinson and El-Geneidy (2009) focus on twenty metropolitan regions in the United States, and derive the scale factor to be between 1.20 and 1.30 for commuting distances between 15km (for 1.30) and 50km (for 1.20) - i.e. the scale factor decreases as the length of the commute increases. For journey of less than 5km they find Euclidean approximation to be 1.58 times smaller. Ballou et al. (2002) conduct a cross county comparison, and find the scale factor for England to be 1.40, compared to 1.46 for Europe as a whole, and 1.20 for the United States, consistent with Levinson and El-Geneidy (2009). Therefore there would appear to be a common consensus in the literature that the scale factor is between 1.2 and 1.3 from the US and Canada, and slightly higher at 1.4 for England. We refrain from using these figure however, as this would introduce more variation around any parameter estimates we obtain.

Further, we do not have any information on the mode of travel that an individual chooses to use, nor on their travel time. We may surmise that people with longer commutes will have to use either public transport or private vehicles, but in contrast we cannot make any assumptions of the mode of travel employed by people with a relatively short commute. In analysing the National Travel Survey, Stokes and Lucas (2011) show that households with higher income are more likely to have access to a car and further are more likely to make trips to work in a car. Conversely, people in lower income quintiles are more likely to walk and use public transport. Bamberg et al. (2003) and Scheiner and Holz-Rau (2007) argue that people's habitual choice of mode of travel to work may be influenced by 'life-events', such as moving home and/or changing jobs. This may indicate that at least some of the people in our sample may alter the way they travel to work after they experience the exogenous shock to their commuting distance. However, we cannot control for this possibility in this current work.

Stokes and Lucas (2011) documents the fact that people who are engaged in full time work have different patterns of commuting distance and time than both those who are not working and those who are working part time. Individuals who work full time have longer commuting distances than both non-workers and part time workers. For that reason our analysis here is concerned with people who are working full time - as indicated by the question relating to full time employment contained within the ASHE.

We use two measures of wage data: (1) basic weekly pay and (2) annual gross pay. Basic weekly pay is the pay an individual receives per week without overtime. If an individual is on an annual salary this basic weekly pay is the salary divided through by weeks in a year, whereas for non-salaried employees we use the provided data. Annual gross pay is pre-tax total pay earned throughout the tax year. As we consider a relatively large time frame, we deflate income to 2005 prices by dividing by the relevant consumer price index (CPI), taken from the Office of National Statistics website (Office for National Statistics, 2013a).

We start with all data from 2000 - 2012 and then impose certain restrictions upon the data in order to obtain our estimation data set. Table 2.1 shows the various restrictions we impose, and the resulting loss of data that this causes. We are left with 144,355 observations from the years 2002 - 2011. It is worth noting here that we lose all data prior to 2000 by using the Standard Occupational Classification (SOC2000) index (2000 version) as all data prior to 2000 are unclassified on SOC2000.

As a starting point, in Table 2.2 we present the basic correlations between commuting distance and (a) deflated annual gross pay and (b) deflated basic weekly pay. As we can see, there is always a positive (and significant) correlation between commuting distance and income following an exogenous shock to commuting, implying that there is financial compensation for longer commutes. We also present the correlations between changes in commuting distance and changes in income by year. These appear to be relatively stable at around 0.01 (for annual income) and 0.026 (for weekly basic pay), which is lower than the figure of 0.08 for Denmark between 2003 and 2005 (as reported in Mulalic et al., 2010) and for a range of other studies, as summarised in Manning (2003). However, the results in Manning include

Table 2.1: Estimation Data Set Generation Process

Restriction/Reason for Dropping	N
Initial sample size	2,779,411
Duplicates[a]	2,440,643
Need at least two periods of data	2,361,305
Full Time (*i.e.* drop part time employees)	1,700,283
People who have the same job[b] in the same firm	1,157,302
People who do **not** move house	698,359
People whose workplace location does move	187,366
At least two periods of data and 'Winsorised'[c]	144,355
Final Sample Size	**144,355**

a: The rolling panel nature of ASHE implies that certain observations are included twice (*i.e.* at the end of, say, the 2004 - 2006 panel and the beginning of the 2006 - 2012 panel).
b: To meet this criteria and individual must (i) have the same job as last year (as indicated by their employer stating so); and (ii) have the same Standard Occupational Classification (2000 scale) between the periods of interest.
c: We drop data from the top and bottom 1% of the distribution of wages, age, and commuting distance. For example, we drop an observation of a one way commuting distance of over 1,000 km and an individual whose age was 102.

endogenous changes in commuting, and the paper by Mulalic uses a gap of two years, as opposed to the year-by-year correlations we present in Table 2.2. To check the robustness of the correlations reported in Table 2.2, we examine the correlation between all changes in commuting distance (i.e. exogenous and endogenous) in the ASHE and compare. Focusing on AGP we get values that appear consistent at around 0.08-0.1 for the period 2002-2011[7] - so when we consider all possible changes in commuting distance we can replicate the findings of Mulalic et al. (2010) and Manning (2003).

It can be seen that in levels the correlation between commuting distance is stronger with annual gross pay, whereas when considering the correlation in the differences

[7] The figures for the correlation in the changes for 2002 - 2011 are respectively: 0.0793, 0.0892, 0.0894, 0.0901, 0.0883, 0.0927, 0.0839, 0.0951, 0.1003, and 0.0954, all of which are significant even at the 1% level.

it is the change in basic weekly pay that is more highly correlated with the change in commuting distance.

Table 2.2: Basic Correlations Across Time and for the Whole Period

	Correlation with Commuting Distance[a]		Correlation in the Changes[b]	
	Deflated AGP	**Deflated BWP**	**Deflated AGP**	**Deflated BWP**
2002	0.1124***	0.1046***	0.0101***	0.0262***
2003	0.0862***	0.0772***	0.0101***	0.0260***
2004	0.1199***	0.1101***	0.0101***	0.0260***
2005	0.1315***	0.1080***	0.0100***	0.0259***
2006	0.0958***	0.0873***	0.0100***	0.0258***
2007	0.1092***	0.1068***	0.0100***	0.0257***
2008	0.1042***	0.1010***	0.0099***	0.0258***
2009	0.0975***	0.0957***	0.0100***	0.0258***
2010	0.0840***	0.0829***	0.0101***	0.0262***
2011	0.1046***	0.1164***	0.0101***	0.0262***
Whole Period	0.1056***	0.0981***	0.0091***	0.0239***

*** $p < 0.01$ (Bonferroni standard errors and significance)
a Defined as corr(y, c) where y is income and c is commuting distance.
b Defined as corr$(\Delta y, \Delta c)$ where y is income and c is commuting distance and Δ is the difference operator.

From the ASHE data we obtain information on the age of the employee. We also observe whether an individual has a managerial role within the firm. Unfortunately a noticeable limitation of using ASHE data is that there is only a limited number of socioeconomic control variables. For example, we cannot control for the ethnicity of an individual nor can we observe the educational attainments of individuals, and hence we cannot control for this. We can justify their omission here as we utilise fixed effects techniques in this analysis, and as gender and ethnicity are assumed to be fixed, they do not contribute to a fixed effects model specification. However, it may have been informative to run separate regressions by observable controls - such as gender - but that is not possible here. For education, we assume that the majority of employees do not change their highest level of educational attainment once they have entered employment, and hence this would also drop out of fixed effects specifications.

For the firm, we observe which sector the firm operates in. The categories are private sector (the omitted category in the regressions we run), a public corporation, central government, local authority, and other (such as voluntary etc). It may have been beneficial to control for the size of the firm, by using measures such as total output (as used by Mulalic et al., 2010), but again we do not have access to this information here.

Table 2.3 provides summary statistics for some key variables included in the regressions. We can see that the average age of a person in our sample is roughly 42 years old. The average (deflated) gross annual pay is £27,435.31 whereas the average deflated basic weekly pay is £480.67. Deflation of income is necessary here as we have data over a long period when prices change, and the period around the 2008 recession is included in our analysis. The majority of the people in this analysis work in the private sector (the omitted category), with local authority and central government employees making up the next two most populated employment group.

Table 2.4 reports similar descriptive statistics for individuals who relocate their household, following an exogenous workplace relocation. These individuals commute for slightly less (30.84km vs. 31.08km) and earn more (£28,419.86 per years vs. £27435.31 per year). Individuals who relocate their house are also, on average, younger (38 years of age vs. 42).

For further comparison, we include descriptive statistics for the whole ASHE data in Table 2.16 in the appendix. When comparing between the whole sample and our estimation sample we can observe that the average commuting distance is 10km higher for our estimation sample (that is to say individuals in our sample commute, on average, for 50% more than individuals in the whole ASHE survey). When looking at (deflated) pay measures large discrepancies occur: for AGP people in our sample receive, on average, twice as much pay that the whole sample (£27,435 compared to £14,320). However, the standard deviation for the whole sample (£27,438) is considerably larger than the standard deviation for our estimation sample (£17,235). The same is true for BWP. We note that these differences are likely to be caused by the fact that our sample only includes employees who are employed on a full-time basis, such that the part-time employees in the overall sample may cause the lower average pay. Finally, people in our sample are roughly two years older than the corresponding figure for the whole sample.

Table 2.3: Selected Descriptive Statistics* for the Whole Period, for our Estimation Dataset (*i.e.* Change in job location, but no change in household location

Variable	Obs.	Mean	Std. Dev
Commuting Distance (km), one way	144355	31.08	63.33
Deflated Annual Gross Pay (AGP)	144355	27435.31	17236.58
Deflated Basic Weekly Pay (BWP)	144355	480.68	278.45
Age	144355	41.67	10.80
Male	144355	0.62	0.49
Manager (d)	144355	0.22	0.42
Private Sector (d)	144355	0.61	0.42
Public Corporation (d)	144355	0.03	0.16
Central Government (d)	144355	0.13	0.33
Local Authority (d)	144355	0.15	0.36
Other Type of Firm (d)	144355	0.08	0.27

Notes:
$*$ It was not possible to include maximum and minimum values due to anonymity concerns.
(d) indicates a dummy variable.

Table 2.4: Selected Descriptive Statistics* for the Whole Period, for our individuals who move both workplace and home location - *i.e.* workers who relocate their home following workplace relocation

Variable	Obs.	Mean	Std. Dev
Commuting Distance (km), one way	12688	30.84	62.64
Deflated Annual Gross Pay (AGP)	12688	28419.86	17387.41
Deflated Basic Weekly Pay (BWP)	12688	495.67	276.73
Age	12688	37.62	9.99
Male	12688	0.64	0.48
Manager (d)	12688	0.25	0.43
Private Sector (d)	12688	0.59	0.49
Public Corporation (d)	12688	0.09	0.28
Central Government (d)	12688	0.13	0.33
Local Authority (d)	12688	0.10	0.30
Other Type of Firm (d)	12688	0.09	0.28

Notes:
* It was not possible to include maximum and minimum values due to anonymity concerns.
(d) indicates a dummy variable.

Table 2.5 shows the average commuting distance, alongside the average deflated annual gross pay and the average deflated basic weekly pay by year. This information is shown graphically in Figure 2.2. We can see that average commuting distance initially increases between 2002 and 2003, and then falls between 2003 and 2005. After 2005 commuting distance steadily rose up until 2010, after which it decreases. Average deflated annual gross pay steadily increases up to 2008, after which it falls. This is as expected due to the well documented financial crises after 2008. A similar pattern is observed for deflated basic weekly pay.

Figure 2.3 graphs the trends in the mean change in commuting distance against the mean change in income. Mean changes in commuting time appears to fluctuate around zero. The mean change in annual gross pay steadily increases between 2002 and 2007, after which is plateaus out for a year, and then declines quite rapidly afterwards. A similar pattern for basic weekly pay is observed, only BWP appears to flatten out a year earlier at 2006.

Table 2.5: Selected Descriptive Statistics by Year

Year	Commuting Distance (km)	Def. Annual Gross Pay (£)	Def. Basic Weekly Pay (£)
2002	29.97	25718.62	450.23
2003	33.08	26329.52	467.13
2004	30.91	27206.63	477.55
2005	27.31	27691.04	480.70
2006	29.55	27737.43	482.44
2007	30.94	28518.09	496.14
2008	31.74	28860.47	503.07
2009	32.72	28552.47	502.50
2010	33.77	27707.86	486.94
2011	32.18	26945.60	476.40

Figure 2.2: Trends in Commuting Distance and Income Across Time

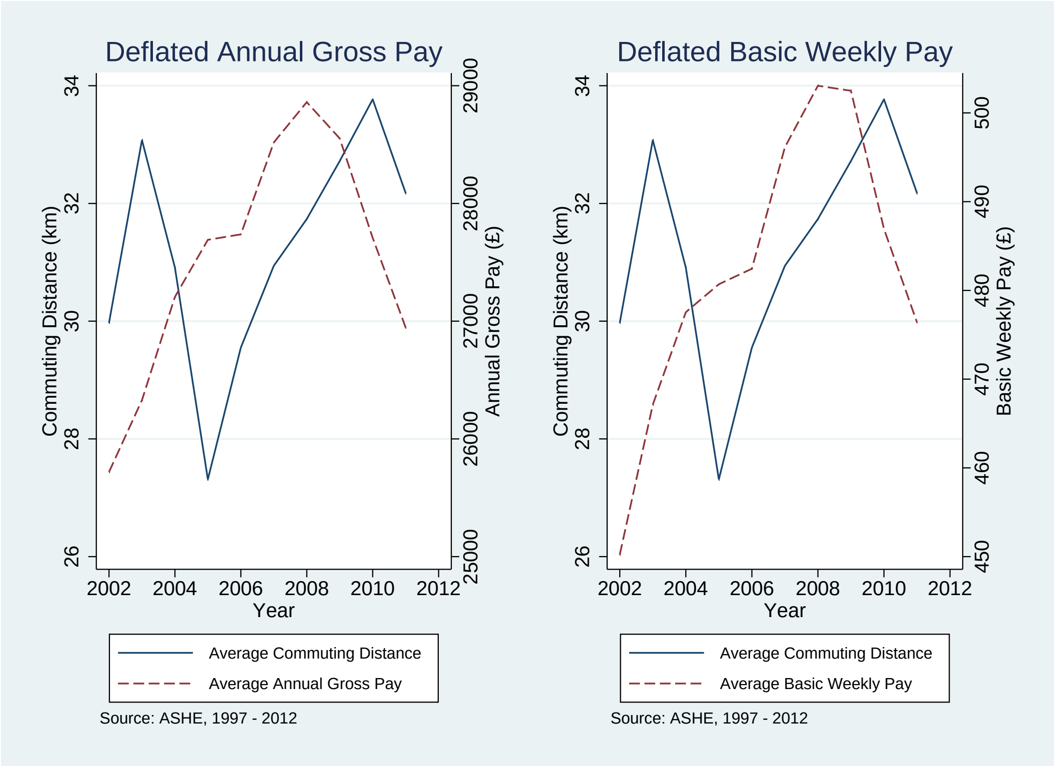
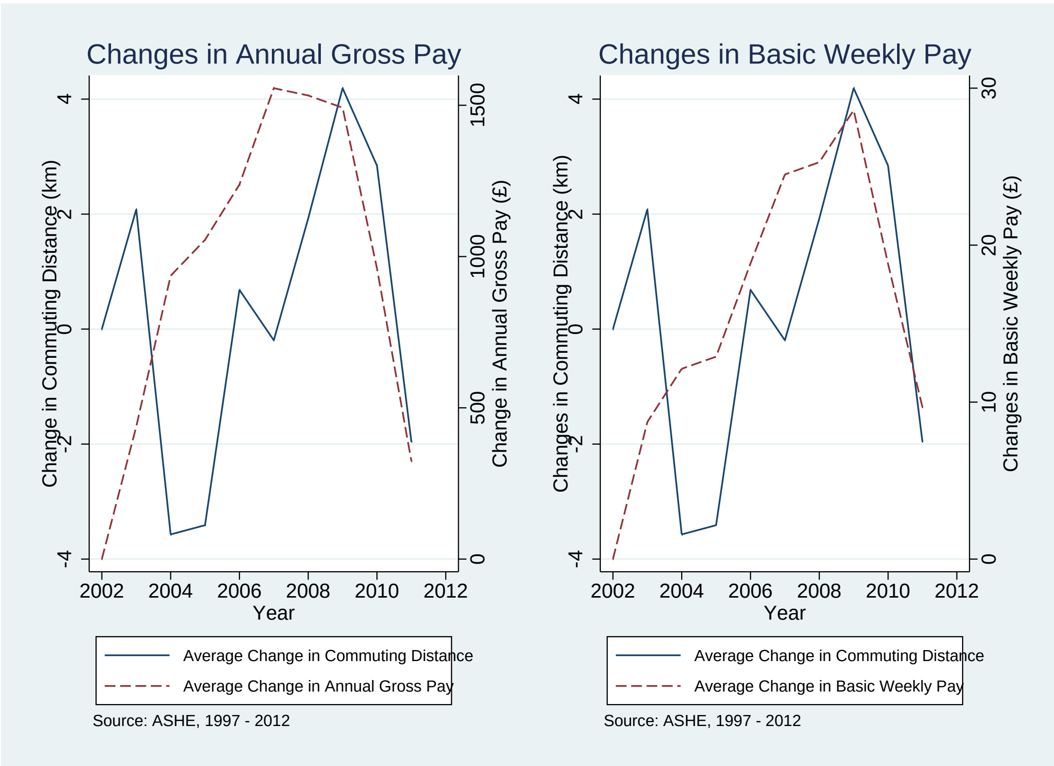


Figure 2.3: Trends in the Changes in Commuting Distance and Income Across Time



Notess:
These figures are based on the 144,355 individuals in our analysis and not on the full ASHE sample. Income is deflated to 2005 prices using the Consumer Price Index.

2.3.2 Economic Model

Let c_{ift} and w_{ift} be the commuting distance and (weekly basic or annual gross) wage income of individual i in firm f at time t, respectively. Then, following Mulalic et al. (2010) the initial model of interest here is:

$$\ln(w_{ift}) = \alpha_0 + \alpha_1 \ln(c_{ift}) + \boldsymbol{\alpha}_2 \mathbf{X}_{ift} + \nu_{ft} + \varepsilon_i + u_{ift} \tag{2.1}$$

where $\mathbf{X}_{it}$ is a matrix of observable exogenous time-varying control variables relating to individual i and firm f at time t, and $\boldsymbol{\alpha}_2$ are the associated coefficients. ε_i is an individual (worker) fixed effect, and u_{ift} is the overall error term in the model. An example of a possible component of ε_i is the underlying skills that an individual possesses. ν_{ft} is the year specific firm fixed effect, and includes information on the type of firm etc. The information contained in ν_{ft} in this analysis is not as rich as in the paper by Mulalic et al. (2010).

Mulalic et al. (2010, 2013) then consider first difference version of Eq. 2.1, defined here as:

$$\ln(w_{ift}) - \ln(w_{ift-1}) = \beta_1(\ln(c_{ift}) - \ln(c_{ift-1})) + \boldsymbol{\beta}_2(\mathbf{X}_{ift} - \mathbf{X}_{ift-1}) + \mu_{ft} + \tau_{ift} \tag{2.2}$$

where $\tau_{ift} = u_{ift} - u_{ift-1}$ and $\mu_{ft} = \nu_{ft} - \nu_{ft-1}$. This allows us to control for changes in the characteristics of the firm whilst estimating the causal effect of a change in commuting distance on changes in annual and weekly pay. Consistent estimation of the parameter of interest, β_1, requires that $\Delta c_{if} = c_{ift} - c_{ift-1}$ is exogenous and as such is not related to the changes in the error term τ_{ift}.

As the change in commuting distance, Δc, can be negative and we consider the natural logarithmic transformation of commuting distance we need to do the following: (i) take the (natural) log of the *absolute* change in commuting distance, and then (ii) multiply this by -1 if the change in negative. That is , we have:

$$\ln(\Delta c) = \begin{cases} = \ln(\Delta c) \quad \text{if} \quad \Delta c > 0 \\ \\ = -1 \times \ln(|\Delta c|) \quad \text{if} \quad \Delta c < 0 \end{cases}$$

Mulalic et al. (2010, 2013) estimate Eq. 2.2 based on comparisons between $T = 2$ years of data[8]. For $T = 2$ fixed effects (FE - Eq. 2.1) and first differencing (FD - Eq. 2.2) give identical results, however for $T > 2$ the results are dependent on which methodology is employed. Both FE and FD techniques are consistent and both are unbiased (see, for example, Wooldridge, 2012), such that unbiasedness cannot be used as a model selection criterion. Therefore other methods, along with some subjective judgement, must be made use of when determining which of FE or FD to use.

One possible argument for using FE is that we only lose one observation if there is a 'gap' in the time series for an individual,[9] whilst you lose two observations with FD when there is a single period missing. For example, in the analysis that follows for the FD model we have $n = 47,479$, compared to $n = 140,951$ in 53,950 groups for FE. Due to the nature of ASHE (that is, it is a legal requirement for the firm to complete the questionnaire), we initially thought this discrepancy was too high.

[8] Initially the estimate 2003 vs 2005 -the short run-, and then estimate 2003 vs 2007 - the long run.

[9] That is, if one or two years of information for a particular individual is missing.

However, when examining the data in more detail we attribute it to people who work in firms that make more than one change in workplace location whilst the individual is in our sample. We do further acknowledge that there are cases of non-reporting by some firms, and hence ASHE does not have a 100% response rate.

FE is also more efficient when the errors terms u_{it} in a FD model are serially correlated, which can be tested by estimating the residual from the FD model and regressing this as a function of the lagged residuals (see, e.g., Wooldridge, 2012 and Greene, 2008). Denote the estimated residual from Eq. 2.2 by $\tau r_{it} = \Delta u_{ift}$, and then estimate the model:

$$\tau_{ift} = \rho_1 \tau_{ift-1} + \rho_2 \tau_{ift-2} + ... + e_{ift} \tag{2.3}$$

If the FD model exhibits substantial serial correlation the parameters ρ_j in Eq. 2.3 will be statistically significant. Estimating Eq. 2.3 including up to lag 3 yields the results:

Table 2.6: A test for serial correlation in the error terms

	AGP Model	BWP Model
Lag 1	-0.4803***	-0.2711***
	(0.0354)	(0.0323)
Lag 2	-0.2515***	-0.0971***
	(0.0453)	(0.0316)
Lag 3	-0.0206	-0.0123
	(0.0424)	(0.0254)
N	20077	20077

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From the results in Table 2.6 it can be seen that the ρ coefficients on the first two lags are significant at the 1% level, independent of which measure of pay we are interested in. From this we conclude there is evidence of substantial negative serial correlation in the Δu_{ift} terms, and hence prefer the FE model specification.

To ensure that this change in commuting distance is exogenous we focus on a specific sub sample of the data. We select only individuals who work for the same firm doing the same job given that the firm has relocated to different premises. To ensure that the same job marker[10] in the ASHE is correctly defined and interpreted we also ensure that the Standard Occupational Classification code (OCC) is consistent for the individual employee of interest. This strict criterion ensures that the change in commuting distance is the result of an employer induced relocation of the workplace and is thus exogenous to the employee. We implicitly assume that the set of firms who decide to relocate is random - although we do control for year specific firm fixed effects. Secondly, we ensure that the individual employee has not moved their home location.

Together, the above two criteria ensure that changes in commuting distance are brought about by exogenous shocks. Mulalic et al. (2010) argue that these shocks are usually unexpected as firms do not like to announce too long in advance of a planned workplace relocation to minimise disruption due to uncertainty, and to lower worker job quitting behaviour and absenteeism.

We initially estimate Eq. 2.1 using both fixed effects and random effects and run

[10] The ASHE data has a variables -*sjob*- which is equal to one if the employee has the same job as they did in the previous wave, and zero if their job description has changed.

a Hausman test to see if using fixed effects is required due to random effects being inconsistent. Let $\widehat{\delta}_{RE}$ and $\widehat{\delta}_{FE}$ denote the vectors of random effects estimates (less the coefficients on time-constant variables) and fixed effects estimates, respectively. Similarly, let $V\left(\widehat{\delta}_i\right)$ denote the covariance matrix of specification $i = RE, FE$. Then the Hausman test statistic is:

$$H = \left(\widehat{\delta}_{RE} - \widehat{\delta}_{FE}\right)' \left[V\left(\widehat{\delta}_{FE}\right) - V\left(\widehat{\delta}_{RE}\right)\right]^{-1} \left(\widehat{\delta}_{RE} - \widehat{\delta}_{FE}\right)$$

The test statistic, H, is assumed to follow a Chi-squared distribution, such that $H \sim \chi^2_M$, where M is the number of coefficients. The null hypothesis is that the unobserved effect is uncorrelated with the explanatory variables (*i.e.*, RE is consistent). If we can reject the null hypothesis, then we favour the fixed effects specification.

2.4 Results

As mentioned in the previous section, we find evidence of substantial negative serial correlation in the FD model, and as such we focus on FE specifications. For completeness, we include the FD results from the basic specification in an appendix (Table 2.17), although discussion of these results is omitted here.

As also outlined above, we initially consider both FE and RE specifications to allow us to test which provides the most efficient and consistent results. Tables 2.7 and 2.8 show the results of the basic RE and FE regressions for annual gross pay and basic weekly pay, respectively. The Hausman Test statistic for AGP is $H = 323335.97$, and follows a χ^2_{15} distribution, such that we can overwhelmingly reject the null hypothesis that RE is consistent, and deduce we favour the FE specifications. Similarly, the test statistic for BWP is $H = 40805.04$, and again we overwhelmingly reject the null hypothesis that RE is consistent. Now that we have establised that the FE specification is the preferred specification of choice, we present the results of various functional forms below. Table 2.9 shows the results of the first functional form considered: the double log model.

Table 2.7: **Fixed Effects vs Random Effects Test on Basic Specification for Annual Gross Pay**

	$\widehat{\delta}_{FE}$	$\widehat{\delta}_{RE}$	$\left(\widehat{\delta}_{FE} - \widehat{\delta}_{RE}\right)$	$V\left(\widehat{\delta}_{FE}\right) - V\left(\widehat{\delta}_{RE}\right)$
log(Commuting Distance)	0.0055076	0.0203097	-0.0148021	0.0001303
Age	0.0820743	0.0808016	0.0012728	0.0016568
Age Squared	-0.0008633	-0.0008893	0.0000259	7.47E-06
Manager	0.0364382	0.0906576	-0.0542194	0.0004584
Yr02	-0.0779787	-0.1062808	0.0283021	0.0124164
Yr03	-0.0689982	-0.1117386	0.0427403	0.0110404
Yr04	-0.0371972	-0.0759894	0.0387922	0.0096308
Yr05	-0.016379	-0.0522114	0.0358324	0.0082941
Yr06	0.0005972	-0.0353117	0.0359089	0.0068458
Yr07	0.0200176	-0.0120036	0.0320212	0.0055673
Yr09	0.0407534	0.009615	0.0311384	0.0028298
Yr10	0.0239669	-0.0068022	0.0307691	0.0009962
Public Corporations	0.0066618	0.0021787	0.0044831	0.0025159
Central Government	-0.0220745	-0.0210889	-0.0009856	0.0042032
Local Authority	-0.0192443	0.0002481	-0.0194925	0.0038715
Other Firm Status	-0.0563466	-0.0723516	0.0160051	0.0021735
Chi2(15)=23335.97				
Prob>Chi2=0.0000				

Table 2.8: Fixed Effects vs Random Effects Test on Basic Specification for Basic Weekly Pay

	$\widehat{\delta}_{FE}$	$\widehat{\delta}_{RE}$	$\left(\widehat{\delta}_{FE} - \widehat{\delta}_{RE}\right)$	$V\left(\widehat{\delta}_{FE}\right) - V\left(\widehat{\delta}_{RE}\right)$
log(Commuting Distance)	0.0076931	0.0193583	-0.0116652	0.0000785
Age	0.0662363	0.0673465	-0.0011102	0.0014232
Age Squared	-0.0007	-0.0007393	0.0000393	6.02E-06
Manager	0.0433709	0.0904953	-0.0471244	0.0002704
Yr02	-0.09133	-0.1007079	0.0093779	0.0107702
Yr03	-0.0749908	-0.0976856	0.0226948	0.0095768
Yr04	-0.0479799	-0.0681254	0.0201455	0.008354
Yr05	-0.0375468	-0.056059	0.0185123	0.0071939
Yr06	-0.0173632	-0.0364945	0.0191313	0.0059365
Yr07	0.0032122	-0.01288	0.0160922	0.0048258
Yr09	0.0311688	0.0149327	0.0162361	0.00244
Yr10	0.0156823	-0.0014596	0.0171419	0.0007977
Public Corporations	0.0735559	0.0563625	0.0171934	0.0018763
Central Government	-0.020911	0.0125679	-0.0334789	0.0034297
Local Authority	0.0037872	0.0496964	-0.0459091	0.0031588
Other Firm Status	-0.0169216	-0.0109052	-0.0060164	0.001691
		Chi2(15)=40805.04		
		Prob>Chi2=0.0000		

Column (1) of Table 2.9 shows that a 1% increase in commuting distance will be compensated, on average, by a 0.00551% increase in annual gross pay (after deflation). If we take the average pay for the whole period (in 2005 prices) of £27,435.31, then we see the annual pre tax gain in income is £151.17. Similarly, column (2) of Table 2.9 shows that a 1% increase in commuting distance will be compensated, on average, by a 0.00769% increase in weekly pay. Again using the average weekly pay for the whole period, this compensation is £3.70 per week, based on the average weekly pay of £480.68. These values are statistically significant, but monetarily quite small. However, we need to consider whether it is appropriate to discuss a 1% increase in commuting distance. More realistically we will consider a 50% increase in commuting distance (*i.e.* from 31km to 46km one way, per day at the mean). Again using the average for the whole period, a 50% increase in commuting distance will increase annual gross pay by £7,558.43 and increase basic weekly pay by £184.82. Further detail of how these monetary values were calculated are presented in Table

Table 2.9: Log-Log and Log-Linear Wage Models with Individual Fixed-Effects

	(1) log(AGP)	(2) log(BWP)	(3) log(AGP)	(4) log(BWP)
log(Commuting Distance)	0.00551***	0.00769***		
	(0.000812)	(0.000716)		
Commuting Distance / 100			0.00938***	0.0153***
			(0.0000267)	(0.0000230)
Commuting Distance Squared / 10000			-0.00153**	-0.00166***
			(5.30e-08)	(4.48e-08)
Age	0.0821***	0.0662***	0.0817***	0.0666***
	(0.00706)	(0.00517)	(0.00686)	(0.00504)
Age Squared / 100	-0.0863***	-0.0700***	-0.0868***	-0.0709***
	(0.0000261)	(0.0000218)	(0.0000262)	(0.0000218)
Manager	0.0364***	0.0434***	0.0361***	0.0425***
	(0.00292)	(0.00249)	(0.00288)	(0.00247)
Public Corporations	0.00666	0.0736***	0.00729	0.0734***
	(0.0111)	(0.00996)	(0.0111)	(0.00984)
Central Government	-0.0221	-0.0209	-0.0222	-0.0212*
	(0.0123)	(0.0108)	(0.0123)	(0.0107)
Local Authority	-0.0192	0.00379	-0.0196	0.00320
	(0.0118)	(0.0104)	(0.0117)	(0.0103)
Other Firm Status	-0.0563***	-0.0169*	-0.0577***	-0.0179*
	(0.00815)	(0.00772)	(0.00807)	(0.00759)
Constant	8.178***	4.493***	8.214***	4.511***
	(0.273)	(0.196)	(0.267)	(0.192)
Year Dummies	Yes	Yes	Yes	Yes
N	140951	140951	144355	144355

Robust standard errors (clustered by individual) in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.10 below.

Table 2.10: Obtaining Monetary Values from the Log-Log Specification

	AGP	BWP
Average CD	31.08	31.08
Average Pay	£27,435.31	£480.68
Pay Coefficient on CD	0.00551***	0.00769***
£↑ in Pay for 1% change in CD[a]	£151.17	£3.70
£↑ in Pay for 50% change in CD[b]	£7,558.43	£184.82

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:
Figure rounded to 2 decimal places.
a: Coefficient multiplied by the average.
b: Coefficient multiplied by the average multiplied by 50.

When considering the other variables in Table 2.9 we can see there is a positive and significant age-income gradient, but the negative, and significant, value on the age squared term indicates that this relationship is non-linear. Applying basic calculus to the function $y = f(a)$, where y is income and a is age we can deduce that the turning point of the age-income function is at around 47 years (47.57 for AGP and 47.29 for BWP). This implies that up to age 47 an employee receives an increase in their wage, whereas after 47 there may be an age penalty. We can also see that managers, on average, receive more income than their non-managerial equivalents. As we stipulate that people should have the same job and same SOC code we deduce that this managerial dummy relates to a change of job status even though, by definition, the job description is the same. The effect of which type of firm an employee works for appears insignificant in this double logarithmic set up. We consider these points is robustness analyses, presented later in this chapter.

Columns (3) and (4) of Table 2.9 present the results from the log-linear model specification. So, for example, if commuting distance increased by 1km then column

(3) implies that annual gross pay will increase by 0.0093%, and similarly column (4) states that basic weekly pay will increase by 0.0153%. These numbers, whilst statistically significant, are again small in magnitude. Even when considering the somewhat unreal prospect of a 100km increase in daily commuting distance, the percentage increase in income will be relatively small - a 0.9% increase in annual gross pay and a 1.53% increase in basic weekly pay. If we evaluate these percentage increases at the mean level of income for the whole period, we see a 100km increase in commuting distance is compensated by £246.90 per year in pre-tax pay, and £7.35 per week in basic weekly pay.

Again there appears to be a peak in the age-income profile at around age 47. The exact figures are 47.06 years for the AGP in column (3) and 46.97 for the BWP presented in column (4). Once more the management dummy is positive and significant. In the log-linear models there is more significance attached to the type of firm an employee works for when considering basic weekly pay. For example, compared to a private sector employee somebody employed in a public corporation would earn approximately 7.34% more. However the results for annual gross pay are less significant.

Table 2.11 presents the results from the linear specification, such that we can talk about purely monetary increases. For example, a 10km increase in commuting distance increases annual pay by £33.12 and weekly pay by £0.89. These numbers again are far too small to be taken seriously, yet they are statistically significant. The linear specification with the quadratic term allows us to examine the shape of the commute-income curve. The negative value on the quadratic term implies the relationship is inverse-U shaped. By applying elementary calculus we find the turning point of the function $y = f(c)$, where y is income and c is commuting distance, to be 341km for annual gross pay and 411km for basic weekly pay. This implies any increase in commuting distance above these points is likely to lead to a decrease in income. Again, however, we note that these values seem unrealistically high. It is not feasible to imagine a situation where an individual's one way commute increase greater than 411km per day.

The age-income gradient peaks at 47.87 for AGP and 48.44 for BWP. In the linear specification the impact of the type of firm an individual works for is more significant. In all cases, the results are negative. This would imply that there are higher wage premiums associated with working in the private sector a not too surprising result. As an example, column (1) of Table 2.11 states that working in central government causes a reduction in annual gross pay of around £1,601.30 compared to a similar individual working in the private sector.

Table 2.11: Linear Wage Models with Individual Fixed-Effects

	(1) AGP	(2) BWP
Commuting Distance	3.212***	0.0887***
	(0.812)	(0.0117)
Commuting Distance Squared	-0.00485**	-0.000108***
	(0.00153)	(0.0000244)
Age	1848.6***	28.19***
	(152.1)	(2.061)
Age Squared	-19.28***	-0.291***
	(0.684)	(0.01000)
Manager	1121.2***	24.41***
	(97.15)	(1.399)
Public Corporation	-95.69	39.24***
	(319.7)	(5.506)
Central Government	-1601.3***	-19.15***
	(315.8)	(5.167)
Local Authority	-1334.3***	-5.971
	(286.3)	(4.508)
Other Firm Status	-1707.4***	-12.47***
	(216.6)	(3.553)
Constant	-15547.6**	-188.5*
	(5775.9)	(76.88)
Year Dummies	Yes	Yes
N	144355	144355

Robust standard errors (clustered by individual) in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the following subsections we consider what happens when we remove certain control variables, and also what happens when we focus on specific subpopulations of our sample. As the double logarithmic specification is our specification of choice, as it leads to easily interpretable results, we focus on that specification in what follows.

2.4.1 Removing Possible Time Invariant Factors

The results presented in Table 2.9 include both a dummy variable to indicate if a person's job includes managerial roles, and a number of dummy variables to indicate which sector the firm primarily operates in. As these do not drop out of fixed effects specifications there must be some variation in both of these. For example, 42,074/144,355 ($\approx$ 29%) of observations have some variation in the managerial responsibility variable. However, this is not alarming, Aggarwal and Samwick (2003) argue that employees are often given more managerial responsibility whilst simultaneously keeping the same basic job description, especially employees that have been at a particular firm for a long time.

Results with no firm status or managerial dummies included

We start by removing the variables which indicate the sector in which the firm operates in, but keeping the managerial responsibility dummy. These results are presented in full in columns (1) and (2) of Table 2.18 in the Appendix. For ease of discussion we present the coefficients of interest below in Table 2.12. It can be seen that not including firm sector increases the coefficient on log commuting distance by

0.0002 for log annual gross pay, whereas the coefficient with respect to basic weekly pay is unchanged. From this we deduce that the effect of controlling for firm sector is negligible.

Table 2.12: Comparison of Coefficients on (log) Commuting Distance

	$\widehat{\beta}^{AGP}$	$\widehat{\beta}^{BWP}$
Effect of Excluding Firm and Management Dummies		
Full model	$\mathbf{0.0055}^{***}$	$\mathbf{0.0077}^{***}$
No firm status	0.0057^{***}	0.0077^{***}
No firm status and no manager dummy	0.0056^{***}	0.0076^{***}

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We then look at what happens when we remove the managerial responsibility dummy. Again these results are presented in full in Table 2.18 -columns (3) and (4) - in the Appendix, but are summarised in Table 2.12. When we do not control for firm sector or managerial responsibility the coefficient with respect to annual gross pay increases by 0.00001 (when compared to the full model) and the coefficient for basic weekly pay drops by 0.00001. Again, we consider these effects negligible and conclude that the choice to include firm sector and managerial responsibility dummies or not does not have a large impact on the observed results.

2.4.2 Results by Covariates

In this section we discuss the results for various specifications based upon observable characteristics at the individual level.

The differences between increases and decreases in commuting time

Following Mulalic et al. (2010) (although not Mulalic et al., 2013), we start by looking at the impact that increases vs decreases in (log) commuting time has on wages. In our sample we have $n = 36,482$ reported instances of an increase in commuting distances and $n = 34,588$ reported instances of a decrease[11]. As often noted in the literature it is unusual for people in the same company doing the same job to experience pay decreases following exogenous shocks (see, for example Mulalic et al., 2013, Manning, 2003, Neumark and Sharpe, 1996, and Bewley, 1999) so *a priori* we do not expect to see much of a significant decrease in pay for workers whose workplace relocates closer to their home.

To look at the effects of increases against decreases we do two things: (i) we run separate models for increases and decreases; and (ii) we run one model with increase and decrease both included[12]. To make the results easier to interpret we include the absolute value of decreases in commuting time in both cases. The results are shown in full in Table 2.19 in the Appendix. The coefficients on the variables of interest are shown in Table 2.13.

For annual gross pay, when considering case (i) the coefficient on increase in commuting distance is 0.0027 compared to 0.0011 for a decrease in commuting distance. For case (ii) the coefficients are, respectively, 0.0028 and 0.0022. In case (i) it is only the coefficent on an increase in commuting that is statistically significant, but for

[11] Note: it is possible for people to experience more than one increase or decrease, and it is also possible for an individual to experience both an increase and decrease in different time periods.

[12] To avoid perfect multi-collinearity we do not include actual changes in (log) commuting distance.

case (ii) both coefficients are significant. In both cases the coefficient on an increase in commuting distance is always larger in absolute terms, and more significant, implying that whilst those employees who benefit from a reduced commuting distance also benefit from higher annual pay, it is those employees whose commute increases who enjoy the greater pay increase, consistent with the theory of van Ommeren and Rietveld (2005).

For basic weekly pay a similar pattern is observed. It is also worth noting here that the coefficients are always much closer when we consider case (ii). Case (ii) is the preferred case, as here we are able to control for possible confounding factors simultaneous with the changes in commuting distance[13]. In case (ii) we can further test to see if $\widehat{\beta}^{\uparrow} = \widehat{\beta}^{\downarrow}$. For AGP the F-statistic is 0.73 and for BWP the F-statistic is 0.28, implying in both cases we cannot reject the hypothesis that the coefficients are equal. From this we deduce that all employees benefit from higher wages in a firm which relocates, not just those whose commute increases. As previously mentioned this is as expected, a firm would not be able to increase the wages of those employees who travel further whilst reducing the wages of employees who traveled less.

[13] It may be possible that there are differences in the factors which lead to commuting increases as opposed to commuting decreases. Controlling for both in the same fixed effects regression helps to alleviate this worry.

Table 2.13: **Comparison of Coefficients on (log) Commuting Distance**

	$\widehat{\beta}^{AGP}$	$\widehat{\beta}^{BWP}$
Effect of including Firm and Management Dummies		
Full model	**0.0055*****	**0.0077*****
No firm status	0.0057***	0.0077***
No firm status and no manager dummy	0.0056***	0.0076***
Increases vs Decreases in Commuting Time		
Full model	**0.0055*****	**0.0077*****
Increase in CD^{a}	0.0027***	0.0063***
Decrease in CD^{a}	-0.00109	-0.00396***
Increase in CD^{b}	0.00283***	0.00377***
Decrease in CD^{b}	-0.00223***	-0.00348***
Managerial vs Non-Managerial Roles		
Full model	**0.0055*****	**0.0077*****
Managerial	0.0041***	0.0052***
Non-Managerial	0.0053***	0.0072***
Sector of the Firm		
Full model	**0.0055*****	**0.0077*****
Public Corporation	0.0121***	0.0089***
Private Company	0.0041***	0.0063***
Central Government (CG)	0.0005	0.0014
Local Authority (LA)	0.0050***	0.0080***
CG and LA Combined	0.0031***	0.0045***
Other Firm Status	0.0043	0.0079**

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

a: Models were estimated separately.

b: Model was run as one equation with increase and decrease in commuting time both included.

Table 2.14: **Managers vs non-Managers in more detail**

	Managers	Non-Managers
N	32,319	112,036
Average CD	33.52	31.90
Average AGP	£36,646.32	£24,778.21
Average BWP	£641.87	434.18
AGP Coefficient on CD	0.00413**	0.00527***
BWP Coefficient on CD	0.00518***	0.00722***
£↑ in AGP for 1% change in CD[a]	£151.35	£130.58
£↑ in BWP for 1% change in CD[a]	£3.32	£3.13
£↑ in AGP for 50% change in CD[b]	£7,567.47	£6,529.06
£↑ in BWP for 50% change in CD[b]	£166.24	£156.74

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

a: Coefficient multiplied by the average.

b: Coefficient multiplied by the average multiplied by 50.

The differences between managers and non managers

It is widely assumed that those employees with managerial responsibilities will be compensated by higher salaries (Aggarwal and Samwick, 2003), and hence it may be beneficial to examine managers and non-managers separately. The full results are presented in the Appendix in Table 2.20 and are summarised in Table 2.13. For both AGP and BWP it can be seen that those with non-managerial roles achieve greater percentage increases in pay for changes in commuting distance, but lower actual increases (when evaluated at the mean). For example, consider Table 2.14. We can see that non-managers receive a higher percentage increase in AGP (0.005 compared to 0.004), but when this is evaluated at the mean the actual monetary increase is smaller for non-managers (£6,529.06 vs 7,567.47). However, in a distributional context it is the percentage change that is more important - and not the actual monetary value. So in this sense non-managers do fare better, but in pure monetary gains it is the managers who fare better.

Differences between firm sectors

Here we seek to determine if the sector in which the firm operates in plays any significant role in determining the impact that commuting has on wages. As previously mentioned we consider five sectors here: public, private, central government, local authority, and other. We examine these sectors separately, and further investigate what happens if central government and local authority are grouped together. The results are presented in full in the Appendix in Tables 2.21 and 2.22. Similar to manager vs non-manager we construct a table to show the percentage gains in wages by sector, and then evaluate these in monetary terms, using the average income by sector. These results are presented in Table 2.15. We observe that the coefficients for the central government sector are insignificant, but when we group this sector with local authority we do get significance.

It would appear that the results based on the small number of people employed in the public sector ($n = 3837$) drive the main results upwards. The public sector employees can expect a 0.0121% increase in their annual gross pay for a 1% increase in commuting. This, when evaluated at the mean AGP, translates to roughly an extra £16,222.36 per year. This figure seems too high for us, and may be driven by outliers[14].

We can further see, with respect to AGP, that when ignoring the public sector, the private sector do best, followed by other firm sector, and then by cental government and local authority (when grouped together). This is true for both percentage

[14] However, we have removed the top and bottom 1% of the pay distribution, so this may not be the case.

increases and monetary increases. When we split central government and local authority up, this changes somewhat and the order becomes public, LA, private, other CG.

When looking at BWP we generally see larger statistical significance on the estimated coefficients. The above is mostly true for BWP too; the public sector does best, followed by LA, other, private and CG.

Table 2.15: The effect of the firm's sector

	All	Public	Private	C.G	L.A.	CG&LA	Other
N	144355	3837	88577	18388	22320	40708	11178
Average CD	31.08	28.26	38.31	24.7	14.07	18.87	19.39
Average AGP	27435.31	26813.81	28263.57	26485.08	26807.46	26641.84	23930.06
Average BWP	480.68	465.86	480.21	483.16	497.46	491.04	452.31
AGP Coefficient on CD	0.00551***	0.0121***	0.00413***	0.000502	0.00497**	0.00306***	0.00430
BWP Coefficient on CD	0.00769***	0.00892***	0.00632***	0.00137	0.00802***	0.00448***	0.00792***
£↑ in AGP for 1% change in CD[a]	151.17	324.45	116.73	13.30	133.23	81.52	102.90
£↑ in BWP for 1% change in CD[a]	4.16	3.03	0.66	3.99	2.20	3.58	
£↑ in AGP for 50% change in CD[b]	7558.43	16222.36	5836.43	664.78	6661.65	4076.20	5144.96
£↑ in BWP for 50% change in CD[b]	184.82	207.77	151.75	33.10	199.48	109.99	179.11

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

a: Coefficient multiplied by the average.

b: Coefficient multiplied by the average multiplied by 50.

2.5 Discussion

All of the results presented above indicate that there is a positive *causal* relationship between commuting distance and income. However, we acknowledge that whilst the results are statistically significant their implication in actual monetary terms is often quite small. However, the fact that we have shown that a 50% increase in one way daily commuting distance leads to an annual income increase of around £7,544.32 shows that our results do have meaningful interpretation.

Our results are consistent with Mulalic et al. (2010) in terms of the direction of the effect and the associated significance levels. Our results, at first glance, appear smaller than those of Mulalic et al. (2010). It is further worth noting here that all of our results are likely to be *overestimates* of the true relationship between commuting distance and income. The fact that we use imputed Euclidean distance as an approximation is likely to be the cause of this overestimation. It seems very unlikely that the actual distance of the commute is exactly equal to the Euclidean distance. In the vast majority of cases we envisage that the straight line connecting home and work is likely to be a considerable smaller distance than the actual road distance that an employee must take.

We have also consistently shown that the peak of the age-income gradient appears to be 47-48 years of age. Up to this age an individual's wage increases at an increasing rate. After this point an additional year of age is likely to lead to a smaller increase in salary.

When considering different sub-groups of workers, we show that both managers and non-managers benefit from increases in wages following firm relocation. Whilst managerial staff benefit from greater monetary increases in pay, it is the non-managerial staff who fare better when we consider the relative percentage increases in pay.

Consistent with the theoretical models of wage bargaining of van Ommeren and Rietveld (2005) and Manning (2003), amongst others, we find evidence to suggest that workers whose commuting distance increases as a result of a workplace relocation benefit in terms of higher levels of pay. However, we also find that people whose commutes decrease as a result of the exogenous shock to commuting distance, benefit from increases in pay too. Whilst this is inconsistent with economic theory, it is consistent with some of the empirical literature such as Bewley (1999) and Neumark and Sharpe (1996).

With respect to the sector in which the firm an employee works for operates in, we find evidence that public and private sector workers often fare better than workers in all other sectors. However, this is as expected as private corporations are more likely to have more control over the wage structure of their employees, as opposed to local authorities and central government employees. Public sector employees seem to do the best, and this is quite surprising if one assumes that public sector workers are subject to similar working structures as government employees.

2.6 Conclusion

We conclude firstly that wage bargaining with respect to commuting distance is an important component of the UK labour markets, consistent with the Danish labour market as found by Mulalic et al. (2010). Secondly, as there is a statistically significant relationship between commuting distance and wages, this implies that there is a monetary cost associated with induced longer commutes. This, in turn, would seem to suggest that there are private as well as societal benefits to improving transport infrastructure, such as the widely debated HS2 project here in the UK.

However, as we use Euclidean distance we would not be able to evaluate time (and actual road distance) saving measures, so there is room to expand this current research to examine actual observed commuting distance and see if improvements in travel infrastructure do lead to reduces in wages, due to time saving mechanisms. In reality, however, we do not expect firms to reduce employees' wages due to reductions in commuting distance, as we find here that workers who benefit from a reduced daily commute also benefit from increases in pay following firm relocation decisions.

Further research in this area would require more detailed socioeconomic information on the individuals contained within ASHE. It is our *a priori* belief that the commuting distance wage gradient will differ by gender. Separate sub-analyses would allow us to attempt to tease out these gender differences. More precise commuting distance information would also benefit this strand of the research.

The fact that we have demonstrated that there is a causal relationship will hopefully encourage researchers to look for more detailed data in an attempt to further this understanding of the causal income-commuting distance relationship.

Appendix 2A: Further tables

Table 2.16: **(Selected) Summary Statistics for the whole ASHE data set**

Variable	Obs.	Mean	Std. Dev.
Commuting Distance (km)	1924763	21.69	56.65
Deflated Annual Gross Pay (AGP)	2758345	14320.09	27438.06
Deflated Basic Weekly Pay (BWP)	2774739	257.52	327.29
Age	2774739	39.98	12.46
Manager	2774739	0.12	0.33
Public Corporation	2774739	0.04	0.19
Central Government	2774739	0.09	0.28
Local Authority	2774739	0.14	0.35
Other Type of Firm	2774739	0.13	0.33

Table 2.17: **First-Difference Wage Equation, for comparison**

	Δ log(AGP)	Δ log (BWP)
Δ Commuting Distance	0.0000637***	0.00000468
	(0.0000167)	(0.00000949)
Age†	0.2288664 ***	0.1622436***
	(0.0186122)	(0.0119613)
Age Squared	-0.0000795***	-0.000050***
	(0.0000101)	(0.000000663)
Manager	0.0117724 ***	0.0099741***
	(0.0025284)	(0.0016612)
Public Corporation	-0.0054827	0.0080045*
	(0.005752)	(0.0040538)
Central Government	0.0180691***	0.0072105***
	(0.0037407)	(0.001953)
Local Authority	0.0137748 ***	0.0098255***
	(0.0029178)	(0.0017172)
Other Firm Status	0.0084692	0.0087948***
	(0.0047193)	(0.0029536)
N	47479	47479

Robust standard errors (clustered by individual) in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† to include age, we specified that the model should not contain a constant term.

Table 2.18: **Wage Equation with No Firm Status**

	With Manager		Without Manager	
	(1) log(AGP)	(2) log(BWP)	(3) log(AGP)	(4) log(BWP)
log(Commuting Distance)	0.0057***	0.0077***	0.0056***	0.0076***
	(0.00064)	(0.00056)	(0.00064)	(0.00057)
Age	0.0823***	0.0668***	0.0833***	0.0681***
	(0.0056)	(0.0041)	(0.0056)	(0.0040)
Age squared	-0.00087***	-0.00071***	-0.00088***	-0.00072***
	(0.000021)	(0.000021)	(0.000021)	(0.000021)
Manager	0.0365***	0.0437***		
	(0.0023)	(0.0019)		
Yr03	0.0089	0.0160***	0.0200	0.0293
	(0.0064)	(0.0048)	(0.0064)	(0.0048)
Yr04	0.0406***	0.0428***	0.0512***	0.0555***
	(0.0125)	(0.0090)	(0.0125)	(0.0091)
Yr05	0.0612***	0.0829***	0.0711 ***	0.0648***
	(0.0182)	(0.0130)	(0.0183)	(0.0132)
Yr06	0.0779***	0.0731***	0.0880***	0.0851***
	(0.0246)	(0.0176)	0.0247)	(0.0178)
Yr07	0.0972***	0.0934***	0.1066***	0.1046***
	(0.0304)	(0.0217)	(0.0306)	(0.0219)
Yr08	0.1087***	0.1060***	0.1182***	0.1175***
	(0.0364)	(0.0258)	(0.0366)	(0.0262)
Yr09	0.1181***	0.1236***	0.1276***	0.1350***
	(0.0425)	(0.0302)	(0.0427)	(0.0306)
Yr10	0.1009**	0.1073***	0.1101**	0.1182***
	(0.0485)	(0.0345)	(0.0488)	(0.0349)
Yr11	0.0767	0.0909**	0.0857	0.1017***
	(0.0544)	(0.0387)	(0.0547)	(0.0392)
Cons.	8.236***	4.568***	8.1371***	4.4499***
	(0.342)	(0.246)	(0.2163)	(0.1565)
N	140951	140951		

Robust standard errors (clustered by individual) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.19: Wage Equations by Increases and Decreases in Commuting Distance

	Increase in Commute		Decrease in Commute		Together	
	(1)	(2)	(3)	(4)	(5)	(6)
	log(AGP)	log(BWP)	log(AGP)	log(BWP)	log(AGP)	log(BWP)
log(Commuting Distance)	0.00271***	0.00634***	0.00109	0.00396***		
	(0.00133)	(0.00114)	(0.00126)	(0.00112)		
Increase in log(Commuting Distance)					0.00283***	0.00377***
					(0.0005)	(0.0004)
Decrease in log(Commuting Distance)					0.00223***	0.00348***
					(0.0005)	(0.0004)
Age	0.0917***	0.0732***	0.0789***	0.0629***	0.0825***	0.0671***
	(0.013)	(0.00967)	(0.0111)	(0.00888)	(0.0056)	(0.0041)
Age squared	-0.000950***	-0.000767***	-0.000913***	-0.000716***	-0.000866***	-0.000707***
	(0.0000525)	(0.0000421)	(0.0000532)	(0.0000458)	(0.0000205)	(0.0000172)
Manager	0.0359***	0.0436***	0.0301***	0.0392***	0.0362***	0.0434***
	(0.00464)	(0.00399)	(0.00505)	(0.00436)	(0.00229)	(0.00196)
Cons.	8.012***	4.414***	8.519***	4.775***	8.241***	4.572
	(0.653)	(0.474)	(0.554)	(0.429)	(0.269)	(0.193)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	69616	69616	65805	65805	140951	140951

Robust standard errors (clustered by individual) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.20: Wage Equations by Manager and Non-manager

	Manager		Non-Manager	
	(1)	(2)	(3)	(4)
	log(AGP)	log(BWP)	log(AGP)	log(BWP)
log(Commuting distance)	0.00413**	0.00518***	0.00527***	0.00722***
	(0.00245)	(0.00215)	(0.000979)	(0.00088)
Age	0.0707***	0.0596***	0.0746***	0.0601***
	(0.0139)	(0.0123)	(0.0116)	(0.00823)
Age squared	-0.000659***	-0.000569***	-0.000862***	-0.000688***
	(0.0000935)	(0.0000771)	(0.000036)	(0.0000288)
Cons.	8.539***	4.816***	8.522***	4.774***
	(0.462)	(0.417)	(0.579)	(0.404)
Year Dummies	Yes	Yes	Yes	Yes
N	31555	31555	109396	109396

Robust standard errors (clustered by individual) in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.21: **Wage Equation by Firm Status I**

	Public		Private		Central Gov.		Local Auth.	
	(1) log(AGP)	(2) log(BWP)	(3) log(AGP)	(4) log(BWP)	(5) log(AGP)	(6) log(BWP)	(7) log(AGP)	(8) log(BWP)
log(Commuting Distance)	0.0121***	0.00892***	0.00413***	0.00632***	0.000502	0.00137	0.00497 **	0.00802***
	(0.00491)	(0.00384)	(0.000973)	(0.000864)	(0.00191)	(0.00166)	(0.00281)	(0.00251)
Age	-0.00530	-0.0280	0.0879***	0.0676***	0.0292***	0.0324***	0.0552***	0.0456***
	(0.0503)	(0.0292)	(0.00805)	(0.00603)	(0.0144)	(0.00812)	(0.00760)	(0.00622)
Age squared	0.000262**	0.000220**	-0.000886***	-0.000691***	-0.000539***	-0.000452***	-0.000708***	-0.000574***
	(0.000155)	(0.000132)	(0.0000351)	(0.0000293)	(0.0000572)	(0.0000477)	(0.0000616)	(0.0000484)
Manager	0.0345	0.0873***	0.0410***	0.0468***	0.00884	0.0106	0.0200***	0.0263***
	(0.0184)	(0.0187)	(0.00413)	(0.00352)	(0.00719)	(0.00550)	(0.00589)	(0.00451)
Cons.	9.779***	6.808***	8.029***	4.479***	9.632***	5.402***	8.940***	5.123***
	(2.194)	(1.262)	(0.376)	(0.272)	(0.551)	(0.283)	(0.243)	(0.201)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3805	3805	85969	85969	18194	18194	22072	22072

Robust standard errors (clustered by individual) in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.22: Wage Equation by Firm Status II

	Public		Private		Central Gov. & LA		Other Status	
	(1) log(AGP)	(2) log(BWP)	(3) log(AGP)	(4) log(BWP)	(5) log(AGP)	(6) log(BWP)	(7) log(AGP)	(8) log(BWP)
log(Commuting Distance)	0.0121***	0.00892***	0.00413***	0.00632***	0.00306 ***	0.00448***	0.00430	0.00792***
	(0.00491)	(0.00384)	(0.000973)	(0.000864)	(0.00162)	(0.00143)	(0.00449)	(0.00401)
Age	-0.00530	-0.0280	0.0879***	0.0676***	0.0418***	0.0405***	0.0579***	0.0477***
	(0.0503)	(0.0292)	(0.00805)	(0.00603)	(0.00836)	(0.00503)	(0.0126)	(0.00964)
Age Squared	0.000262**	0.000220**	-0.000886***	-0.000691***	-0.000644***	-0.000528***	-0.000849***	-0.000674***
	(0.000155)	(0.000132)	(0.0000351)	(0.0000293)	(0.0000426)	(0.0000348)	(0.000107)	(0.0000932)
Manager	0.0345	0.0873***	0.0410***	0.0468***	0.0151**	0.0199***	0.0335***	0.0455***
	(0.0184)	(0.0187)	(0.00413)	(0.00352)	(0.00467)	(0.00359)	(0.0101)	(0.00967)
Cons.	9.779***	6.808***	8.029***	4.479***	9.698***	5.487***	8.935***	5.088***
	(2.194)	(1.262)	(0.376)	(0.272)	(0.378)	(0.203)	(0.406)	(0.285)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3805	3805	85969	85969	40266	40266	10859	10859

Robust standard errors (clustered by individual) in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

Congestion Charging and Social Capital: The Impact of the Western Extension Zone

3.1 Introduction

A key concept in welfare economics is the principle that individuals should directly pay for the externalities and costs they impose on others. This principle ensures that individuals have an incentive to use the available resources more efficiently. This concept can be easily applied to private motor vehicle use, and in fact urban traffic congestion is a well cited as an example of this principle (Small and Verhoef, 2007). Transport economists have long advocated the use of road tolls and/or congestion charging policies to encourage the use of more efficient transport systems, whilst simultaneously addressing congestion and pollution problems. The overall outcome should be the provision of a net benefit to society. However, in reality, few cities have introduced congestion charging policies. Notable exceptions include Singapore, Oslo, Bergen and Stockholm, amongst others[1]. London, the city of interest for the analysis presented in this chapter, decided to introduce a congestion charging scheme in 2003. In theory London is an ideal city to implement road pricing policies: there is relatively limited road capacity[2] and there are plenty of available substitutes to own vehicle use (such as the extensive tube and bus networks).

The London Congestion Charge (LCC) was introduced in February 2003 by the then Mayor of London, Ken Livingston, with the aim of reducing both congestion and pollution by discouraging the use of cars, vans and motorcycles. Banister (2003) states that:

> *"Congestion Charginging in Central London is the most radical transport policy to have been proposed in the last 20 years ..."*

Banister (2003); p.259

The area covered by the congestion charge (CC) included, amongst others, Westminster, the City, Lambeth and Charing Cross. The full congestion charging zone can be seen in Figure 3.1. To drive a vehicle into the shaded (orange) area in Figure 3.1 cost drivers £5 per day in 2003. The price steadily increased to £8 in April 2005, and at the time of writing (2013) stands at £10. The fee is applicable between

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[1] However, whilst these cities all have congestion charging schemes, the motivation for their introduction varies by location.

[2] It is argued that the London road network has barely changed since its introduction (Litman, 2011).

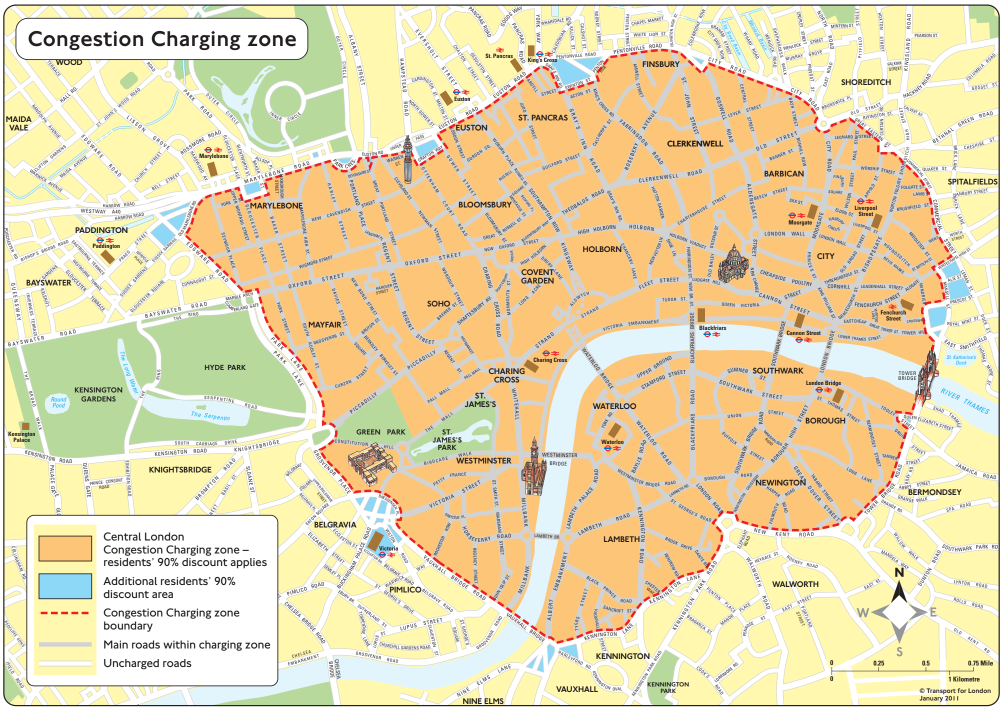
07:00 and 18:00 Mondays to Fridays, excluding public holidays[3]. The charge is paid for driving, or parking, a vehicle inside the LCC zone, irrespective of the length of time the vehicle is inside the zone.

According to Transport for London (TfL) research, at peak times just over one million people enter central London on a typical weekday during the hours 07:00 - 10:00 (Transport for London, 2004). On average 85% of these trips are made by public transport. Prior to the introduction of the CC 12% of these peak time trips were made by private vehicle (car or motorcycle). During the first six months of the CC this figure had dropped to 10%, implying there was a 20% reduction in private vehicle usage - around 20,000 fewer vehicles per day (Transport for London, 2004). A later study (Transport for London, 2005) notes that this reduction is not as severe in the longer term, with a 12% drop in the number of private vehicles inside the zone over a one year period.

Whilst the congestion charging was not without criticism, it cannot be argued that it was a political failure - mayor Ken Livingston was re-elected in the 2004 mayoral elections. Some existing literature examining the economic impacts of the London CC are detailed in the next section. To our knowledge, all of the previous analysis concerned with the economic effectiveness of the London CC has been concerned with tangible factors such as: house prices, the effect on retail sales volumes, pollution and congestion, and not with intangible concepts such as social capital, which is studied here. In a more general CC policy setting, very little, if any, research has been carried out to examine the social impacts that congestion charging policies

[3] Including the period 25th December - 1st January each year, for which there is no charge.

Figure 3.1: The area covered by the initial (and current) Congestion Charging Scheme



Source: http://www.tfl.gov.uk

have had. Examining the London congestion charge, Prud'homme and Bocarejo (2005) claim that when other socioeconomic factors (such as the effect on trade, for example) are considered, in fact, the overall net economic costs may outweigh the net social benefit of reduced pollution and congestion. The main motivation of this chapter is to examine the role congestion charging policies play in determining an individual's level of social capital. Whilst the area shown in Figure 3.1 is predominantly retail and business sector based, the area to the immediate west is considerably more residential, and this residential area is the area of focus in this study.

Prior to the 2004 mayoral elections, proposals were drawn up to consider expanding the zone to include boroughs to the west of the zone, to include the more residential areas. These new boroughs included Kensington, Chelsea, and Pimlico, amongst others.[4] The new, larger, zone would include an additional 80,000 residents, taking the overall number of affected individuals to around 230,000. A consultation document was drawn up to canvas local opinion, but was not distributed until after Livingston's reelection in 2004. This document was duly released, and the results of the consultation indicated that a large majority were opposed to the planned extension. Despite the opposition, however, mayor Ken Livingston still planned on implementing the Western Extension.

Finally, some two and a half years after the initial consultation, in February 2007 the Western Extension Zone (WEZ) was implemented. Figure 3.2 shows the new boroughs included. The WEZ extended the CC zone to a further 17 square kilometres. The extended CC scheme operated as one complete zone. The same charges, discounts and exemptions apply to everyone who drives a vehicle inside the new extended zone.

This newly formed larger CC zone provides an ideal area to examine the impact that congestion charging has on stocks of social capital, as proxied by frequency of visiting friends and family. A similar analysis on the original CC zone was not possible due to lack of data. Immediately prior to, and during, the western extension a panel survey was carried out on behalf of Transport for London (TfL) by a Accent (a private market research firm). This panel survey asked, amongst other things, how many visits an individual made to friends and relatives in a variety of settings. The aim of this chapter is therefore to analyse these new data to look for changes in the stock of social capital brought about by the introduction of the western extension

[4] See Figure 3.2 for full details.

Figure 3.2: **The additional area introduced (and subsequently removed) known as the Western Extension Zone**

Source: http://www.tfl.gov.uk

zone. To our knowledge, this chapter is unique in two regards: (i) this is the first empirical piece of work to analyse this particular data set in an econometric context; and (ii) this is the first analysis to examine the *ex post* impact that congestion charging has on social capital.

The chapter proceeds as follows: Section 2 will provide a literature review; Section 3 outlines the available data and methodology; Section 4 presents the results obtained and provides a discussion of these; and Section 5 concludes.

3.2 Literature Review

The aim of this chapter is to investigate what impact road pricing policies have on social capital, something which we believe has not been done before. Therefore this section is split into two component sub-sections: the first will briefly review the growing body of empirical literature that examines social capital; and the second will look at previous studies that evaluate existing road pricing schemes. A small subsection of the existing literature is concerned with the *ex-ante* evaluation of road pricing, with regards to social inclusion/exclusion - a not wholly dissimilar concept to social capital. However, our area of focus in this analysis is an *ex-post* evaluation.

3.2.1 Social Capital

Social capital (SC) is a term whose origins are in sociology and psychology. No precise definition exists, but in his synthesis Woolcock (1998) defines social capital as:

> *"...a broad term encompassing the norms and networks facilitating collective action for mutual benefit."*

Woolcock (1998); p.155

Portes (2000) further examines the origins of social capital and looks at its applications in modern sociology and psychology. He argues that social capital encompasses all that is good about sociability and hence has a place in sociological theory, but concludes, however, that *"excessive extensions of the concept may jeopardize its* *heuristic value."* (Portes, 2000 pp. 43). In a sociological setting, Coleman (1994) points out that social capital is an '*intangible concept*', which is a view held by many sociologists. Because of this perceived intangibility, the majority of the sociological work on social capital has focused on the conceptual understanding, as opposed to actually measuring it and determining how individuals can influence their stock of social capital.

One of the most influential works on social capital in recent years is Putnam (2000) - the influential *Bowling Alone: The Collapse and Revival of American Community.* In this book, Putnam argues that, amongst other things, changes in commuting behaviour have had a detrimental affect on how Americans engage with each other, *i.e.* it has reduced their stocks of social capital. Putnam (2000) argues that there are two distinct strands of social capital: (1) bonding -or exclusive- social capital; and (2) bridging -or inclusive- social capital. The former relates to strong social ties between homogenous individuals (*i.e.* within families and/or existing networks of friends) whereas the latter is concerned with attempting to expand social networks to include a more diverse social grouping (*i.e.* religious movements and social meetings organised through a common place of work). As a result of these two separate strands of social capital, Putnam uses many instruments for social capital - including, most notably, the uptake of bowling in social and competitive environments. He argues that bowling is an American social tradition - an activity associated with friendship. However, he also uses data on the frequency of visits to friends and family, which links in to what we do here, and to some extent validates our choice of SC proxy.

Islam et al. (2006) systematically reviewed the literature on social capital, building on the two definitions Putnam proposed. They further include structural and cognitive components to social capital, where structural refers to the density of social networks and cognitive relates to an individual's perception of (amongst other things) levels of interpersonal trustand reciprocity.

Steven Durlauf has written comprehensively on the use of social capital as a socioeconomic indicator for an individual. Durlauf (2002) argues that the exact definition of social capital is ambiguous in the majority of empirical studies, and as such no true causal relationship can actually be identified. He further argues that this has led to a variety of disparate ideas emerging within the social capital literature. Durlauf and Fafchamps (2004) extend further this argument by accusing social capital of possessing '*conceptual vagueness*'. However, despite its limitations, Durlauf and Fafchamps (2004) do conclude that social capital is an important concept in social science research, and its determinants should still be investigated.

Kan (2007) propose further extensions to social capital by including spatial dimensions. He proposes social capital be broken down into local social capital (local SC) and distant social capital (distant SC). Local SC includes friendship ties with individuals living nearby, and may be beneficial to the wider local community by (amongst other things) reducing crime rates and improving the local physical geography of a neighbourhood. Alternatively, distant SC can be thought of as family and friends living far away from an individual, and hence reducing the possible benefits of strong social ties. Kan exploits these differing spatial aspects of social capital to look at residential mobility, conjecturing that high levels of local social capital are likely to reduce the geographic mobility of an individual. Using the Panel Survey of Income Dynamics, especially questions like those mentioned in the paragraph above, he finds that (as expected) high levels of local social capital deter people from moving, hence reducing residential mobility.

In addition to the above, the factors which determine an individual's level, or stock, of social capital have been the focus of much recent empirical work in the economic literature. However, as no precise definition exists, many proxies have been used. For example Alesina and La Ferrara (2000) use participation in voluntary groups in the United States as a proxy and find that the racial make up of a groups plays a great role in determining who participates in that group. Kan (2007) analyses American data and proxies social capital with people's beliefs on how friendly their neighbourhood is[5]. They deduce that higher levels of local social capital imply residents are less likely to be residentially mobile.

Nicolas Sirven and Thierry Debrand have extensively analysed the relationship between an individual's stock of social capital and their health in later life. Both Sirven and Debrand (2008) and Sirven and Debrand (2012) find that people with higher stocks of social capital are more likely to be healthier, and remain healthier, as they age. In their later paper, they note that the relationship health has on social capital is stronger than the effect social capital has on health. However, if social capital does impact upon the health levels of a population then social capital should be a key area for economic policy, given the recent well documented increase in life expectancy.

Whilst many individual proxies for social capital have been used in the literature, Gannon and Roberts (2012) argue that, if possible, a composite index of social

[5] Using questions such as: *" Do you think someone living nearby would help you in an emergency? "*

capital should be created. This index should be based on a wealth of information relating to an individual's social decisions, and should be created using principal component analysis. Their work is based on the rich data contained in the Survey of Health Aging and Retirement in Europe, which encompass many variables which may be justified as proxies for social capital. Unfortunately, the data available on social capital in this study is not as rich, and hence individual proxies are utilised.

As well as investigating the determinants of social capital, some empirical papers include social capital as an explanatory variable. For example, Karlan (2005) includes trust (as a proxy for social capital) in an 'actual' Trust Game[6] using members of a nonprofit "village banking" organisation in Ayacucho, the capital city of Huamanga Province, Ayacucho Region, Peru. He finds that, amongst other things: "*...trustworthiness is an important component in determining the success of group lending programmes.*" (Karlan, 2005 p. 1698). Interestingly he also finds that the geographic distance to a player's game partner significantly correlates with the probability of returning more in the game, which can be thought to tie in with Kan's (2007) idea that local social capital is a more important factor than distant social capital.

No empirical papers have, to our knowledge, studied the impact that congestion charging policies have on social capital. Hence this study is unique as it is the first to do so. Some related research topics have been briefly touched upon in the empirical literature, and these are summarised in the next subsection.

[6] Most Trust Games are carried out in a laboratory environment, as opposed to this actual experiment.

For more detail discussion on social capital see, amongst others, Durlauf and Fafchamps (2004), Islam et al. (2006) and Gannon and Roberts (2012).

3.2.2 Congestion Charging Policies

Whilst the impact that congestion charging has on social capital, *per se*, has not been examined in the literature, its impact (or *expected impact*) on related concepts has been examined. For example Bonsall and Kelly (2005) argue that if congestion charging was introduced in the UK city of Leeds, then the impact would depend on the precise definition of the charge area, as well as on the charges and exemptions provided. They examine six hypothetical policies in turn. Their main area of focus is what they call 'at risk groups'. These people are already among the most socially excluded within the city, and include low income individuals, and disabled individuals. They argue that any road pricing policy would place these people into higher levels of social exclusion, especially those on low incomes with no realistic public transport alternatives to the car journeys they make. They conclude that the policy with the less serious consequences for social exclusion is a policy based on charges proportional to the distance driven within any charge area.

Similar to the above, Rajé (2003) examines what could happen to social exclusion in Bristol (UK) following any road usage pricing policy. She argues that it may be possible to promote social inclusion, and hence reduce social exclusion, if the monies raised from a congestion charge are used to improve current conditions - including enhancing public transport - and to promote public transport usage.

Whilst the studies of Bonsall and Kelly (2005) and Rajé (2003) provide useful insights as to what may happen as a result of a congestion charge policy, they are both *ex-ante*. The evaluation we propose here is *ex-post* as it is based on an evaluation of a CC policy that had already been implemented.

The London CC has been examined in relation to a number of other key economic areas. For example, Schmöcker et al. (2006) analyse survey data collected in partnership with a large department store in order to examine the impact of the London Congestion Charge. The department store in question, John Lewis, had large stores both within and outside the area affected by the CC. Customers at both of these stores were surveyed in store, along with a postal survey issued to all store card holders belonging to the store *inside* the CC cordon. The authors apply binary and ordered logit models to the data to show that the CC had caused a significant drop in the frequency of customers who shopped in the store located inside the CC. They also estimate that the congestion charge led to an approximate 7% fall in sales volume of the central store (located inside the CC cordon). Schmöcker et al. (2006) conclude that the main reason for this reduction of visits to the central store was caused by the implementation of the LCC. The authors do however conclude that there were other factors that could have influenced this, such as the heightened level of anti-terrorism measures in place in central London at the time, but further analysis show that these other factors are more temporary than the CC policy.

Further to the study above, Quddus et al. (2007) analyse data from the same store and employ a seasonal autoregressive integrated moving average model to forecast sales data from 2000 to 2002 and then estimate what should have happened in 2003, *i.e.* they artificially create a counterfactual. They then compare this to what was actually observed and deduce that sales volume predicted by their model after the introduction on the congestion charge were considerably higher than those actually observed. Their model had predicted before congestion sales volumes quite accurately. Similar to Schmöcker et al. (2006), they control for other possible confounding factors. Quddus et al. (2007) conclude that the drop in sales of the John Lewis store inside of the congestion zone attributed to the introduction of the CC was 5.5% based on their time series model, and 8.2% based on a panel data model they ran. They also note that whilst car drivers were the most likely to reduce the frequency of their visits to the central John Lewis store, those shoppers who kept patronising the store did not increase their expenditure at their more infrequent visits, thus implying a fall in revenue for the store.

Zhang and Shing (2006) examine the impact that the London congestion charge had on house prices in London; both inside and outside the congestion zone. After employing quasi-experimental difference-in-difference techniques, they find, to their surprise, that the gap between prices inside and outside the zone had actually fallen as a result of the policy. They expected an asymmetric impact as people living inside the cordon should benefit from less congestion, whilst those living outside should suffer due to the increase in travel costs to areas inside the zone, and increased congestion outside the zone. However they fail to account for the charges that potential new residents inside the LCC cordon would face every time they moved their private motor vehicle.

In addition to the literature relating to the LCC, several further studies have looked at the introduction of the Stockholm Congestion Charge (SCC) scheme. Stockholm introduced a trial charge during 2006 - 3 years after the LCC was introduced. As a result of the trial, the congestion charging policy was introduced permanently at the beginning of August 2007. Eliasson et al. (2009) provide an overview of the effect of the SCC, noting that the SCC had reduced congestion far and above the expected levels. They further argue that the SCC resulted in *"favourable economic and environmental effects"* (Eliasson et al., 2009 p240), including positive effects on both the regional economy and on retail.

Karlström and Franklin (2009) analyse what impact the SCC had on the mode of travel a commuter chose, and on a commuter's departure time. They recognise that morning commuters are usually quite persistent in their preferences, and so there is very little change in both variables of interest as a result of the SCC. They do find, however, that there is a 15 percentage points higher rate of switching from car to public transport for commuters who must cross the SCC toll zone, when compared to commuters who do not cross the cordon. They also find a weak effect on departure time, with the SCC encouraging commuters to depart earlier. This is quite surprising, as one would expect a policy aimed at reducing congestion would encourage people to depart later, if congestion, and hence total journey time, had been reduced[7]. The fact that, on average, commuters chose to leave earlier would tend to suggest that the people surveyed placed a higher value on the monetary costs of the SCC as opposed to the benefits of a shorter commute, as there are reductions and exemptions before certain times[8].

Finally Karlström and Franklin (2009) look at the distributional effects of the SCC,

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[7] Assuming there were no other confounding factors which acted to simultaneously increase total journey time.

[8] For example, there is no charge for journeys made before 06:29, whereas the price increases to 10SEK for journeys between 06:60 and 06:59, increasing to a maximum charge of 20SEK if journeys are made between 07:30 and 08:29.

by examining its impact by income groups hypothesising that lower income groups should feel the greatest burden of the impact of the SCC. However, their overall Gini Coefficient is insignificant. This insignificance may be caused by the fact that it is the lowest income group and the highest income group that appear to be worse off as a result of the SCC. The lowest income group is as expected, but the fact that the highest income group (and the second highest income group) are statistically significantly worse off is surprising. However, the authors note that they do not control for differing marginal utilities of money across the income groups, and they also assume that all groups have a constant value of time.

Schuitema et al. (2010) compare and contrast the opinions of residents of Stockholm before and after the implementation of the SCC. Residents were encouraged to complete a questionnaire both before and after the SCC trail period in 2006. The initial (pre-trial) survey was carried out in December, 2005 and the post-trial survey was carried out in August 2006.[9] Both surveys asked respondents their beliefs, and their *expectations* in the case of the pre-trial study, about the CC on a number of issues, including congestion, parking problems, travel costs, etc. Schuitema et al. found that acceptance of the trial was actually higher than the predictions people made about their acceptability judgements before the trial was implemented. The net result was respondents believed that the charge had more positive impacts (such as reducing congestion, reducing pollution and decreasing parking problems) than negative consequences (such as the expected financial burden of the CC). They also find that before the implementation individuals were more concerned about the consequences to their own travel behaviour (especially the cost), whereas after the

[9] Which is after the trial, but before the main SCC was introduced.

trial most people were more concerned with the perceived consequences of their car use (especially the parking problems they encountered). This, again, highlights the differences in the *ex-ante* reservations regarding the SCC as opposed to the *ex-post* realisations - implying people's views had changed.

All three studies based around the SCC found that public perception of the scheme was more positive during the trial than had been expected. Evidence was found that congestion had been reduced, and that the use of public transport had increased.

3.3 Data and Methodology

3.3.1 Data

This chapter will analyse data provided by Transport for London (TfL).[10][11] This data set has not previously been examined in an econometric context, implying that this chapter is exploiting a new data set in order to address the yet unanswered question: *"what role does congestion charging have on social capital?"*. A panel survey consisting of five waves was commissioned to canvas opinion on the WEZ. A random sample of representative individuals were contacted by an initial telephone call in which they were asked if they would like to participate in further waves of the main survey. If they agreed they were then contacted, if possible, in all five waves. The telephone interviews relating to specific waves were carried out approximately

[10] The data was made available thanks to the support of Claire Sheffield.

[11] The data collection was performed by Accent - a private market research company.

3 - 4 months apart. Table 3.1 shows the approximate dates of the interviews and the number of respondents, along with the response rate as a percentage of the initial sample. Whilst there was attrition in the survey (Wave 5 had only 23% of the initial sample remaining), there were no respondents in later waves who were not in Wave 1 (*i.e.* there was no late recruitment of respondents to boost the sample).

Therefore the total number of observations in the analysis that will follow is 1,312 - *i.e.* all those people in wave 2 who are remaining in wave 4. As we utilise difference in difference methodologies, we require observations both before (wave 2) and after (wave 4) the policy was implemented. The fact that waves 2 and 4 are only c. 10 months apart means that any results found here are likely to be driven by the implementation of the WEZ. Such a relatively small time frame would indicate that other confounding factors may not have had sufficient time to 'kick-in'[12].

As the data had not been analysed in an econometric sense before, some considerable time and effort was invested in setting up the data for analysis. Careful cross-referencing of the actual questionnaires against the data was required to ensure variables were matched across waves. Further effort was required to sort questions where there multiple outcomes - the question numbers in the questionnaire did not always match up with question numbers in the data set.

Whilst the data is a panel in the sense that it follows the same group of people through time, it is not a true panel as unfortunately the same questions are not consistently asked in all five waves. Table 3.1 provides a general description of the

[12] An internet search showed that there were no major travel problems in London during the time frame considered here. There were storms and snow in January 2007, although these were not overly severe, and they were prior to the implementation of the WEZ.

Table 3.1: **Details of the five waves of available data**

Wave	Date	Respondents (%)	Questions Asked
1	c. 09/2006	4021 (100%)	Socioeconomic Information and expectations
2	c. 01/2007	2437 (61%)	Frequency of visiting friends and family (F&F)
3	c. 05/2007	1755 (44%)	Shopping & Childcare information
4	c. 11/2007	1312 (33%)	Frequency of visiting F&F
5	c. 02/2008	939 (23%)	incomplete
Estimation data set sample size: $N = 1,312$			

type of questions asked in each wave. The two waves of particular interest in this chapter are waves 2 and 4. Wave 2 has detailed information on the frequency of visits to friends and family, as does wave 4. Whilst the main body of socioeconomic questions are contained in Wave 1, it is possible to impute some of this information into the later waves. When analysis is carried out both with and without this socioeconomic information it is found that results are remarkably similar. For that reason only the results that do control for individual characteristics are presented in this chapter.[13] The data in wave 2 are concerned with the frequency of visiting friends and relatives before the WEZ was implemented, whereas wave 4 has data collected during the tenure of the WEZ.

The main questions of interest to us here are questions relating to the frequency of visits to friends and family. In wave 2 everyone in the survey is asked: *"...in the western extension zone, between 7am and 6pm on weekdays, how often do you...?"* and were given five different questions:

(i) *"Visit family members who live in the western extension zone in their home"*;

(ii) *"Meet up with family members who live in the western extension zone at a*

[13] These results, whilst qualitatively similar to the results that do not control for socioeconomic changes, provide more scope for discussion.

location in the WEZ other than their home";

(iii) *" Visit friends who live in the WEZ in their home"*;

(iv) *"Meet up with friends who live in the western extension zone at a location in the WEZ other than their home"*; and

(v) *" Visit someone on their home in the WEZ as a carer/volunteer "*.

A similar set of five questions are then asked to the subset of respondents who live inside the WEZ, only the additional questions they answer are concerned with visiting friends and family who live outside of the WEZ. For example (ii) above becomes: *"...outside of the WEZ, between 7am and 6pm on weekdays, how often do you meet up with family members who live* ***outside*** *the WEZ at a location outside the WEZ other than their homes? "*

The responses to all ten questions above were coded on a ten point scale, where (1) corresponded to a response of 5 days a week or more, through to (9) which indicated never. (10) was not applicable. Hence, lower scores scores to the appropriate questions indicate a higher frequency of visiting friends and relatives. Figure 3.3 shows a comparison before and after for the group of questions that are asked to all WEZ users. It was decided to recode the responses so higher values related to higher frequencies of visits, and hence higher levels of social capital. The new scale, as used in the analysis that follows in this chapter, is:

0. Never [0];
1. Less than once or twice a year $(0, 2]$;

2. Once or twice a year $(2, 6]$;
3. Every few months $(6, 12]$;
4. Every month or so $(12, 24]$;
5. A few times a month or so $(24, 52]$;
6. 1-2 days a week $(52, 156]$;
7. 3-4 days a week $(156, 260]$; and
8. 5 days a week or more $(260, 365]$

The numbers in brackets[14] indicate, approximately, how many times per year visits are made. This annualised data will be utilised when employing interval regression techniques, as outlined in the methodology section[15].

If we assume that the frequency of visiting friends and family is an important component of social capital, such that it may be used as a suitable proxy (e.g. Putnam, 2000), then any significant changes to an individual's responses between waves 2 and 4 is likely to indicate that congestion charging has affected their stock of social capital.

In wave 1, around a third of respondents (c. 1300) reported having friends and family living inside the area encompassed by the WEZ. Those with friends and family in the zone were more likely to travel there regularly by all modes, which is unsurprising and consistent with the local social capital idea of Kan (2007).

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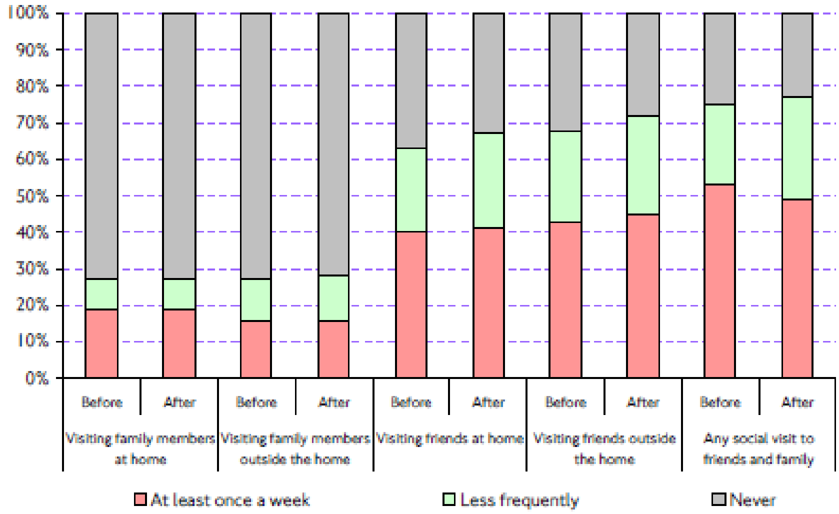
[14] Where traditional notation is employed, such that $x \in (a, b] \Rightarrow a < x \leq b$.

[15] The results based upon these categories are robust to slight changes in the upper and lower limits.

Figure 3.3: Frequency of visiting friends and family in the western extension zone during charging hours



Source: www.tfl.gov.uk/.../sixth-annual-impacts-monitoring-report-2008-07.pdf

In wave 2 around 40% of all respondents said that they sometimes met up with friends and family in the WEZ, including 13% who were doing so at least once a week. After the introduction of charging in 2007, around a third of respondents in wave 4 said that they sometimes met up with friends and family in the WEZ, including 9% who were doing so at least once a week. This represented a 16 percent decrease in the reported proportion ever meeting up with friends and family in the WEZ during charging hours, and approximately a thirty percent decrease in the reported proportion doing so at least once a week.

When asked in wave 4 whether or not they had changed the number of times they meet up with friends and family in the WEZ, 6 percent of respondents said that they had. This was lower than the value reported in wave 1, where 11 percent of respondents anticipated a reduction in the number of visits they would make. The impact of this may be felt particularly by those who live within the area encompassed by the WEZ, or who find it hard to travel elsewhere to meet their friends and family, which ties in with the social exclusion arguments of Rajé (2003) and Bonsall and Kelly (2005).

Those who reported a reduction in meetings with their friends and family were three times more likely than respondents in general to say that they were worse off[16] as a result of the introduction of charging in the western extension (54 percent compared to 17 percent).

Information on the mode of travel used to make social visits was also obtained. When asked in wave 1 what car trips people were likely to give up due to the introduction of the WEZ, 38% said they thought the would stop using their car to visit friends and family who lived inside the WEZ. When comparing waves 2 and 4 it was actually found that 36% of respondents gave up making these trips to visit friends and relatives by car. When probed for the reasons, 38% (of those who stopped visiting friends and relatives by car) changed mode compared to 20% who stopped making the trips altogether. Other reasons (and percentages) are: a change in location[17] (11%); combining trips (3%); changing the time of the trip (17%); and "other".

The reported proportion of London residents with friends and family in the western extension zone travelling to the area once a week or more by car during charging

[16] A questions asks: *"As a result of the inclusion of the WEZ, do you think you are:"* with responses: (i) worse off; (ii) the same; (iii) better off.

[17] However these moves do not include crossing the boundaries of the WEZ.

Table 3.2: Changes in mode of travel of visits to friends and family between waves 2 and 4

	Visiting Family	Visiting Friends	Overall
Car	-7 % points [25% - 18%]	-6% points [19% - 13%]	-6% points [23% - 17%]
Public Transport	+5% points [52% - 57%]	-2% points [59% - 57%]	+3% points [54% - 57%]
Walk	+3% points [17% - 20%]	+6% points [17% - 23%]	+3% points [17% - 20%]

hours dropped by about a quarter from 23 percent to 17 percent, whereas travel by all other modes increased. Public transport increased by around a twentieth, whereas walking increased by about a tenth. Table 3.2 shows how the choice of mode changes for all trips, irrespective of the frequency. It can be seen that people travelling to visits inside the WEZ were less likely to use their car, and more likely to use either public transport or to walk.

Other variables of interest

As well as dummy variables for time-period, location, and their interaction (see next section) other socioeconomic information are included in the regression model. Due to the limited nature of the data, the set of socio-demographic variables is not as rich as would be preferred. However, we do have information on changes in income and employment status. It was hoped to include age (in banded groups) but this was not possible as age only appears in wave 4. As age is banded, it is not possible to impute previous values. For example, if a respondent was in the 25 - 44 age bracket in wave 4, we cannot ascertain if this individual was in this bracket in wave 2, or whether they have moved from the 18 - 24 age range.

When considering income, a question is asked about whether an individual's income has increased, decreased or remained constant. Between waves 2 and 4, 165 people reported an increase in income (12.58%), 167 reported a decrease in income (12.73%) and the remaining 980 had constant income (74.75%). No question is asked about actual income, only about changes in income. Although we cannot observe the magnitude of the change, we can observe the direction (if there is a change). However, in regression type analysis it is normally the direction of the change that we are most interested in. There was very little change in employment status between waves 2 and 4. The figures are: for wave 2 [wave 4]: employee 567 [569]; employer 39 [41]; self-employed 268 [275]; student 72 [63]; other employment 31 [29]; and not working/retired 335 [335]. In the analysis which follows, the omitted dummy for employment status is not-employed/retired.

3.3.2 Methodology

As a starting point, it was thought useful to compare the average frequency of visits to friends and family before and after the implementation of the WEZ. As previously stated, there is only a c. 10 month time frame between waves 2 and 4. This relatively short time frame is beneficial to the analysis here. If there are changes in the frequency of visits, we can infer that these were induced by the introduction of the WEZ, and not by other possible confounding factors. As mentioned above, there were only relatively minor travel distributions reported in London in the time frame under consideration here - no worse than during any other time period.

Define $\overline{y}_2$ and $\overline{y}_4$ as the average number of visits in waves 2 and 4, respectively.

These averages treat the ordered responses as cardinal values; that is we explicitly assume that, for example a score of 2 (once a twice a year) is half as 'good' as a score of 4 (every few months or so). Cardinality further assumes that an increase from, say 0 (never) to 1 (once or twice a year) has the same weighting to an individual as a move from 7 (3-4 days a week) to 8 (5 days a week or more). When modelling ordinal outcomes as cardinal scores, Ferrer-i-Carbonell and Frijters (2004) find that there is very little difference between assuming cardinality or ordinality. However, their result is purely empirical and not based on any proven theoretical results.

There are ten variables of interest, as outlined in Table 3.3. The value of interest here is $\Delta y = \overline{y}_4 - \overline{y}_2$, which shows the difference in the frequency of visits before and after the implementation of the WEZ. As we are comparing group means, we employ a paired t-test to examine the significance of the results obtained.

Table 3.3: Social capital variables under consideration

	Questions asked to:	
	Everyone in Sample	**WEZ Residents Only**
Frequency of visiting:	Family in WEZ at their home	Family outside WEZ at their home
	Family in WEZ away from their home	Family outside WEZ away from their home
	Friends in WEZ at their home	Friends outside WEZ at their home
	Friends in WEZ away from their home	Friends outside WEZ away from their home
	As a carer in WEZ at home	As a carer outside the WEZ, at home

Difference-in-Difference

The available data lends itself to utilising difference-in-difference (D-i-D) techniques. Define the outcome variable of choice of person i in area s in period t as Y_{ist}, where s refers to either living inside or outside of the proposed WEZ area. The policy intervention of interest here affects the people who live inside the western extension zone (WEZ), hence they are defined as *the treated*. Those people living outside of the WEZ are the *untreated*[18]. Therefore Y_{1ist} is the dependent variable of interest if the person lives in the area that is subject to treatment (that is, if an individual lives within an area of London that is incorporated into the WEZ) in period t, whereas Y_{0ist} is the corresponding outcome variable if an individual is untreated (they live in an area of London not effected by the incorporation of the WEZ) in period t. As with all studies of this type it is only possible to observe one state of the world. We can never observe the true counterfactual - only the estimated counterfactual. That is to say we only observe what has happened to the treatment group given that they have been treated. It is not possible to observe what happens to the treated group, given that they were not treated. The same applies for the untreated, we do not observe what happens to them given that they were treated.

We assume:

$$E\left[Y_{0ist}|s,t\right] = \beta_s + \gamma_t$$

where β_s is the time-invariant area effect and γ_t is a time effect, common across people both within and outside of the WEZ area. Further assume D_{st} is a dummy variable, such that $D_{st} = 1$ if, and only if, an individual lives inside the WEZ *and* the time period is after the WEZ CC policy had been implemented[19], and $E\left[Y_{1ist} - Y_{0ist}|s,t\right] = \delta$ is the treatment effect, then observed social capital proxies can be written:

$$Y_{ist} = \beta_s + \gamma_t + \delta D_{st} + \epsilon_{ist} \tag{3.1}$$

[18] However, this distinction is not strictly met here: see discussion of D-i-D assumptions later in this section.

[19] As discussed later in this Section, we do not observe any individuals who move either from outside the WEZ to inside it, nor do we observe any individuals who move from inside the cordon to outside it.

where ϵ_{ist} is an $i.i.d$ error term.

Let s = In for those individuals living inside the WEZ, and s = Out otherwise. Similarly let $t = 4$ if the data is from Wave 4 (after), and $t = 2$ if it is from Wave 2 (before). Then comparing between changes in the dependent variable of interest for those inside and outside of the WEZ gives an estimator of the D-i-D parameter:

$$\begin{aligned} & E\left[\widehat{Y}_{ist}|s = \text{In}, t = 4\right] - E\left[\widehat{Y}_{ist}|s = \text{In}, t = 2\right] \\ - & E\left[\widehat{Y}_{ist}|s = \text{Out}, t = 4\right] - E\left[\widehat{Y}_{ist}|s = \text{Out}, t = 2\right] = \delta \end{aligned}$$

where sample means, $\widehat{Y}$, are used as estimates of true population means, $\overline{Y}$.

Regression Based Difference-in-Difference

A more efficient way to estimate D-i-D is by applying regression analysis, requiring estimation of the model:

$$Y_{ist} = \alpha + \beta(\text{WEZ}_s) + \gamma(\text{Post}_t) + \delta(\text{WEZ}_s \times \text{Post}_t) + \epsilon_{ist} \tag{3.2}$$

where $\text{WEZ}_s = 1$ if person i lives inside the WEZ, and 0 otherwise. $\text{Post}_t = 1$ if the data relates to Wave 4 (*i.e.* after the implementation of the WEZ), and 0 otherwise. Interpretation of the parameters in Eq. (3.2) is as follows: α shows the value of the dependent variable for those outide the WEZ before the CC was implemented; $\alpha+\gamma$ relates to people outside the WEZ after its introduction; $\alpha + \beta$ defines the value of Y_{ist} for individuals living inside the WEZ before its introduction; and $\alpha+\beta+\gamma+\delta$ is the value of Y_{ist} for people living inside the affected area after the WEZ was introduced.

The coefficient of interest from Eq. (3.2), therefore, is the parameter δ - defined as *the difference-in-difference* parameter; alternatively denoted the *treatment effect*.

The main benefit of using regression-based D-i-D is it allows for standard errors to be created and examined, and also it easily generalises to allow the inclusion of relevant socioeconomic characteristics. For example, the vector $\mathbf{x}_{ist}$ in Eq. (3.3) contains information on employment status and changes in income of individual i in time t in area s. The vector ψ contains the corresponding coefficients.

$$Y_{ist} = \alpha + \beta(\mathrm{WEZ}_s) + \gamma(\mathrm{Post}_t) + \delta(\mathrm{WEZ}_s \times \mathrm{Post}_t) + \psi\mathbf{x}_{ist} + \epsilon_{ist} \tag{3.3}$$

In Eq, (3.3) we do not control for macroeconomic variables. Given that the policy affected whole areas of London we assume that the macro effects are constant for the whole of the treatment group and similarly are constant for the whole of the control group. This ensures that the Stable Unit Treatment Assumption (SUTVA) (e.g. Cox, 1958, Hudgens and Halloran, 2008) is satisfied here, as the treatment for all of the treated individuals is constant. We further assume that the treatment status of any given individual does not affect the potential outcome for another individual. That is, we assume that the visiting friends and family behaviour of an untreated individual (who lives outside the WEZ) is unaffected by the fact that an individual who lives inside the WEZ is treated[20]. The variable Post_t will further pick up any

[20] This assumption may be violated if, say, an individual outside the WEZ visits a relative more to make up for the reduction of visits to that relative by an individual who lives inside the WEZ. However, as we cannot identify friendships and family ties within our data we cannot test for this,

unobserved macro effects in this model setup.

For the results presented in the next section to be unbiased, D-i-D analysis requires that certain assumptions are met. Firstly it is necessary to assume that the treatment is exogenous, secondly the D-i-D approach assumes a common trend across control and treatment groups, and finally it is necessary to assume that the composition of control and treatment groups is stable over time.

The third assumption is automatically met here, as this analysis is based upon a balanced panel (by definition, we only analyse data on members of the sample who remain with the survey until at least wave 4). This criterion is further strengthened by the fact that the sample contains no individuals whose home moves across the WEZ border - that is everyone who lives inside the WEZ in wave 2 still does so in wave 4. The common trends assumption is not possible to test here, as data is only available for one period before the intervention (wave 2), and one period after the intervention (wave 4). If wave 1 contained similar data this common trend assumption could be tested, but unfortunately it does not.

The main concern here is that the treatment of interest (the implementation of the WEZ) is not exogenous - the treatment (WEZ) can impact upon both the treated (WEZ residents) and the non-treated (non-WEZ residents). We only have information on three categories: visits by WEZ residents to other WEZ residents; visits to WEZ residents to non-WEZ residents; and visits by non-WEZ residents to WEZ residents. The fourth, and missing category, is the group to whom the treatment would be completely exogenous, *i.e.* the frequency of visits of non-WEZ

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and hence we assume that the assumption is valid.

residents to other non-WEZ residents, as these individuals are truly untreated by the WEZ as they have no need to cross the cordon.

Whilst this is a concern, it is believed that D-i-D techniques can still be of use here. Non-WEZ residents have the option to stop visiting friends and family who live inside the cordon if they so wish, whilst WEZ residents do not have this option. That is, non-WEZ have the option to be exempt from the WEZ CC scheme - they can chose not to travel within the cordon, whereas WEZ residents, by definition, have to pay the CC fee if they wish to make any journey by private motor vehicle.

At the very least, D-i-D can test the hypothesis of local social capital (Kan, 2007): if there is a decrease in local social capital we would expect the D-i-D coefficient to be negative[21]. This negative coefficient would imply that people living inside the WEZ make fewer visits to other WEZ residents as a result of the congestion charging policy, and hence their stock of social capital would diminish more than that of people who live outside the area encompassed by the WEZ.

The Ordered Probit Model

D-i-D regression techniques usually utilise ordinary least squares (OLS) regression methodologies. However, given that the response to the questions relating to frequencies of visits are in fact an ordinal measure, it could be argued that it is methodologically preferable to utilise the ordered probit (OP) model. The OP model is used to model ordinal responses, where the responses take ordered multinomial outcomes

[21] Assuming that journeys between locations in the WEZ are 'shorter' than those from other locations into the WEZ - and hence more 'local'.

for each individual i. In general, $y_i = 1, 2, ..., K$[22]. The OP model is of the form:

$$y_i = k \quad \text{if} \quad \mu_{k-1} < y_i^* \leq \mu_k \quad k = 1, ..., K \tag{3.4}$$

where here the latent variable, y^*, is expressed as:

$$y^*_{ist} = \alpha + \beta(\text{WEZ}_s) + \gamma(\text{Post}_t) + \delta(\text{WEZ}_s \times \text{Post}_t) + \psi\mathbf{x}_{ist} + \epsilon_{ist} \tag{3.5}$$

where $\epsilon_{ist} \sim N(0, 1)$ and $\mu_0 = -\infty$, $\mu_k \leq \mu_{k+1}$, and $\mu_K = \infty$. For ease, let $\tau\mathbf{z}_{ist} = \alpha + \beta(\text{WEZ}_s) + \gamma(\text{Post}_t) + \delta(\text{WEZ}_s \times \text{Post}_t) + \psi\mathbf{x}_{ist}$. Then given that we assume that the error term is normally distributed, then the probability of observing a particular value of y is:

$$P_{ist,k} = P(y_{ist} = k) = \Phi(\mu_k - \tau\mathbf{z}_{ist}) - \Phi(\mu_{k-1} - \tau\mathbf{z}_{ist}) \tag{3.6}$$

where $\Phi(.)$ is the standard normal distribution function. The log-likelihood ($\mathcal{LL}$) of the ordered probit model is given by:

$$\mathcal{LL}(\mu, \tau) = \sum_{i=1}^{n} \sum_{k=0}^{8} (P_{ik}) \tag{3.7}$$

The Interval Regression Model

The technique of interval regression (IR), first developed by Stewart (1983), is concerned with estimating model parameters when the response categories are subsec-

[22] Here there are 9 outcomes, ranging from $y_i = 0$ through to $y_i = 8$.

tion of the real number line (that is there are upper bounds, u_k, and lower bounds, l_k, such that $y_i = k$ if $l_k \leq y_i^* \leq u_k$). Given that the ordinal response categories may be annualised here (see previous section), it is possible to fix the value of the μ_k parameters in the OP model above. For example, $y_{ist}^* = 8$ implies that respondents make visits 5 days a week or more, which corresponds to between 260 and 365 days a year. These values of 260 and 365 can be imputed as values for μ_7 and μ_8, such that $y_{ist} = 8$ if $265 < y_{ist}^* \leq 365$[23]. Because the value of the μ's are known, the estimates of the τ coefficients are more efficient. It is also possible to identify the variance of the error term, denoted σ^2, and therefore the scale of y_{ist}^* (Jones, 2000).

The likelihood function of the IR model subsumes that of the tobit model. In the case here, all data observations are in an interval or left censored (by zero)[24]. Denote observations that are in an interval as $j \in \mathcal{I}$, where observation y_j is in the interval given by $[y_{1j}, y_{2y}]$. The bounds under consideration here are outlined in the data section. Further denote the left (or zero-) censored observations as $j \in \mathcal{L}$. Then the log-likelihood function is:

$$\mathcal{LL} = \sum_{j \in \mathcal{L}} \log \Phi\left(\frac{y_{\mathcal{L}_j} - \tau \mathbf{z}}{\sigma}\right) + \sum_{j \in \mathcal{I}} \log \left\{ \Phi\left(\frac{y_{2j} - \tau \mathbf{z}}{\sigma}\right) - \Phi\left(\frac{y_{1j} - \tau \mathbf{z}}{\sigma}\right) \right\} \quad (3.8)$$

In a recent working paper, Brown et al. (2012) aim to extend IR models by introducing a zero-inflated component, and hence create zero-inflated IR (ZIIR) models. Zero inflated models initially model the probability that an outcome is zero or not,

[23] The remianing μ's are fixed at: 2,6,12,24,52, and 156

[24] In certain applied examples, the data analysed are a mixture of point data, left-censored data, right-censored data, and interval data. For the full log-likelihood function refer to the Stata help file, e.g. type -help intreg- in Stata.

using binary response models (usually probit or logit). Then in a second step, given the outcome is non-zero, a particular function from is applied (in this case IR). They analyse health care costs; a data with traditionally large numbers of zeros. When their model is complete, it may be useful to repeat the analysis presented here using ZIIR models for comparison. However, as there is not a problem here with large numbers of zeros here we expect the results to be similar. We recognise that in some related data sets there may be a large clusterings of observations at zero. Therefore, if further research is done in this area, it may be worth considering the ZIIR model as opposed to standard IR models.

As a comparison to IR models based upon the OP specification, we run the OLS specification on the same data where we specify the mid-point of the interval as the dependent variable. For example, the highest category utilised in the IR model is 260 - 365, so we impute 312.5 as the value of y in the mid-point OLS regression.

3.4 Results

3.4.1 Simple Differences

When examining the basic differences ($\Delta\overline{y} = \overline{y}_4 - \overline{y}_2$), a negative value would indicate a fall in the frequency of visits to friends and family. Recall higher values relate to higher frequencies of visits implying that if the number of visits fell in wave 4 compared to wave 2, then the difference will be negative. The results from this basic analysis are shown in Table 3.4 below. The standard errors are calculated using a paired t-test.

Table 3.4 shows that, on average, people who have friends and family living inside the area encompassed by the WEZ have reduced the frequency of which they visit friends and family, both at their homes and at other locations. Note that these averages contain people who do not make any visits to friends and family. However, everybody in wave 2 who made no visits also made no visits in wave 4, and *vice-versa*. Therefore, for this subgroup $\Delta y = 0$, and so hence the averages reported above may be biased downwards[25]. This fall in the number of visits is consistent across residents and non-residents of the WEZ. Further, the number of times people visit residents within the WEZ to act as an informal carer has also dropped, implying the most socially excluded face further barriers to social visits (Rajé, 2003). This in itself is an interesting result, possibly implying that the burden of care placed onto other people has increased. The fact that all values are negative and significant in itself implies that the introduction of the WEZ has reduced the frequency of visiting friends and relatives. From these basic differences we may deduce that this particular congestion charging policy reduced an individual's stock of social capital, on average.

The final column of Table 3.4 shows how residents who live inside the WEZ cordon have changed their number of visits to friends and family who live outside the area encompassed by the WEZ. Again, all values are negative and significant (with the exception of caring). If Kan (2007) local and distant social capital hypotheses are true, then Table 3.4 provides evidence that the WEZ has seen both decrease.

Therefore it can be seen that not only is the WEZ limiting WEZ residents' visits

[25] The averages conditional on making at least some visits are, actually, very similar to those presented above in Table 3.4

to friends and relative inside the cordon, but also their visits to people outside the cordon. Based on these results it would appear that, on average, all respondents visit people less, but it is WEZ residents who bear the greatest burden, consistent with Kan (2007).

Table 3.4: Differences in the amount of visits to friends and family before and after the introduction of the WEZ

	Visits Inside WEZ				Visits Outside WEZ
	Everyone	WEZ Residents	Non-WEZ Residents	Difference Significant[a]	WEZ Residents[b]
Family at home	-0.243*	-0.429**	-0.025	Yes*	-0.334***
Family away from home	-0.294***	-0.504***	-0.066**	Yes **	-0.669***
Friends at home	-0.433***	-0.406***	-0.429***	No	-0.357***
Friends away from home	-0.356***	-0.392***	-0.303***	No	-0.614***
As a carer/volunteer	-0.167*	-0.321*	-0.021	Yes*	-0.058

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
a: The difference is Column (2) - Column (1). Significance is found from a paired t test.
b: The last column refers to the differences in the amount of visits to friends and family who live outside the WEZ made by WEZ Residents before and after the introduction of the WEZ.

3.4.2 OLS Difference-in-Difference

Table 3.5 shows the results from the OLS difference-in-difference analysis. The results displayed assume that the behaviour of London residents (including those who live inside the WEZ) and the behaviour of those who live inside the WEZ are suitable for this difference-in-difference type analysis (see the previous section).

The difference-in-difference coefficients are the interaction terms (the δ parameters). Identical to the results in Table 3.4, the difference-in-difference coefficient is negative for four out of the five categories, the exception being visiting friends at home. If the WEZ has had a greater impact on people living inside the 'treated' zone, than

Table 3.5: OLS Difference-in-Difference Estimates with Controls

	Family at Home	Family not Home	Friend at Home	Friend not Home	As carer
WEZ Resident (β)	0.873***	0.547***	1.566***	1.127***	0.410***
	(0.182)	(0.163)	(0.159)	(0.153)	(0.129)
Post (γ)	-0.028	-0.072	-0.432***	-0.306**	-0.024
	(0.182)	(0.164)	(0.148)	(0.146)	(0.125)
WEZ $\times$ Post (δ)	-0.404*	-0.438**	0.023	-0.089	-0.300*
	(0.239)	(0.224)	(0.214)	(0.210)	(0.181)
Increase in Income	0.039	0.252	-0.257	0.192	-0.228
	(0.283)	(0.252)	(0.234)	(0.225)	(0.197)
Decrease in Income	-0.406*	0.055	-0.067	-0.139	0.055
	(0.246)	(0.224)	(0.226)	(0.217)	(0.181)
Employed	-0.494**	0.052	-0.754***	-0.649***	-0.068
	(0.226)	(0.202)	(0.199)	(0.192)	(0.161)
Employer	-0.963	-0.486	-0.895*	-0.760*	-0.165
	(0.498)	(0.449)	(0.464)	(0.447)	(0.364)
Self Employed	-0.290	0.362	-0.056	0.126	0.066
	(0.254)	(0.226)	(0.220)	(0.212)	(0.182)
Student	1.312***	1.374**	0.815**	0.982***	0.528*
	(0.418)	(0.373)	(0.369)	(0.356)	(0.299)
Other Employment	0.194	0.011	0.207	-0.124	0.358
Status	(0.629)	(0.560)	(0.509)	(0.490)	(0.436)
Observations	999	996	1230	1231	905

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

we would expect to observe negative values, as we do. The coefficients on visiting family (both at their home, and other locations) are negative and significant, as is the coefficient on caring. The coefficients on visiting friends are statistically insignificant.

If the decision to incorporate the western extension zone had a detrimental affect on the frequency of visiting friends and family we would expect the coefficient on the 'Post' (γ) variable to be negative. It can be seen that all coefficients are indeed negative, hence indicating a fall in the number of visits. The coefficient on visiting friends at their home is significant at the 1% level, whereas the coefficient on visiting friends away from their home is significant at the 5% level. The remaining three coefficients are negative but insignificant at the 10% level.

When looking at the coefficients on the 'WEZ Resident' (β) variable, we can see that before the introduction of the WEZ people who lived inside the zone encompassed by the western extension visited friends and family inside the zone more often than those who lived outside the zone. This is due to the positive (and highly significant) coefficient on all five dependent variables, and is as expected. People are more likely to visit friends and family who live close to home more often than friends and relatives who live further afield. This is again, consistent with the local social capital hypothesis of Kan (2007)

Table 3.5 indicates that people who are employed, relative to those out of the labour market (including retired), make fewer visits to friends and family. These negative coefficients are significant for three out of the five categories: visiting family at home; visiting friends and home; and visiting friends away from their home. The remaining two coefficients are insignificant, and much smaller in magnitude. Students are much more likely to make more visits to all five response categories - the coefficient in all five cases is positive and significant. One possible explanation for this may be the fact that students are likely to be more socially active when compared to those inactive in the labour market.

It would appear that changes in income play no significant role in determining the frequency of visits to friends and family. This is an interesting finding; one would expect a decrease in income, coupled with an increase in the price of making visits, to lead to a decrease in the number of visits if the cost of making the visits was the main deterrent. However, the insignificant income change coefficients may indicate that the changes in visiting behaviour may be attributed to other factors, such as the administration of having to pay the congestion charge, etc.

3.4.3 OP and Interval Regression Difference-in-Difference

Tables 3.6 and 3.7 show the results from the OP and interval regression D-i-D models, respectively. The majority of the discussion will be based around Table 3.7 as the results are easier to quantify. For example, we can see that WEZ Residents visit family members at their home around 64 times a year more, when compared to non-WEZ residents. The coefficients on WEZ Residents are positive and significant for all five categories.

Table 3.6: Ordered Probit Difference-in-Difference Estimates

	Family at Home	Family not Home	Friend at Home	Friend not Home	As carer
WEZ Resident (β)	0.394***	0.279***	0.659***	0.509***	0.364***
	(0.083)	(0.083)	(0.066)	(0.065)	(0.118)
After (γ)	-0.008	-0.044	-0.164***	-0.148**	0.003
	(0.080)	(0.082)	(0.060)	(0.606)	(0.118)
Interaction (δ)	-0.115	-0.187*	-0.002	-0.050	-0.189
	(0.110)	(0.108)	(0.088)	(0.084)	(0.156)
Increased Income	0.019	0.105	-0.099	0.055	-0.231
	(0.132)	(0.127)	(0.098)	(0.094)	(0.200)
Decreased Income	-0.203*	0.058	-0.018	-0.057	0.040
	(0.112)	(0.114)	(0.093)	(0.092)	(0.159)
Employed	-0.247**	0.005	-0.341***	-0.266***	-0.067
	(0.102)	(0.104)	(0.082)	(0.080)	(0.145)
Employer	-0.495**	-0.222	-0.355*	-0.274	-0.192
	(0.247)	(0.241)	(0.192)	(0.188)	(0.320)
Self Employed	-0.119	0.161	-0.040	0.056	0.064
	(0.113)	(0.113)	(0.089)	(0.088)	(0.157)
Student	0.548***	0.551***	0.239	0.360**	0.472**
	(0.173)	(0.173)	(0.147)	(0.147)	(0.233)
Other Employment	0.077	0.008	0.070	-0.064	0.313
Status	(0.273)	(0.281)	(0.201)	(0.203)	(0.343)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Interval Regression Difference-in-Difference Estimates

	Family at Home	Family not Home	Friend at Home	Friend not Home	As carer
WEZ Resident (β)	63.807***	29.495***	66.665***	42.888***	84.899***
	(13.607)	(8.628)	(6.195)	(5.491)	(28.231)
After (γ)	-0.658	-5.760	-14.456**	-13.288**	-1.492
	(13.308)	(9.282)	(6.038)	(5.632)	(32.000)
Interaction (δ)	-25.047	-21.732*	-1.636	-6.336	-48.624
	(17.822)	(12.668)	(8.322)	(7.891)	(40.004)
Increased Income	2.927	9.784	-8.991	3.063	-54.570
	(21.461)	(13.182)	(9.268)	(8.098)	(46.890)
Decreased Income	-33.198*	7.612	-1.605	-5.645	8.794
	(18.133)	(11.808)	(8.782)	(7.863)	(37.164)
Employed	-40.660**	0.990	-32.903***	-22.097***	-13.855
	(16.568)	(10.781)	(7.730)	(6.884)	(33.926)
Employer	-81.744**	-22.203	-32.971*	-21.809	-46.420
	(40.274)	(24.982)	(18.261)	(16.163)	(86.765)
Self Employed	-19.139	16.333	-4.457	4.645	14.859
	(18.349)	(11.770)	(8.431)	(7.538)	(36.644)
Student	87.059***	54.894***	18.221	27.210**	110.427**
	(27.861)	(18.051)	(13.963)	(12.555)	(54.748)
Other Employment	12.103	0.155	5.5897	-5.518	76.856
Status	(43.994)	(29.199)	(19.051)	(17.380)	(79.215)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When examining the 'After' (γ) coefficients, we can see that visits to family members (both at, and away from, their homes) are small in value and insignificant. The same applies for the case of making visits as a carer. However, when looking at the number of visits to friends, we can see that the WEZ policy has caused a decrease of around 14 visits a year to friends at their home (inside the WEZ), and a decrease of around a 13 visits a year to friends at other locations in the WEZ. Both of these values relate to approximately one social visit fewer per month.

The interaction coefficients appear to be the opposite of those on the after variable - for the interactions, it is visits to family and those as a carer that are the numerically larger coefficients (in absolute terms). Whilst the coefficient in the carer specification is insignificant, it is strikingly large. The figure implies that the implementation of the WEZ has caused around 1 few visit per week to act as a carer, when comparing WEZ residents to non-WEZ residents. Given the recent interest in the provision of informal care, this is a large number. However, it is insignificant, so the result is not as powerful. This value, if significant, would add weight to the social inclusion/exclusion arguments of Bonsall and Kelly (2005) and Rajé (2003).

Relative to being unemployed or retired, employed people visits family members at home around 40 days a year fewer. The coefficient on visits to family away from their homes is both small and insignificant. Visits to friends are also lower for the employed - they visit friends at home around 33 times fewer per year. The employers in the sample make fewer visits per year too. Again, we can see that students, on average, make the most social visits per year. As examined above this is not so surprising, given the higher weights students and younger people place on social activities. However, it is interesting to note that students make over 110 more visits per year to act as a volunteer or carer, when compared to those not in the labour market. One explanation could be that it is the voluntary sector that is contributing to this hugh difference, although it could be argued that the retired are also likely to participate in voluntary work.

The results of Table 3.6 are consistent with those outlined above, only less easy to quantify.

The results presented in Table 3.8 show the estimated coefficients based on the OLS specification, where we use the mid-point of the interval as the dependent variables. Whilst these results are quite similar to those presented in Table 3.7, they are not

Table 3.8: Midpoint OLS Regression Difference-in-Difference Estimates

	Family at Home	Family not Home	Friend at Home	Friend not Home	As carer
WEZ Resident (β)	41.474***	21.303***	48.459***	36.157***	24.189**
	(9.928)	(7.775)	(5.305)	(5.122)	(11.858)
After (γ)	3.842	-15.697**	-8.298	-18.278***	-24.057
	(11.242)	(8.533)	(5.834)	(5.410)	(25.926)
Interaction (δ)	-7.818	-2.714	-1.282	2.031	-18.508
	(14.216)	(11.187)	(7.649)	(7.292)	(31.585)
Increased Income	12.731	4.838	-7.211	-3.533	-12.071
	(17.027)	(11.459)	(8.787)	(7.573)	(43.047)
Decreased Income	-42.273**	18.434*	2.399	3.011	-7.446
	(20.123)	(10.736)	(8.074)	(7.495)	(30.816)
Employed	-17.509**	11.106	-12.201**	-12.331***	16.537
	(8.562)	(7.182)	(4.929)	(4.743)	(19.619)
Employer	-80.084***	-40.264**	-13.453	-7.685	-83.584
	20.501)	(16.839)	(11.456)	(11.254)	(56.033)
Self Employed	2.159	9.595	-3.985	-0.732	-11.801
	(9.748)	(7.911)	(5.322)	(5.156)	(20.941)
Student	43.063***	24.017**	2.688	14.914*	81.673***
	(13.005)	(10.938)	(8.219)	(8.022)	(26.206)
Other Employment Status	37.332*	4.824	-8.842	-27.056**	10.985
	(21.561)	(18.630)	(11.411)	(11.853)	(37.209)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

identical. For example, all of the coefficients on the WEZ Resident variable in the OLS specification are lower than those for the IR model. Further, some of the significant variables in the IR specifications become insignificant when utilising OLS, and *vice-versa*. We conclude that these differences are based on the differing model specifications, and advocate the use of IR model specifications when faced with a choice between the two.

3.5 Conclusions

This chapter provides a unique insight into the *ex-post* effect that congestion charging policies have on social capital. Difference in difference techniques, based on a number of model specifications, are employed to evaluate the impact that the Western Extension Zone of London's Congestion Charging scheme had on the frequency of visits to friends and family.

When analysing simple differences, it is noticeable that all values are negative, and most are significant. This implies that the WEZ implementation has caused a fall in the frequency of visits to friends and family. The fact that the time period under consideration (c. 10 months) is relatively small adds weight to these results. In a longer time frame, it is possible that other confounding factors may have contributed to this marked drop in visits. However, such a small time frame would seem to imply that the WEZ in the main driver of these results.

When looking at difference-in-difference techniques, it can be seen that residents who live inside the WEZ visit other residents of the WEZ considerably more than when compared to the visiting behaviour of non-residents who visit people inside the WEZ (consistent with Kan's (2007) hypothesis of local social capital). For example, WEZ residents visit friends in their home inside the WEZ some 67 times a year more than non-residents do. Similarly, WEZ residents make 85 visits a year more as a carer or volunteer inside the zone, when compared to the visiting behaviour of non-residents who care or volunteer inside the WEZ.

The implementation of the extension had the greatest impact on the frequency of visiting friends, both at their home (located inside the WEZ) and at other locations inside the WEZ. Visits to friends at home fell by 15 visits a year after the policy was implemented, whereas visits to friends at other locations fell 13 visits a year. The WEZ appears to have had no significant impact on the frequency of visits to family, nor on the visits as a carer/volunteer.

The difference-in-difference terms in the various regression models are mainly insignificant. However, one exception is the frequency of visits to family away from their home. The WEZ has caused 22 fewer visits per year for WEZ residents compared to non-WEZ residents. One interesting D-i-D coefficient is that on visits as a carer/volunteer. It seems to suggest that the WEZ has led to 50 fewer visits per year as a carer, equivalent to roughly one per week. However, this coefficient in insignificant at the 10% significance level.

Changes in income have no significant explanatory power on the frequency of visits to friends and family. This in itself is an interesting finding. It may be argued that increases in income offset the financial costs imposed by the WEZ, hence the increase in income coefficients are insignificant as visits are maintained at a similar frequency. However, if the reduction in visits caused by the WEZ was solely due to the increased financial burden, then we would expect to see those with a reduction in their income make even fewer visits, *per se*. However, the decrease in income coefficient is always insignificant, with the exception of visits to family at home - in which case it is always significant (although usually at the 10% level). This may imply that factors other than cost, such as the administrative aspects, may be the main reason for the reduction in visits to friends and family.

Those in employment, and those who are employers seem to make fewer visits when compared to those who are not in the labour force (either retired or unemployed or inactive). However, students seem to make considerably more visits.

Whilst this chapter in limited by the omission of the 'true control group', the results are nevertheless policy relevant. It would appear the congestion charging schemes do reduce the number of times and individual visits his/her friends and/or family. At a time when the importance of social inclusion is becoming more prominent, these are interesting results. Are the gains in pollution and congestion reduction sufficiently large to offset the losses in social capital? Further study, with more detailed data is needed before one can fully answer that question.

Chapter 4

The Relationship Between Well-being and Commuting Re-visited: Does the choice of methodology matter?

Disclaimer: this Chapter is joint work with my two supervisors, Prof. Andy Dickerson and Dr. Arne Risa Hole. A condensed version of this chapter has been submitted to a spatial health econometric edition of Regional Science and Urban Economics and is currently under the revise and resubmit process.

4.1 Introduction

Measures of subjective well-being are increasingly used as a proxy for individual welfare in applied economics. Summaries and overviews of this rapidly expanding literature include: Frey and Stutzer (2002a), Frey and Stutzer (2002b), Layard (2005), Kahneman and Krueger (2006), Di Tella and MacCulloch (2006), Clark et al. (2008), Dolan et al. (2008), Stutzer and Frey (2010) and MacKerron (2012). Survey respondents are typically asked a question like 'How satisfied are you with your life overall?' and asked to give a response on a Likert scale with the lowest and highest values corresponding to 'Not satisfied' and 'Completely satisfied', respectively. Econometrically this raises the question of how to model this type of data. Since well-being as a proxy for individual welfare or utility is strictly speaking an ordinal rather than a cardinal measure - a 1-point increase from 2 to 3 on the well-being scale may not imply the same increase in well-being as an increase from 6 to 7, for example - the standard econometric approach would be to use an ordered logit or probit model. However, in an influential paper, Ferrer-i-Carbonell and Frijters (2004) compare the results from a linear fixed-effects (FE) model, and thus implicitly treating well-being as a cardinal measure, with those from their FE ordered logit specification, and find that they obtain similar results. An equivalent finding has been documented by Frey and Stutzer (2000). This has led authors in several subsequent studies to analyse their data using linear models (e.g. Stutzer and Frey, 2008), presumably because linear FE models are considered to be more straightforward to implement in practice and lead to more easily interpretable results than ordered FE models. More recently, however, Baetschmann et al. (2011) have shown that the FE ordered logit estimator used in the Ferrer-i-Carbonell and

Frijters (2004) comparison is, in fact, inconsistent. Hence, the similarity between the linear FE and the ordered FE results is not particularly informative.

In this chapter we revisit the debate surrounding the appropriate methodology for modelling subjective well-being data in the context of the relationship between commuting and well-being. According to microeconomic theory, individuals would not choose to have a longer commute unless they were compensated for it in some way, either in the form of improved job characteristics (including pay) or better housing prospects (Stutzer and Frey, 2008). Even if commuting in itself is detrimental to well-being we would therefore not expect individuals with longer commutes to report lower levels of life satisfaction. As far as we are aware, Stutzer and Frey (2008) and Roberts et al. (2011) are the only previous papers that attempt to test this hypothesis by modelling the relationship between commuting and subjective well-being. Using data from the German Socio-Economic Panel (GSOEP), Stutzer and Frey (2008) estimate linear FE models in which satisfaction with life overall (measured on a scale from 1 to 10) is specified as a function of commuting time and a set of control variables. The authors find that a one standard deviation (18 minutes) increase in commuting time lowers reported satisfaction with life overall by 0.086. To put this estimate into context Stutzer and Frey (2008) report that it is equivalent to about 1/8 of the effect on well-being of becoming unemployed. The authors conclude that commuting is a stressful activity which does not pay off, a result which they refer to as the 'commuting paradox' as it does not correspond to the predictions from microeconomic theory.

Using data from the British Household Panel Survey (BHPS), Roberts et al. (2011) model the relationship between well-being, commuting times and other personal and household characteristics. Well-being is measured by the GHQ (General Health Questionnaire) score, which is derived as the sum of the responses to 12 questions related to mental health. Using linear FE models, the authors find that longer commutes are associated with lower levels of subjective well-being among women but not among men. They suggest that this is likely to be a result of women having greater responsibilities for day-to-day household tasks, such as childcare and housework, and that this makes them more sensitive to longer commuting times. The authors of both papers acknowledge that the dependent variable in their models is categorical, but justify the use of a linear model based on the findings in the study by Ferrer-i-Carbonell and Frijters (2004).

While there is limited empirical evidence on the relationship between commuting and well-being, there is a substantial body of work on commuting in the urban economics literature with recent contributions including van Ommeren and Gutiérrez-i-Puigarnau (2011), Ross and Zenou (2008) and Pierrard (2008). Roberts et al. (2011) review the literature on differences in commuting behaviour between men and women. Also of relevance to our study is the large literature devoted to estimating the value of travel time; Abrantes and Wardman (2011) present a recent meta-analysis of UK estimates. As we will demonstrate, models of well-being provide an alternative to more traditional travel demand models for estimating the value of time spent commuting.

Using data from the British Household Panel Survey, we compare the results from linear FE models and ordered logit models with and without fixed-effects. We find that while the results from the pooled ordered logit models suggest that there is a negative relationship between longer commutes and reported satisfaction with life overall, no such relationship is found in the (linear and ordered) FE models.[1] This confirms Ferrer-i-Carbonell and Frijters' finding that the results from linear and ordered models of subjective well-being are qualitatively similar once unobservable individual fixed-effects are controlled for. We also find that the choice of estimator for the fixed-effects ordered logit model has little qualitative impact on the results. However, unlike Stutzer and Frey (2008) and Roberts et al. (2011) we do not find evidence that commuting is related to lower levels of subjective well-being, in general. This suggests that the relationship between well-being and commuting times may depend on differences in culture (the UK vs. Germany) and the choice of well-being measure (overall life satisfaction vs. the GHQ score).

The chapter is structured as follows: section two describes the econometric methodology, section three presents the data used in the analysis and section four presents the modelling results. Section five concludes.

4.2 Methodology

In this section we briefly review various estimators for the FE ordered logit model that have been suggested in the literature[2]. Our starting point is a latent variable model:

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[1] We attribute this difference between pooled and FE models to omitted variable bias - *i.e.* we infer that there exists individual specific traits (or fixed effects) which contribute to this difference. One possible explanation is that unhappy people get worse jobs than happier people. This explanation is only speculative, however.

[2] For simplicity we omit some technical details and focus on what we believe are the most important practical issues. We refer interested readers to the comprehensive review by Baetschmann et al. (2011).

$$y_{it}^* = x_{it}'\beta + \alpha_i + \varepsilon_{it}, \quad i = 1, ..., N \quad t = 1, ..., T \tag{4.1}$$

where y_{it}^* is a latent measure of the well-being of individual i in period t, x_{it} is a $(L \times 1)$ vector of observable characteristics related to well-being and β is a $(L \times 1)$ vector of coefficients to be estimated. α_i is a time-invariant unobserved component which may be correlated with x_{it} and ε_{it} is a white noise error term. We observe y_{it} which is related to y_{it}^* as follows:

$$y_{it} = k \ \text{ if } \ \mu_k < y_{it}^* \leq \mu_{k+1}, \quad k = 1, ..., K \tag{4.2}$$

The threshold parameters, μ_k, are assumed to be strictly increasing in k ($\mu_k < \mu_{k+1}$ $\forall k$) with $\mu_1 = -\infty$ and $\mu_{K+1} = \infty$. Assuming that ε_{it} is independent and identically distributed (IID) logistic the probability of observing outcome k for individual i at time t is:

$$\Pr(y_{it} = k | x_{it}, \alpha_i) = \Lambda(\mu_{k+1} - x_{it}'\beta - \alpha_i) - \Lambda(\mu_k - x_{it}'\beta - \alpha_i) \tag{4.3}$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function. As explained by Baetschmann et al. (2011), there are two problems with direct maximum likelihood estimation of this expression. The first is that only the difference between the thresholds and the fixed-effect $\alpha_{ik} = \mu_k - \alpha_i$ can be identified. The second is that under fixed-T asymptotics α_{ik} cannot be estimated consistently due to the incidental parameter problem (Neyman and Scott, 1948). This unfortunately also affects the estimates of β, and it has been found that the bias can be substantial in short panels (Greene, 2004).

Winkelmann and Winkelmann (1998) suggest that a way of getting around this problem is to collapse y_{it} to a binary variable and use Chamberlain's estimator for fixed effects binary logit models. Following Baetschmann et al. (2011) we define a variable $d_{it}^k = I(y_{it} \geq k)$ where $I(\cdot)$ is the indicator function and k is a cutoff value. In other words, d_{it}^k is equal to one if y_{it} is greater than or equal to the chosen cutoff value and zero otherwise. The probability of observing a particular sequence of outcomes $d_i^k = (d_{i1}^k, ..., d_{iT}^k)$ conditional on the number of ones in the sequence (a_i) is given by:

$$\Pr\left(d_i^k | \sum_{t=1}^{T} d_{it}^k = a_i\right) = \frac{\exp\left(\sum_{t=1}^{T} d_{it}^k x_{it}' \beta\right)}{\sum_{l_i \in B_i} \exp\left(\sum_{t=1}^{T} l_{it} x_{it}' \beta\right)} \tag{4.4}$$

where l_{it} is either zero or one, $l_i = (l_{i1}, ..., l_{iT})$ and B_i is the set of all possible l_i vectors with the same number of ones as d_i^k. Chamberlain (1980) shows that maximizing the conditional log-likelihood $LL^k = \sum_{i=1}^{N} \ln \left[\Pr(d_i^k | \sum_{t=1}^{T} d_{it}^k = a_i)\right]$ gives a consistent estimate of β.

While in principle any cutoff $2 \leq k \leq K$ can be used in the estimation it is important to note that individuals with constant d_{it}^k do not contribute to the likelihood[3]. This implies that any particular choice of cutoff is likely to lead to some observations being discarded and the question is then whether we can do better than choosing a

[3] This is because $\Pr\left(d_i^k = 1 | \sum_{t=1}^{T} d_{it}^k = T\right) = \Pr\left(d_i^k = 0 | \sum_{t=1}^{T} d_{it}^k = 0\right) = 1$.

single cutoff. We will review three alternative estimators that have been proposed in the literature: the Das and Van Soest (1999) estimator, the 'Blow-up and Cluster' estimator (Baetschmann et al., 2011) and the Ferrer-i-Carbonell and Frijters (2004) estimator.

4.2.1 The Das and Van Soest (DvS) estimator

Since the estimator of β at any cutoff ($\widehat{\beta}^k$) is consistent, Das and Van Soest (1999) proposed estimating the model using all $K-1$ cutoffs and combine the estimates in a second step. The efficient combination weights the estimates by their variance so that

$$\widehat{\beta}^{DvS} = \arg\min_b \left(\widehat{\beta}^{2\prime} - b', ..., \widehat{\beta}^{K\prime} - b'\right) \widehat{\Omega}^{-1} \left(\widehat{\beta}^{2\prime} - b', ..., \widehat{\beta}^{K\prime} - b'\right)' \tag{4.5}$$

where $\widehat{\Omega}^{-1}$ is an estimate of the variance-covariance matrix of the coefficients. The solution to this problem is

$$\widehat{\beta}^{DvS} = \left(H'\widehat{\Omega}^{-1}H\right)^{-1} H'\widehat{\Omega}^{-1} \left(\widehat{\beta}^{2\prime}, ..., \widehat{\beta}^{K\prime}\right)' \tag{4.6}$$

where H is a matrix of $K-1$ stacked identity matrices of dimension L. The variance-covariance matrix of $\widehat{\beta}^{DvS}$ is given by

$$Var\left(\widehat{\beta}^{DvS}\right) = \left(H'\widehat{\Omega}^{-1}H\right)^{-1} \tag{4.7}$$

Appendix A.1 presents code for implementing the DvS estimator in Stata.

The drawback of the DvS estimator is that in many real settings some cutoff values are going to lead to very small estimation samples. This may lead to convergence problems and/or imprecise estimates of the variance-covariance matrix $\widehat{\Omega}^{-1}$, and it may therefore be necessary to use only some of the possible cutoffs when implementing the DvS estimator in practice.

4.2.2 The 'Blow-up and Cluster' (BUC estimator)

Baetschmann et al. (2011) have recently suggested an alternative to the DvS estimator which avoids the problem of small sample sizes associated with some cutoff values. Essentially the BUC estimator involves estimating the model using all $K-1$ cutoffs simultaneously, imposing the restriction that $\beta^2 = \beta^3 = \cdots = \beta^K$. In practice this can be done by creating a dataset where each individual is repeated $K-1$ times, each time using a different cutoff to collapse the dependent variable. The model is then estimated on the expanded sample using the standard Chamberlain approach. Since some individuals contribute to several terms in the log-likelihood function it is necessary to adjust the standard errors for clustering at the level of the respondent, hence the name 'Blow-up and Cluster' (Baetschmann et al., 2011).

Appendix A.2 presents code for implementing the BUC estimator in Stata with an example using simulated data. Baetschmann et al. (2011) also present Stata code for estimating the BUC model, but we have found that their code can inadvertently drop observations from the estimation sample in some circumstances. The root of the problem is that a new individual ID variable is generated by multiplying the original ID by 100 and adding a small number. Since the new ID variable is stored as a 'long' and the maximum value for longs is 2,147,483,620 in Stata, any individual with an original ID greater than 21474836 will drop out of the sample as their new ID will be set to 'missing'. This is an issue of practical importance using the original ID variable in the BHPS data - in our estimation sample a substantial proportion of respondents are incorrectly dropped when using the code by Baetschmann et al.

4.2.3 The Ferrer-i-Carbonell and Frijters (FF) estimator

An alternative estimator to the ones described above was proposed by Ferrer-i-Carbonell and Frijters (2004). Their estimator involves identifying an optimal cut-off for each individual, where the optimal cutoff is the value which minimises the (individual) Hessian matrix at a preliminary estimate of β. Many applied papers have instead used a computationally simpler rule for choosing the cutoff, such as the individual-level mean or median of y_{it} (e.g. Booth and van Ours (2008), Booth and van Ours (2009), Kassenboehmer and Haisken-DeNew (2009), Jones and Schurer (2011)). Baetschmann et al. (2011) show that FF-type estimators are in general inconsistent since the choice of cutoff is endogenous. In a simulation experiment they find that the downward bias in the FF estimates can in some cases be substantial, while the DvS and BUC estimators generally perform well[4]. Code for implementing the Ferrer-i-Carbonell and Frijters (2004) estimator in Stata is available from the authors on request.

[4] As expected the DvS estimator performs less well in situations where some cutoffs are associated with very small sample sizes.

4.3 Data

This paper uses data from waves 6 to 18 (1996-2008) of the British Household Panel Survey (BHPS)[5], a nationally representative panel survey conducted by the Institute for Economic and Social Research. The households in the sample are re-interviewed on an annual basis and by wave 18 (2008), about 16,000 individuals participated in the survey. Waves 6 to 18 were chosen as they represent the only waves for which data on overall life satisfaction are available (although no data are available for wave 11 (2001) when the life satisfaction question was omitted from the survey questionnaire).

We restrict the sample to include only respondents of working age, defined to be individuals between the ages of 17 and 65 inclusive. Similarly only people who respond that they are employed are retained in the sample. Self-employed respondents are not included, since they are more likely to work from home and generally have different commuting patterns to employees (Roberts et al., 2011).

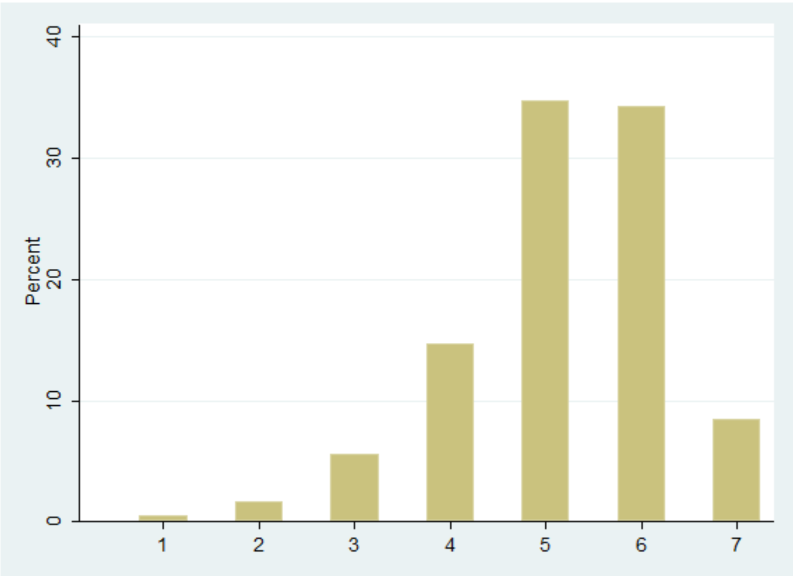
As our dependent variables we use data from the following two questions: 'How dissatisfied or satisfied are you with your life overall' and 'How dissatisfied or satisfied are you with amount leisure time you have'. Respondents are asked to give a response on a seven-point scale, where the lowest value (1) is labelled 'Not Satisfied at all' and the highest value (7) is labelled 'Completely Satisfied'.[6] Figures 1 and 2 present

[5] However, the satisfaction questions were not asked in wave 11, and as such we do not use information from this wave in our main analysis.

[6] From wave 12 (2002) onwards the number 4 on the satisfaction scale was labelled 'Not satisfied/dissatisfied', while it was unlabelled in earlier waves. Conti and Pudney (2011) find evidence that whether or not textual labels are assigned to values can have an impact on the results. As a robustness check we have therefore run the analysis in the paper on both the full (1996-2008) sam-

the distribution of the satisfaction with life overall and satisfaction with leisure time variables using data from all 12 waves available. It can be seen from the figure that the distribution of the overall life satisfaction data is highly skewed, with the majority of the responses at the top end of the distribution. This is a common finding in the literature on subjective well-being (Dolan et al., 2008). The distribution of the satisfaction with leisure time data is less skewed, but again the majority of respondents report relatively high values.

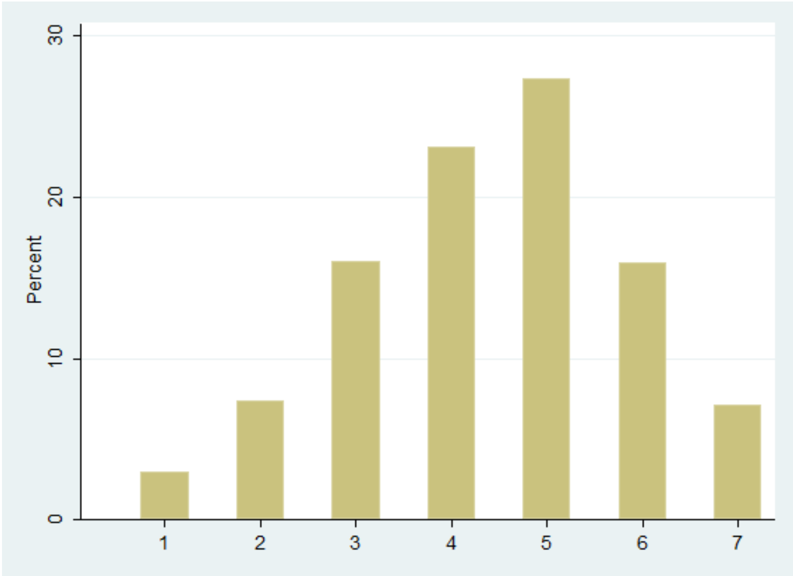
Figure 4.1: Distribution of Satisfaction with Life Overall



As a robustness check, and to be consistent with Roberts et al. (2011), we also use the GHQ score as an alternative dependent variable in our analysis. The GHQ score is derived as the sum of the responses to 12 questions related to mental health each scored on a 4 point scale (from 0 to 3), where a high value represents a low level of mental health. In our analysis the score has been reversed so that a higher score represents better well-being. The distribution of the GHQ score using data from all 12 waves is shown in Figure 4.3.

ple and the 2002-2008 sub-sample. As the results are very similar we only report the full-sample analysis.

Figure 4.2: Distribution of Satisfaction with Leisure Time

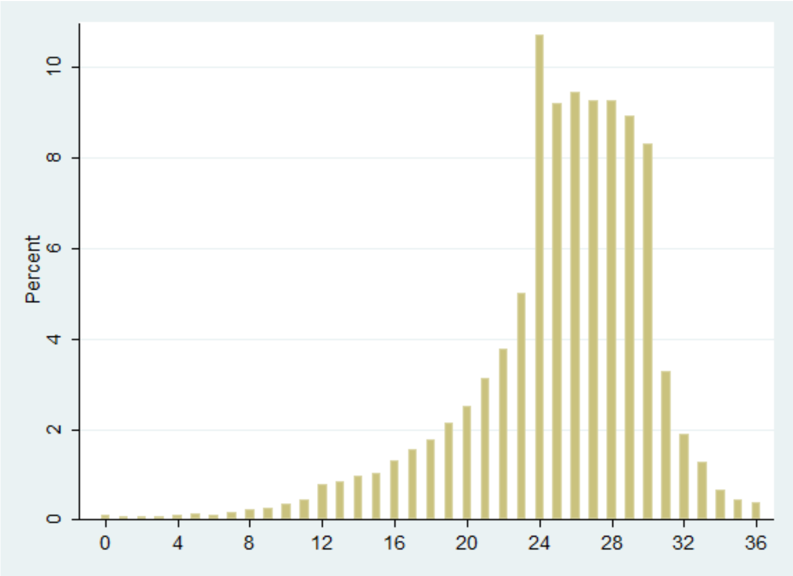


The BHPS includes information on both commuting time and the mode of transport used for commuting trips[7]. The respondents are asked 'How long does it usually take you to get to work each day, door to door?'. The answer is recorded in minutes and corresponds to a one-way commute. The respondents are then asked 'And what usually is your main means of travel to work?'. The response is coded as one of the following alternatives: car driver, car passenger, rail, underground, bus, motor bike, bicycle, walking and other. Figure 4.4 presents the distribution of the commuting time variable using data from all 12 waves.

In addition to commuting time, which is the main explanatory variable of interest in our analysis, we control for a range of factors that have been found to be related to subjective well-being in previous work. These include age, hours worked, real household income (at 2008 prices), marital status, number of children in the household, a dummy for saving regularly and a dummy for having a university degree. As a

[7] The BHPS does not have data on commuting distance, but commuting time may in any case be argued to be more closely related to the opportunity cost of commuting than the distance travelled (Stutzer and Frey, 2008) and is therefore a more relevant variable in this context.

Figure 4.3: Distribution of GHQ Score



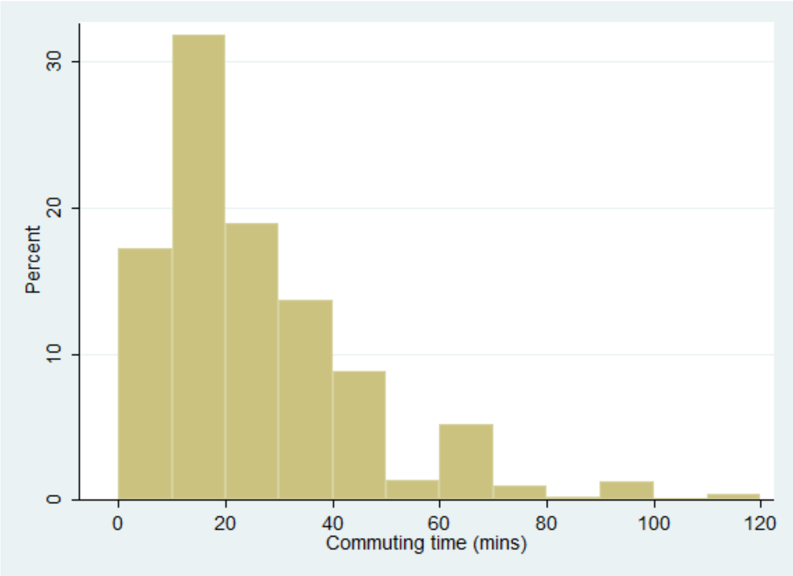
sensitivity test we also interact commuting time with gender and commuting mode to investigate whether the impact of an increase in commuting time on well-being varies by gender and mode of transport.

Table 4.1 provides summary statistics for the dependent and independent variables. It can be seen that the average daily commute is about 24 minutes (one way) and that most people drive a car to work. The average age in the sample is 39, about three quarters are married or cohabiting and the average number of children in the household is 0.7. About half of the sample make regular savings, 18% have a university degree and the average real monthly household income is £3,900.

Table 4.1: Summary statistics

	Mean	SD	Min	Max
Satisfaction with life overall	5.18	1.12	1.00	7.00
Satisfaction with leisure time	4.41	1.45	1.00	7.00
GHQ score	25.07	5.11	0.00	36.00
Commuting time (minutes)	23.50	20.68	0.00	500.00
Age	39.02	11.38	17.00	65.00
Female	0.53		0.00	1.00
Hours worked	34.16	10.12	0.00	99.00
Monthly real household income ('000s)	3.88	2.29	0.05	96.23
Number of children in household	0.70	0.96	0.00	7.00
Married or cohabiting	0.73		0.00	1.00
Saves regularly	0.51		0.00	1.00
University degree	0.18		0.00	1.00
Car driver	0.66		0.00	1.00
Car passenger	0.07		0.00	1.00
Train	0.03		0.00	1.00
Underground	0.01		0.00	1.00
Bus	0.07		0.00	1.00
Motorbike	0.01		0.00	1.00
Bicycle	0.03		0.00	1.00
Walk	0.11		0.00	1.00
Other mode	0.01		0.00	1.00

Figure 4.4: **Distribution of Daily Commuting Time (one way)**



4.4 Results

4.4.1 Satisfaction with life overall

Table 4.2 presents the results from the models of satisfaction with life overall[8] [9] [10]. It can be seen that while the coefficient for commuting time is negative and significant in the pooled ordered logit model (Pooled OL), it is insignificant in all the fixed-effects specifications. In line with Blanchflower and Oswald (2008) amongst others, we find that satisfaction is U-shaped in age, with a minimum at around 54 years of age in the ordered FE specifications. Other significant variables include: (log)

[8] We 'Winsorise' the commuting time, hours worked and monthly household income data at the 99th centiles given the extreme upper values for these variables. Similar results to those presented in the paper are obtained if we simply trim the sample at the 99th centiles for these three variables, or Winsorise or trim at the 95th centile (results available on request).

[9] We used 4, 5, 6 and 7 as the satisfaction cutoff-values in the DvS models as very few respondents report lower levels of life satisfaction than 4. This is the reason why the reported sample size for the DvS model is somewhat smaller than for the other models.

[10] For comparison we ran the pooled ordered logit model on the same sample as the fixed effects models, i.e. excluding those respondents who reported the same level of satisfaction in all waves.

real household income (implying diminishing marginal utility of income), whether the respondent is married or cohabiting and whether he/she makes regular savings. These results are consistent with previous findings in the literature (Dolan et al., 2008, Wong et al., 2006).

The insignificant commuting time coefficient in the FE models contrasts with the findings by Stutzer and Frey (2008) and Roberts et al. (2011) who find that increases in commuting time are associated with lower levels of subjective well-being. Since Roberts et al. also use data from the BHPS but a different measure of subjective well-being (the GHQ score), we can test whether it is the choice of well-being measure that is driving the difference in the results. To do this we re-run our analysis using the GHQ score as the dependent variable instead of overall life satisfaction.

The results are reported in Table 4.3. We find no evidence of a negative relationship between commuting times and the GHQ measure of well-being in our sample, but when we re-run the analysis using data from waves 1-14 of the BHPS (the sample used by Roberts et. al) we are able to replicate their result that longer commuting times are associated with lower levels of well-being. We also find that when we interact the commuting time variable with a dummy for being female this is found to be negative and significant in both samples, which supports Roberts et. al's finding that longer commutes are associated with lower levels of subjective well-being among women. We also attempted to include this interaction in the life satisfaction models, but it was found to be insignificant (see appendix, Table 4.10 for the full regression results). This illustrates that different measures of subjective well-being may lead to different conclusions regarding policy relevant variables.

Table 4.2: Satisfaction with Life Overall

	(1) Pooled OL	(2) Linear FE	(3) DvS	(4) BUC	(5) FF
Commuting time (hours)	-0.237***	-0.0122	-0.0389	-0.0298	-0.0282
	(0.039)	(0.021)	(0.049)	(0.051)	(0.045)
Age	-0.104***	-0.0399***	-0.102***	-0.0958***	-0.108***
	(0.008)	(0.006)	(0.014)	(0.014)	(0.012)
Age squared / 100	0.121***	0.0373***	0.0933***	0.0895***	0.104***
	(0.010)	(0.007)	(0.017)	(0.018)	(0.014)
Hours worked	-0.00529***	-0.000744	-0.00267	-0.00162	-0.00140
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Log of real household income	0.197***	0.0448***	0.0995***	0.0962***	0.0852***
	(0.026)	(0.014)	(0.031)	(0.032)	(0.029)
Married or cohabiting	0.589***	0.206***	0.464***	0.466***	0.403***
	(0.032)	(0.021)	(0.047)	(0.049)	(0.040)
Number of children in household	-0.0509***	-0.00936	-0.0348*	-0.0303	-0.0207
	(0.015)	(0.009)	(0.021)	(0.021)	(0.018)
Saves regularly	0.299***	0.0886***	0.212***	0.216***	0.200***
	(0.022)	(0.010)	(0.023)	(0.024)	(0.023)
University degree	-0.0219	0.0530	0.0975	0.126	0.175
	(0.035)	(0.052)	(0.123)	(0.128)	(0.109)
Individuals	9930	9930	9863	9930	9930
Observations	62786	62786	62537	62786	62786

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3: **GHQ score**

	(1) Pooled OL	(2) Linear FE	(3) DvS	(4) BUC	(5) FF
Commuting time (hours)	-0.0760**	-0.168	-0.0650	-0.0793	-0.00470
	(0.036)	(0.106)	(0.045)	(0.049)	(0.041)
Age	-0.0831***	-0.171***	-0.0847***	-0.0804***	-0.0838***
	(0.007)	(0.026)	(0.012)	(0.013)	(0.011)
Age squared / 100	0.0918***	0.155***	0.0749***	0.0728***	0.0764***
	(0.009)	(0.031)	(0.015)	(0.016)	(0.013)
Hours worked	0.0113***	-0.00800**	-0.00300**	-0.00385**	-0.00339**
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Log of real household income	0.0892***	0.157**	0.0752***	0.0693**	0.0356
	(0.022)	(0.065)	(0.028)	(0.031)	(0.026)
Married or cohabiting	0.131***	0.384***	0.116***	0.155***	0.146***
	(0.030)	(0.100)	(0.040)	(0.044)	(0.036)
Number of children in household	0.000709	0.0147	0.000870	0.00274	-0.00246
	(0.013)	(0.041)	(0.018)	(0.020)	(0.017)
Saves regularly	0.170***	0.331***	0.145***	0.165***	0.126***
	(0.020)	(0.047)	(0.021)	(0.023)	(0.020)
University degree	-0.00960	0.271	0.132	0.141	0.152
	(0.033)	(0.227)	(0.095)	(0.108)	(0.097)
Individuals	11410	11410	11407	11410	11410
Observations	67871	67871	67860	67871	67871

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We examine the choice of subjective well-being proxy, and the time frame in the BHPS in more detail in further analysis, which is reported in later subsection.

Stutzer and Frey (2008) use a very similar measure of well-being to ours, i.e. self-reported satisfaction with life overall. In this case the different findings may be due to cultural differences between the UK and Germany, although we concede that this is a somewhat speculative explanation[11]. What is clear, however, is that the 'commuting paradox' documented by Stutzer and Frey (2008) does not hold in general, as we find no evidence of a negative impact of commuting times on life satisfaction in our application.

In line with Ferrer-i-Carbonell and Frijters (2004) we find that the results from the linear and ordered FE models are quite similar (in that the variables have the same signs and significance, the quadratic in age has a similar minimum point etc.), considering the different assumptions underlying these models. This finding contributes to the stock of evidence suggesting that a linear FE model is an acceptable substitute for an ordered FE model in the context of modelling life satisfaction. However, this result needs to be tested on a case-by-case basis as there is no guarantee that it holds in general.

One advantage of the linear model over the ordered model is that the coefficients in the linear model can be interpreted as marginal effects, while the coefficients in the ordered model cannot be interpreted quantitatively since they refer to an underlying

[11] One hypothesis we considered is that longer average commuting times may impact on social norms which in turn could potentially make the link between commuting times and well-being less strong. However, the average commuting time in our sample is only slightly higher than in the GSOEP sample used by Stutzer and Frey (24 vs 22 minutes) so this is unlikely to explain the differences in the results.

latent variable. In fact it is not possible to calculate marginal effects based on the FE ordered logit results at all since the fixed effects are conditioned out of the likelihood function. However, as shown by Frey et al. (2009), Luechinger (2009), and Luechinger and Raschky (2009) for example, the ratios of the coefficients in the ordered model can be used to evaluate the trade-off between commuting time and income using the so-called 'life satisfaction approach'.

To illustrate, let $U = U(C, Y)$, where C is commuting time and Y is income. Totally differentiating and setting $dU = 0$ yields:

$$\frac{dY}{dC} = -\frac{MU_C}{MU_Y}$$

For our linearised specification with log income, $U = \beta C + \gamma lnY$, this gives $MU_C = \beta$, $MU_Y = \gamma/Y$ and hence

$$\frac{dY}{dC} = -\frac{\beta Y}{\gamma}$$

Evaluating this expression at median household income Y_M gives $dY/dC = £1,079$ using the BUC estimates in Column 4 of Table 2. Thus, at the median, commuters require compensation of £1,000 of monthly household income per additional hour of (one-way) daily commuting time. This is equivalent to around £25 per hour of commuting time[12]. Since the coefficient for commuting time is imprecisely estimated we cannot reject the null that dY/dC is equal to zero[13] but this example nevertheless shows that the coefficients in the ordered FE models can be given a useful quantitative interpretation.

[12] Based on 20 days per month of commuting.

[13] The lower and upper limit of a 95% CI calculated using the delta method is -£2,570 and £4,727, respectively.

We therefore suggest that researchers implement ordered FE models when assessing the determinants of subjective well-being, rather than simply reporting the results from linear FE regressions which has become common in the literature. Treating well-being as an ordinal measure of individual welfare rather than assuming cardinality as is required in the linear model is clearly preferred theoretically. And empirically, given the ease of implementation of the BUC and DvS estimators, plus the ability to interpret the ratio of coefficients in these specifications, means that an ordered approach can also yield interesting and interpretable findings to the researcher.

To test the robustness of the results we ran two further models. First, to examine the importance of travel mode choice, we analyse the life satisfaction data by looking at the interaction of commuting time with the dummy variables that indicate an individual's choice of travel mode. These results are presented in Table 4.11 in the appendix. From Table 4.11, we observe that the interaction variable for all modes of travel is insignificant and conclude that with respect to commuting behaviour the mode of travel does not impact on people's SWB.

The results reported above are for employees only. We relax this assumption by including self-employed individuals in our estimation sample.We ran this model to make our sample as similar as possible to that used by Stutzer and Frey (2008), who included the self-employed in their analysis. Table 4.12, in the appendix, presents the results for this specification. We observe no change in magnitude or significance of the commuting variable when we include the self-employed. From this we deduce that the choice of including the self-employed is arbitrary. We observe a similar pattern when we consider GHQ as an outcome measure, although the results are omitted here. Because of this consistency, further analysis is concerned with those people who are employees only.

We examine several other factors that could influence our results in a later subsection.

4.4.2 Satisfaction with leisure time

Table 4.4 presents the results from the models of satisfaction with leisure time. In contrast to the life satisfaction results we find that the coefficient for commuting time is negative and significant in all the specifications, suggesting that an increase in commuting time has a negative impact on the satisfaction with leisure time, as expected. Once again, there is evidence of a U-shaped relationship with age (with a minimum at around 40 years of age) and a positive relationship with making regular savings. Satisfaction with leisure time is found to be negatively related to hours worked, household income, the number of children in the household and being married or cohabiting. As in the life satisfaction case the coefficients in the linear and ordered FE models generally have the same signs and significance.

4.4.3 Further Exploration

In order to look deeper into the effects that commuting has on well-being, we do a number of things. We start by looking at the type of job an individual employee has

Table 4.4: Satisfaction with Leisure Time

	(1) Pooled OL	(2) Linear FE	(3) DvS	(4) BUC	(5) FF
Commuting time (hours)	-0.350***	-0.167***	-0.298***	-0.284***	-0.309***
	(0.039)	(0.028)	(0.049)	(0.048)	(0.043)
Age	-0.0908***	-0.0270***	-0.0634***	-0.0500***	-0.0441***
	(0.008)	(0.008)	(0.014)	(0.014)	(0.011)
Age squared / 100	0.111***	0.0334***	0.0752***	0.0624***	0.0554***
	(0.010)	(0.009)	(0.017)	(0.017)	(0.014)
Hours worked	-0.0209***	-0.0154***	-0.0273***	-0.0262***	-0.0240***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Log of real household income	0.0385	-0.0536***	-0.0885***	-0.0888***	-0.0805***
	(0.025)	(0.018)	(0.032)	(0.031)	(0.028)
Married or cohabiting	-0.0806***	-0.146***	-0.209***	-0.251***	-0.177***
	(0.031)	(0.026)	(0.046)	(0.045)	(0.038)
Number of children in household	-0.233***	-0.146***	-0.251***	-0.258***	-0.224***
	(0.014)	(0.012)	(0.022)	(0.021)	(0.017)
Saves regularly	0.198***	0.0374***	0.0707***	0.0679***	0.0708***
	(0.021)	(0.012)	(0.023)	(0.022)	(0.021)
University degree	-0.218***	0.0633	0.159	0.127	0.135
	(0.035)	(0.068)	(0.116)	(0.118)	(0.103)
Individuals	10746	10746	10239	10746	10746
Observations	66231	66231	63895	66231	66231

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

by including the Standard Occupational Classification of the employee, and interacting this with commuting time. Further we include a dummy variable, interacted with commuting time, to examine whether being a part time worker is an important factor. Secondly, we look at a subsample of the estimation sample who live at the same address and have the same job, but experience changes in their commuting time. Thirdly, we look at what happens to people who move their household location, or get a new job, and consider the possibility that household and workplace locations change together. Finally, we look at the effect that the sample period under consideration has on our results. For reasons of space we only present the results for three model specifications: (1) Pooled Ordered Logit; (2) Linear FE: and (3) the BUC FE-OL model. For the first two explorations above, we focus only on overall life satisfaction, but when examining the effect that the period has we look at overall life satisfaction, GHQ and satisfaction with leisure time.

The Importance of the Type of Job

We start by considering what impact the type of occupation an individual works in, when interacted with their commuting time, has on their overall life satisfaction. To do this we use the Standard Occupational Classification (SOC), based on 1990 definitions, to define nine levels of occupation. These are taken from the BHPS documentation, and are: (1) managerial and administrative workers; (2) professional occupations; (3) associate professionals and technical professions; (4) clerical occupations; (5) craft occupations; (6) personal and protective occupations; (7) sales; (8) plant and machine operatives; and (9) all other occupations. The results of interacting these nine levels of occupation with commuting time are shown in Table

4.5.

From Table 4.5, it can be seen that none of the nine SOC levels, when interacted with commuting time, are significant in a fixed effects specification. To check the robustness of our results, we then decided to check whether grouping the SOC codes into three levels of job classification can influence the results. Our three groups are high (1 and 2 above), middle (3, 4, or 5 above), and low (6, 7, 8, or 9 above)[14].

Table 4.6 shows that the choice of using three or nine levels of SOC is arbitrary here, as it does not influence the results. That is, the occupational level of the employee is not an important factor when determining the commuting time - overall life satisfaction relationship. Although the commuting time/SOC interactions are insignificant in Table 4.6, it can be seen that middle and high occupations have positive coefficients, with high having a larger coefficient than middle, and that the low SOC variable has a negative sign. This could imply there was some increasing trend, however these results are not statistically significant, even at the 10% level.

We have already considered the impact of being self-employed above. However, for completeness we now examine the impact of working part-time. These results are presented in Table 4.7, from which we can see there is no difference, in terms of statistical significance, between part-time and full-time employees, with both being negative and insignificantly affected by longer commutes. It is worth noting that the interaction of commuting time and being part time is insignificant even in the pooled ordered logit model (OL). However part-time and hours worked are likely to be collinear, and when we remove hours worked as an explanatory variable the

[14] Our results are robust to a number of different groups of high, middle, and low.

coefficient on CTH×part-time becomes negative and significant in the pooled OL, but remains insignificant in both fixed effects models.

Exogenous Shocks to Commuting

Next, we consider what effect possible exogenous shocks to commuting time have on well-being. If an individual lives at the same residential address and keeps the same job, but experiences a change in commuting time, given they use the same mode of transports to travel to work, we conclude that this change is exogenous to the individual. We acknowledge here that it is possible that the location of the workplace may have changed, but we cannot control for this here[15]. For this analysis we keep 6,093 individuals (out of a possible 16,550), but given we require some change in overall life satisfaction score (see methodology section) our estimation is based on 5,993 individuals.

The results for this subsample of the population are presented in Table 4.8, from which we can see that the results are consistent with the overall sample. That is, commuting time has a statistically insignificant impact upon overall life satisfaction. This is true for both men and women, although the gender specific results are not presented here.

[15] The BHPS asks if an employee workers for the same company, and has the same job. However, no information on the workplace location is collected.

Table 4.5: Satisfaction with Life Overall: Including Standard Occupational Classification codes I

	(1) Pooled OL	(2) Linear FE	(3) BUC
CTH×manager	-0.224***	0.0211	0.0569
	(0.053)	(0.030)	(0.076)
CTH×professional	-0.250***	-0.0145	-0.0407
	(0.073)	(0.037)	(0.097)
CTH×technical	-0.261***	0.0169	0.0452
	(0.067)	(0.033)	(0.083)
CTH×clerical	-0.391***	-0.0354	-0.0860
	(0.066)	(0.034)	(0.083)
CTH×craft	-0.194**	0.0270	0.0665
	(0.091)	(0.049)	(0.119)
CTH×personal services	-0.131	-0.00549	-0.0177
	(0.111)	(0.059)	(0.127)
CTH×sales	-0.497***	-0.00966	-0.0277
	(0.095)	(0.054)	(0.123)
CTH×plant operatives	-0.263**	-0.0655	-0.154
	(0.123)	(0.057)	(0.130)
CTH×other	-0.485***	-0.0628	-0.148
	(0.127)	(0.054)	(0.124)
Other demographics[a]	Yes	Yes	Yes
Individuals	9930	9930	9930
Observations	62786	62786	62786

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

a Control variables are as above.

Table 4.6: Satisfaction with Life Overall: Including Standard Occupational Classification codes II

	(1) Pooled OL	(2) Linear FE	(3) BUC
CTH×High SOC	-0.192***	0.0246	0.0656
	(0.051)	(0.028)	(0.071)
CTH×Middle SOC	-0.271***	0.00105	0.00419
	(0.046)	(0.024)	(0.059)
CTH×Low SOC	-0.299***	-0.0290	-0.0691
	(0.062)	(0.032)	(0.072)
Age	-0.105***	-0.0405***	-0.0973***
	(0.008)	(0.006)	(0.015)
Age squared / 100	0.122***	0.0379***	0.0910***
	(0.010)	(0.007)	(0.018)
Hours worked	-0.00540***	-0.000788	-0.00173
	(0.001)	(0.001)	(0.002)
Log of real household income	0.185***	0.0441***	0.0947***
	(0.026)	(0.014)	(0.032)
Married or cohabiting	0.593***	0.206***	0.466***
	(0.032)	(0.021)	(0.049)
Number of children in household	-0.0529***	-0.00934	-0.0302
	(0.015)	(0.009)	(0.021)
Saves regularly	0.297***	0.0885***	0.216***
	(0.022)	(0.010)	(0.024)
University degree	-0.0606*	0.0514	0.121
	(0.035)	(0.052)	(0.128)
Individuals	9930	9930	9930
Observations	62786	62786	62786

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7: Satisfaction with Life Overall: Including part-time identification

	(1) Pooled OL	(2) Linear FE	(3) BUC
Commuting time (hours) (CTH)	-0.238***	-0.00972	-0.0236
	(0.040)	(0.022)	(0.052)
CTH× part-time	0.0113	-0.0197	-0.0487
	(0.091)	(0.040)	(0.098)
Age	-0.104***	-0.0398***	-0.0957***
	(0.008)	(0.006)	(0.014)
Age squared / 100	0.121***	0.0373***	0.0896***
	(0.010)	(0.007)	(0.018)
Hours worked	-0.00518***	-0.000929	-0.00206
	(0.002)	(0.001)	(0.002)
Log of real household income	0.197***	0.0446***	0.0960***
	(0.026)	(0.014)	(0.032)
Married or cohabiting	0.588***	0.206***	0.466***
	(0.032)	(0.021)	(0.049)
Number of children in household	-0.0510***	-0.00923	-0.0301
	(0.015)	(0.009)	(0.021)
Saves regularly	0.299***	0.0886***	0.216***
	(0.022)	(0.010)	(0.024)
University degree	-0.0219	0.0529	0.126
	(0.035)	(0.052)	(0.128)
Individuals	9930	9930	9930
Observations	62786	62786	62786

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8: Satisfaction with Life Overall: Exogenous Shock to Commuting

	(1) Pooled OL	(2) Lin. FE	(3) BUC
Commuting time (hours)	-0.238***	-0.0407	-0.103
	(0.054)	(0.032)	(0.077)
Age	-0.110***	-0.0345***	-0.0839***
	(0.012)	(0.008)	(0.021)
Age squared / 100	0.128***	0.0303***	0.0734***
	(0.014)	(0.009)	(0.024)
Hours worked	-0.00785***	-0.00181*	-0.00454*
	(0.002)	(0.001)	(0.003)
Log of real household income	0.150***	0.0415**	0.0927*
	(0.037)	(0.020)	(0.049)
Married or cohabiting	0.566***	0.193***	0.433***
	(0.047)	(0.033)	(0.077)
Number of children in household	-0.0655***	-0.00279	-0.0120
	(0.019)	(0.012)	(0.029)
Saves regularly	0.314***	0.0952***	0.232***
	(0.029)	(0.014)	(0.034)
University degree	-0.0587	0.106	0.271
	(0.049)	(0.084)	(0.205)
Individuals	5993	5993	5993
Observations	33748	33748	33748

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Job and Home Movers

The reverse logic to that above is now considered. We look at what effect that either moving house or changing job has on life satisfaction, with respect to commuting. We further consider the possibility that an individual both moves home and job in the same time period. For this we consider three specifications, (1) we include commuting time and indicators of residential and employment relocation; (2) we include commuting time and interact commuting time with the relocation dummies; and (3) we include everything, that is commuting time, relocation indicators, and their interactions. These results are shown in Table 4.9.

Columns (1) - (3) in Table 4.9 shows the effect of relocation decisions. We can see that in the fixed-effects specifications commuting time remains insignificant. However, the dummy variables to indicate a change in job and household relocation are positive and significant, however the interaction term for a dual move is negatively insignificant. Columns (4) - (6) look at what happens when we interact moving decisions with commuting time. For this specification we observe a negative and significant coefficient on commuting time in both fixed effects specifications. From this we deduce that people who do not move are negatively impacted upon by longer commutes. We can also see here that the interaction of commuting time with getting a new job is positive and significant, as is the interaction with moving to a different household location. Interestingly, however, the interaction between change of job, change of home and commuting time is negative and significant. This may indicate that there are benefits (in terms of the commuting - well-being relationship) of moving job or home, but there are consequences to well-being of moving both house and job in the same calendar year. However, when we sum the relevant coefficients the net effect is still positive (the resultant coefficient based on the BUC specification (column (3)) is 0.246, with a standard error of 0.047, hence implying significance at any chosen level).

Finally, columns (7) - (9) examines what happens if we control for both movements in locations, and the interaction of these movements with commuting time. In this scenario the commuting time variable returns to being insignificant, but the interaction of commuting time with moving to a new home is positive and significant. The interaction of everything remains negative and significant.

All of the discussion above does not take into account the possibility that household and/or job relocation decisions are likely to be influenced by, in some way, commuting time. We are unable to control for this possible endogeneity here, but include the results as they do show that there is some evidence that people's well-being, with respect to commuting, is affected by relocation decisions, both in terms of household and workplace. Because of this possible endogeneity we refrain from including relocation variables in the further analysis that follows.

Table 4.9: Satisfaction with Life Overall: Changes in Household and/or Workplace Location

	(1) Pooled OL	(2) Lin. FE	(3) BUC	(4) Pooled OL	(5) Lin. FE	(6) BUC	(7) Pooled OL	(8) Lin. FE	(9) BUC
Commuting time (hours)	-0.186***	-0.00293	-0.00787	-0.208***	-0.0489***	-0.135***	-0.223***	-0.0209	-0.0593
	(0.032)	(0.016)	(0.043)	(0.036)	(0.018)	(0.048)	(0.040)	(0.019)	(0.052)
New job	-0.00538	0.0552***	0.146***				-0.0236	0.0405***	0.106***
	(0.020)	(0.009)	(0.025)				(0.030)	(0.014)	(0.037)
New home	0.0764***	0.0693***	0.192***				-0.00575	0.0305	0.0820
	(0.028)	(0.015)	(0.039)				(0.043)	(0.023)	(0.061)
New job and new home	-0.102**	-0.0269	-0.0923				-0.0739	0.0298	0.0527
	(0.043)	(0.024)	(0.060)				(0.066)	(0.036)	(0.091)
CTH × new job				0.0161	0.0894***	0.241***	0.0463	0.0362	0.0995
				(0.034)	(0.016)	(0.045)	(0.052)	(0.025)	(0.066)
CTH × new home				0.193***	0.135***	0.382***	0.198***	0.0950**	0.274**
				(0.049)	(0.026)	(0.073)	(0.074)	(0.041)	(0.114)
CTH×new job × new home				-0.174**	-0.0998**	-0.290***	-0.0741	-0.137**	-0.360**
				(0.074)	(0.041)	(0.112)	(0.115)	(0.062)	(0.167)
Other Demographics[a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	14902	14902	14902	14902	14902	14902	14902	14902	14902
Observations	72118	72118	72118	72118	72118	72118	72118	72118	72118

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes:

a Control variables are as above.

Further exploration into the importance of SWB proxy and time period considered

As the data we consider in this chapter are in effect taken from two sup-panels[16], we thought it may be useful to examine these two sub-panels separately, and then compare to the results obtained from the whole panel.

Firstly we start by looking at the effect that commuting has on overall life satisfaction for the whole sample, and breaking the effects down into the three time samples. These results are shown in Table 4.13. From this we can see that the results are relatively stable across time; the results from the two FE models considered are always insignificant. However the direction of the effect does change between period 1 (1996-2000) and period 2 (2002-2008) from negative to positive. It would appear that the earlier period results drive the results for the whole sample (1996-2008), as these results are insignificantly negative. For the pooled OL models the coefficients are always negative and highly significant.

Secondly, we repeat the above, but now consider GHQ as a proxy for SWB. These results can be seen in Table 4.14. For GHQ the time period under consideration does have a significant impact on the results, and hence the conclusions. We can see that initially the coefficient on commuting time is negative and significant, implying that longer commutes are associated with lower levels of reported GHQ. This results is consistent with Roberts et al. (2011). We examine this in more detail later. Whilst commuting has a significant impact in the earlier period, it is insignificant

[16] Recall we use data from 1996-2008, but there was no life satisfaction data available for 2001. So we have data for 1996-2000; 2002-2008; and 1996-2008 excluding 2001.

in determining GHQ scores in the latter period. Further, it appears the latter period dominates the earlier, as when we consider the whole period as one the results remain insignificant. From this we conclude that the negative relationship between commuting and SWB, when proxied by GHQ, is temporal. The statistical significance dissipates over time. This could imply that the period under observation is a key factor when examining the relationship between commuting and SWB, especially when utilising mental health measures such as GHQ.

Thirdly, we re-investigate the effect that gender has on SWB (with respect to commuting) over time by interacting commuting time with gender, as we did above. We do this for both overall life satisfaction and GHQ scores. The results are presented in Tables 4.16 and 4.17, respectively. The results for overall life satisfaction appear to be consistent by gender, and consistent with the whole sample. That is the results change from insignificantly negative to insignificantly positive, with the result an insignificant effect for the whole period for both men and women.

From Table 4.17, however, we can see that the negative and significance relationship between commuting time and GHQ for females is present throughout the whole period, and in both sub-samples when analysed separately. The results for males remain insignificant for the whole period. These results are consistent with Roberts et al. (2011) and imply, as previously mentioned, that their results are robust to later waves of data. Applying the life satisfaction approach, albeit with GHQ scores as opposed to life satisfaction as the dependent variable[17] - and using the BUC

[17] This distinction implies we are now considering monetary compensation for a one unit change in GHQ, and not a one unit change in life satisfaction. However, as both outcomes are, strictly speaking, ordinal measures this approach is applicable here.

coefficients presented in Table 4.17 column (9), we can deduce that, at the median, female commuters require compensation of £7928 of monthly household income per additional hour of daily commuting time. This compensation figure is twice as large as the median household income, and indicates that women are seriously negatively affected by longer commutes, when GHQ is the SWB proxy of interest.

Fourthly in Table 4.15 we look at the effect that commuting time has on satisfaction with the amount of leisure time an individual receives for the three separate periods. We can see that the results barely change, and that (as expected) higher commuting times cause people to be less satisfied with the amount of leisure time they receive. The only thing to note is that the statistical significance appears to get stronger over time.

Finally we examine the effect that the interaction of commuting time with the mode of travel has on overall life satisfaction across time. Here, as reported in Table 4.18, we observe very little statistical significance for any mode of travel in any period, and conclude that the choice of mode of travel is not important when analysing the effect on commuting time on life satisfaction. For reasons of space we do not repeat this analysis for GHQ.

4.5 Conclusion

This chapter provides an assessment of alternative estimators for the fixed-effects ordered logit model in the context of estimating the relationship between subjective well-being and commuting behaviour. In contrast to Stutzer and Frey (2008) we find no evidence that longer commutes are associated with lower levels of subjective well-being as measured by self-reported overall life satisfaction. When using the GHQ score as an alternative measure of subjective well-being we find, in line with Roberts et al. (2011), that longer commutes are associated with lower levels of well-being for women but not for men. Taken as a whole these findings suggest that the ‘commuting paradox’ documented by Stutzer and Frey (2008) does not hold in general.

Further analysis shows that the period of observation does not, in general, lead to significantly different results. However, when analysing the BHPS data on satisfaction it is worth bearing in mind that the variables of interest are not in every wave, and as such robustness checks by period can only be beneficial.

While our results support earlier findings in the literature that linear and ordered fixed-effects models of life satisfaction give similar results, we argue that ordered models are more appropriate since they do not require the researcher to make the questionable assumption that life satisfaction scores are cardinal. We also demonstrate that the ordered models are straightforward to implement in practice and lead to readily interpretable results. We therefore recommend that ordered fixed effects models are used to model life satisfaction instead of linear models, as the latter rely on an empirical regularity that may not always hold.

Appendix 4A

Stata code

DvS Stata code

```
local y y              // Specify name of dependent variable after the first "y"
local x x1 x2          // Specify names of independent variables after the first "x"
local id id            // Specify name of id variable after the first "id"

* Mark estimation sample
marksample touse
markout `touse' `y' `x' `id'

* Run clogit for each cutoff and combine using suest
* Note that with many (most?) datasets this part of the
* code will have to be edited since not all cutoffs can
* be used to estimate the model
qui sum `y' if `touse'
local ymax = r(max)
tempvar esample
gen `esample' = 0
tempname BMAT
forvalues i = 2(1)`ymax' {
        tempvar y`i'
        qui gen `y`i'' = `y' >= `i' if `touse'
        qui clogit `y`i'' `x' if `touse', group(`id')
        qui replace `esample' = 1 if e(sample)
        estimates store `y`i''
        local suest `suest' `y`i''
        capture matrix `BMAT' = `BMAT', e(b)
        if (_rc != 0) matrix `BMAT' = e(b)
}
qui suest `suest'

* Calculate Das and Van Soest estimates
tempname VMAT A B COV
local k : word count `x'
matrix `VMAT' = e(V)
matrix `A' = J((`ymax'-1),1,1)#I(`k')
matrix `B' = (invsym(`A''*invsym(`VMAT')*`A')*`A''*invsym(`VMAT')*`BMAT'')'
matrix `COV' = invsym(`A''*invsym(`VMAT')*`A')

* Tidy up matrix names and present results
matrix colnames `B' = `x'
matrix coleq `B' = :
matrix colnames `COV' = `x'
matrix coleq `COV' = :
matrix rownames `COV' = `x'
matrix roweq `COV' = :

qui cou if `esample'
local obs = r(N)
ereturn post `B' `COV', depname(`y') obs(`obs') esample(`esample')
ereturn display

* Calculate the number of individuals
tempvar last
bysort `id': gen `last' = _n==_N if e(sample)
cou if `last'==1
```

BUC Stata code

```
capture program drop bucologit
program bucologit
        version 11.2
        syntax varlist [if] [in], Id(varname)

        preserve

        marksample touse
        markout `touse' `id'

        gettoken yraw x : varlist
        tempvar y
        qui egen int `y' = group(`yraw')

        qui keep `y' `x' `id' `touse'
        qui keep if `touse'

        qui sum `y'
        local ymax = r(max)
        forvalues i = 2(1)`ymax' {
                qui gen byte `yraw'`i' = `y' >= `i'
        }
        drop `y'

        tempvar n cut newid
        qui gen long `n' = _n
        qui reshape long `yraw', i(`n') j(`cut')
        qui egen long `newid' = group(`id' `cut')
        sort `newid'
        clogit `yraw' `x', group(`newid') cluster(`id')

        restore
end

/* Example using simulated data */

set more off
set seed 12345

* Generate simulated data
drop _all
set obs 1000
gen id = _n
gen u = 0.5*invnormal(uniform())
expand 10
sort id
matrix means = 0,0
matrix sds = 1,1
drawnorm x1 x2, mean(means) sd(sds)
replace x1 = 0.5*x1 + 0.5*u
gen e = logit(uniform())
gen y_star = x1 + 0.5*x2 + u + e
gen y = 1 if y_star < -4
replace y = 2 if y_star >= -4 & y_star < -2.5
replace y = 3 if y_star >= -2.5 & y_star < -1.5
replace y = 4 if y_star >= -1.5 & y_star < -0.5
replace y = 5 if y_star >= -0.5 & y_star < 0.5
replace y = 6 if y_star >= 0.5 & y_star < 2
replace y = 7 if y_star >= 2

*Run BUC model using the -bucologit- command
bucologit y x1 x2, i(id)
*Note: the i() option is equivalent to group() in the -clogit- syntax

*Compare results with standard ordered logit
ologit y x1 x2
```

Further Tables

Table 4.10: **Satisfaction with Life Overall: Interaction with gender**

	(1) Pooled OL	(2) Linear FE	(3) DvS	(4) BUC	(5) FF
Commuting time (hours)	-0.179***	0.00457	0.00699	0.00751	0.0222
	(0.039)	(0.024)	(0.057)	(0.059)	(0.051)
Commuting time × Female	0.00368	-0.0112	-0.0201	-0.0216	-0.0326
	(0.051)	(0.035)	(0.083)	(0.086)	(0.077)
Age	-0.103***	-0.0398***	-0.102***	-0.0957***	-0.107***
	(0.008)	(0.006)	(0.014)	(0.014)	(0.012)
Age squared / 100	0.120***	0.0367***	0.0919***	0.0882***	0.101***
	(0.010)	(0.007)	(0.017)	(0.018)	(0.014)
Hours worked	-0.00442***	-0.000714	-0.00262*	-0.00157	-0.00157
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Monthly household income ('000s)	0.0411***	0.00713**	0.0194***	0.0162**	0.0195***
	(0.006)	(0.003)	(0.007)	(0.008)	(0.007)
Married or cohabiting	0.619***	0.212***	0.477***	0.479***	0.415***
	(0.032)	(0.021)	(0.047)	(0.049)	(0.040)
Number of children in household	-0.0510***	-0.0101	-0.0361*	-0.0317	-0.0233
	(0.015)	(0.009)	(0.021)	(0.021)	(0.018)
Saves regularly	0.309***	0.0900***	0.215***	0.219***	0.205***
	(0.022)	(0.010)	(0.023)	(0.024)	(0.023)
University degree	-0.0197	0.0545	0.0899	0.130	0.170
	(0.036)	(0.052)	(0.123)	(0.128)	(0.109)
Constant		5.928***			
		(0.116)			
Individuals	9930	9930	9930	9930	9930
Observations	62786	62786	62537	62786	62786

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.11: Satisfaction with Life Overall: Interaction with mode of travel

	(1) Pooled OL	(2) Linear FE	(3) DvS	(4) BUC	(5) FF
Commuting time (hours)	-0.138***	-0.00151	0.0100	-0.00420	0.0125
	(0.040)	(0.020)	(0.048)	(0.050)	(0.044)
Commuting time × Car passenger	-0.00618	0.0225	-0.0270	0.0464	-0.0152
	(0.091)	(0.044)	(0.099)	(0.101)	(0.096)
Commuting time × Rail	-0.0801	0.00534	-0.0113	0.00979	0.0275
	(0.059)	(0.033)	(0.079)	(0.083)	(0.073)
Commuting time × Tube	-0.137	-0.0321	-0.147	-0.0898	-0.153
	(0.108)	(0.060)	(0.134)	(0.142)	(0.138)
Commuting time× Bus	-0.159**	-0.00517	-0.0321	-0.00767	0.00142
	(0.079)	(0.037)	(0.082)	(0.084)	(0.077)
Commuting time × Motorbike	-0.311	-0.0460	-0.298	-0.139	-0.297
	(0.309)	(0.122)	(0.263)	(0.270)	(0.280)
Commuting time × Bicycle	-0.125	0.0124	-0.0818	0.0134	0.0384
	(0.233)	(0.127)	(0.261)	(0.288)	(0.242)
Commuting time× Walk	-0.235*	-0.0287	-0.159	-0.0825	-0.00879
	(0.131)	(0.065)	(0.150)	(0.152)	(0.142)
Age	-0.105***	-0.0411***	-0.106***	-0.0986***	-0.110***
	(0.008)	(0.006)	(0.014)	(0.015)	(0.012)
Age squared / 100	0.122***	0.0373***	0.0942***	0.0896***	0.104***
	(0.011)	(0.007)	(0.017)	(0.018)	(0.014)
Hours worked	-0.00536***	-0.000888	-0.00301*	-0.00196	-0.00170
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Log of household income	0.171***	0.0448***	0.103***	0.0968***	0.0894***
	(0.024)	(0.014)	(0.031)	(0.032)	(0.028)
Married or cohabiting	0.591***	0.206***	0.465***	0.465***	0.404***
	(0.032)	(0.021)	(0.047)	(0.049)	(0.040)
Number of children in household	-0.0520***	-0.00955	-0.0350*	-0.0307	-0.0242
	(0.014)	(0.009)	(0.021)	(0.021)	(0.018)
Saves regularly	0.299***	0.0886***	0.211***	0.216***	0.200***
	(0.022)	(0.010)	(0.023)	(0.024)	(0.023)
University degree	-0.0281	0.0526	0.0893	0.125	0.168
	(0.036)	(0.052)	(0.123)	(0.128)	(0.109)
Individuals	9929	9929	9929	9929	9929
Observations	62781	62781	62532	62781	62781

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: Satisfaction with Life Overall: Including the self-employed

	(1) Pooled OL	(2) Linear FE	(3) DvS	(4) BUC	(5) FF
Commuting time (hours)	-0.174***	-0.00161	-0.00244	-0.00337	0.00255
	(0.033)	(0.017)	(0.039)	(0.040)	(0.036)
Age	-0.105***	-0.0424***	-0.107***	-0.103***	-0.114***
	(0.008)	(0.006)	(0.014)	(0.014)	(0.011)
Age squared / 100	0.122***	0.0400***	0.0986***	0.0970***	0.111***
	(0.010)	(0.007)	(0.016)	(0.017)	(0.014)
Self employed	0.216***	0.0419	0.0908	0.102	0.108*
	(0.047)	(0.028)	(0.067)	(0.068)	(0.062)
Hours worked	-0.00435***	-0.000252	-0.00143	-0.000524	-0.000224
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Log of household income	0.144***	0.0312***	0.0604**	0.0677***	0.0649***
	(0.021)	(0.011)	(0.024)	(0.025)	(0.022)
Married or cohabiting	0.613***	0.207***	0.468***	0.469***	0.391***
	(0.031)	(0.021)	(0.046)	(0.047)	(0.038)
Number of children in household	-0.0507***	-0.00771	-0.0367*	-0.0262	-0.0238
	(0.014)	(0.008)	(0.020)	(0.020)	(0.017)
Saves regularly	0.299***	0.0888***	0.211***	0.217***	0.203***
	(0.021)	(0.009)	(0.022)	(0.023)	(0.022)
University degree	-0.0291	0.0411	0.0666	0.0974	0.152
	(0.034)	(0.050)	(0.119)	(0.124)	(0.106)
Constant		5.745***			
		(0.129)			
Individuals	10587	10587	10587	10587	10587
Observations	67698	67698	67424	67698	67698

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.13: Satisfaction with Life Overall, by period

	1996-2000			2002-2008			1996-2008		
	(1) Pooled OL	(2) Linear FE	(3) BUC	(4) Pooled OL	(5) Linear FE	(6) BUC	(7) Pooled OL	(8) Linear FE	(9) BUC
Commuting time (hours)	-0.286***	-0.0474	-0.112	-0.209***	0.0312	0.0785	-0.237***	-0.0122	-0.0298
	(0.058)	(0.041)	(0.097)	(0.045)	(0.028)	(0.069)	(0.039)	(0.021)	(0.051)
Age	-0.118***	-0.0739***	-0.173***	-0.0979***	-0.0267***	-0.0626**	-0.104***	-0.0399***	-0.0958***
	(0.012)	(0.019)	(0.047)	(0.010)	(0.010)	(0.026)	(0.008)	(0.006)	(0.014)
Age squared / 100	0.140***	0.0622***	0.142**	0.113***	0.0208*	0.0467	0.121***	0.0373***	0.0895***
	(0.016)	(0.024)	(0.059)	(0.012)	(0.012)	(0.031)	(0.010)	(0.007)	(0.018)
Hours worked	-0.00281	-0.000814	-0.00180	-0.00685***	-0.000224	-0.000497	-0.00529***	-0.000744	-0.00162
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Log of real household income	0.234***	0.0663**	0.141**	0.174***	0.0265	0.0634	0.197***	0.0448***	0.0962***
	(0.036)	(0.028)	(0.064)	(0.031)	(0.018)	(0.044)	(0.026)	(0.014)	(0.032)
Married or cohabiting	0.616***	0.194***	0.411***	0.574***	0.199***	0.465***	0.589***	0.206***	0.466***
	(0.045)	(0.042)	(0.091)	(0.038)	(0.029)	(0.069)	(0.032)	(0.021)	(0.049)
Number of children in household	-0.0661***	0.00460	-0.00254	-0.0405**	-0.00419	-0.0167	-0.0509***	-0.00936	-0.0303
	(0.020)	(0.022)	(0.051)	(0.017)	(0.013)	(0.032)	(0.015)	(0.009)	(0.021)
Saves regularly	0.313***	0.119***	0.287***	0.290***	0.0538***	0.138***	0.299***	0.0886***	0.216***
	(0.031)	(0.018)	(0.043)	(0.026)	(0.013)	(0.033)	(0.022)	(0.010)	(0.024)
University degree	-0.113**	-0.0681	-0.154	0.0229	0.0224	0.0459	-0.0219	0.0530	0.126
	(0.049)	(0.118)	(0.309)	(0.039)	(0.078)	(0.191)	(0.035)	(0.052)	(0.128)
Individuals	7076	7076	7076	8298	8298	8298	9930	9930	9930
Observations	23116	23116	23116	39670	39670	39670	62786	62786	62786

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.14: GHQ score, by period

	1996-2000			2002-2008			1996-2008		
	(1) Pooled OL	(2) Linear FE	(3) BUC	(4) Pooled OL	(5) Linear FE	(6) BUC	(7) Pooled OL	(8) Linear FE	(9) BUC
Commuting time (hours)	-0.156***	-0.439**	-0.211**	-0.0298	-0.0683	-0.0301	-0.0760**	-0.168	-0.0793
	(0.052)	(0.210)	(0.099)	(0.042)	(0.139)	(0.066)	(0.036)	(0.106)	(0.049)
Age	-0.0823***	-0.206**	-0.0939**	-0.0844***	-0.237***	-0.112***	-0.0831***	-0.171***	-0.0804***
	(0.010)	(0.087)	(0.045)	(0.008)	(0.047)	(0.024)	(0.007)	(0.026)	(0.013)
Age squared / 100	0.0915***	0.186*	0.0832	0.0933***	0.194***	0.0891***	0.0918***	0.155***	0.0728***
	(0.013)	(0.106)	(0.057)	(0.010)	(0.055)	(0.030)	(0.009)	(0.031)	(0.016)
Hours worked	0.0139***	-0.00650	-0.00296	0.00976***	-0.00579	-0.00290	0.0113***	-0.00800**	-0.00385**
	(0.002)	(0.007)	(0.003)	(0.001)	(0.005)	(0.002)	(0.001)	(0.003)	(0.002)
Log of real household income	0.0793***	0.230*	0.101	0.0958***	0.167*	0.0757*	0.0892***	0.157**	0.0693**
	(0.031)	(0.128)	(0.062)	(0.027)	(0.088)	(0.043)	(0.022)	(0.065)	(0.031)
Married or cohabiting	0.177***	0.586***	0.236***	0.103***	0.442***	0.176***	0.131***	0.384***	0.155***
	(0.041)	(0.194)	(0.084)	(0.035)	(0.147)	(0.064)	(0.030)	(0.100)	(0.044)
Number of children in household	-0.0124	0.0229	0.00320	0.00921	-0.0272	-0.0173	0.000709	0.0147	0.00274
	(0.017)	(0.103)	(0.049)	(0.016)	(0.063)	(0.032)	(0.013)	(0.041)	(0.020)
Saves regularly	0.206***	0.427***	0.217***	0.148***	0.199***	0.102***	0.170***	0.331***	0.165***
	(0.028)	(0.083)	(0.042)	(0.024)	(0.060)	(0.031)	(0.020)	(0.047)	(0.023)
University degree	-0.0137	0.0999	0.0493	-0.00769	0.492	0.255	-0.00960	0.271	0.141
	(0.047)	(0.501)	(0.265)	(0.037)	(0.331)	(0.174)	(0.033)	(0.227)	(0.108)
Individuals	7917	7917	7917	9273	9273	9273	11410	11410	11410
Observations	25269	25269	25269	42602	42602	42602	67871	67871	67871

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.15: Satisfaction with Leisure Time, by period

	1996-2000			2002-2008			1996-2008		
	(1) Pooled OL	(2) Linear FE	(3) BUC	(4) Pooled OL	(5) Linear FE	(6) BUC	(7) Pooled OL	(8) Linear FE	(9) BUC
Commuting time (hours)	-0.376***	-0.0937*	-0.152	-0.335***	-0.196***	-0.348***	-0.350***	-0.167***	-0.284***
	(0.054)	(0.056)	(0.093)	(0.045)	(0.035)	(0.063)	(0.039)	(0.028)	(0.048)
Age	-0.102***	-0.0641***	-0.113***	-0.0863***	-0.0155	-0.0332	-0.0908***	-0.0270***	-0.0500***
	(0.011)	(0.024)	(0.043)	(0.009)	(0.013)	(0.024)	(0.008)	(0.008)	(0.014)
Age squared / 100	0.127***	0.0548*	0.0945*	0.104***	0.0270*	0.0578**	0.111***	0.0334***	0.0624***
	(0.014)	(0.030)	(0.055)	(0.012)	(0.015)	(0.029)	(0.010)	(0.009)	(0.017)
Hours worked	-0.0197***	-0.0148***	-0.0245***	-0.0216***	-0.0144***	-0.0255***	-0.0209***	-0.0154***	-0.0262***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Log of real household income	0.0967***	-0.0160	-0.0173	-0.00166	-0.0818***	-0.144***	0.0385	-0.0536***	-0.0888***
	(0.033)	(0.035)	(0.059)	(0.030)	(0.023)	(0.042)	(0.025)	(0.018)	(0.031)
Married or cohabiting	-0.0841**	-0.178***	-0.299***	-0.0746**	-0.110***	-0.205***	-0.0806***	-0.146***	-0.251***
	(0.041)	(0.050)	(0.085)	(0.037)	(0.035)	(0.063)	(0.031)	(0.026)	(0.045)
Number of children in household	-0.234***	-0.158***	-0.273***	-0.233***	-0.154***	-0.288***	-0.233***	-0.146***	-0.258***
	(0.019)	(0.028)	(0.049)	(0.017)	(0.017)	(0.033)	(0.014)	(0.012)	(0.021)
Saves regularly	0.186***	0.0176	0.0309	0.205***	0.0384**	0.0741**	0.198***	0.0374***	0.0679***
	(0.029)	(0.022)	(0.039)	(0.025)	(0.016)	(0.030)	(0.021)	(0.012)	(0.022)
University degree	-0.350***	0.0168	0.0298	-0.156***	0.0470	0.0905	-0.218***	0.0633	0.127
	(0.049)	(0.142)	(0.250)	(0.039)	(0.091)	(0.173)	(0.035)	(0.068)	(0.118)
Individuals	7535	7535	7535	8866	8866	8866	10746	10746	10746
Observations	24448	24448	45371	41783	41783	90046	66231	66231	172483

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.16: Satisfaction with Life Overall interacted with Female, by period

	1996-2000			2002-2008			1996-2008		
	(1) Pooled OL	(2) Linear FE	(3) BUC	(4) Pooled OL	(5) Linear FE	(6) BUC	(7) Pooled OL	(8) Linear FE	(9) BUC
Commuting time × Female	-0.267***	-0.0581	-0.132	-0.141***	0.0326	0.0889	-0.184***	-0.00813	-0.0175
	(0.073)	(0.057)	(0.134)	(0.053)	(0.034)	(0.089)	(0.048)	(0.026)	(0.062)
Commuting time × Male	-0.219***	-0.0219	-0.0587	-0.167***	0.0316	0.0788	-0.186***	0.00380	0.00585
	(0.058)	(0.045)	(0.112)	(0.044)	(0.030)	(0.077)	(0.039)	(0.024)	(0.059)
Age	-0.118***	-0.0740***	-0.173***	-0.0982***	-0.0267***	-0.0623**	-0.104***	-0.0399***	-0.0958***
	(0.012)	(0.019)	(0.047)	(0.010)	(0.010)	(0.026)	(0.008)	(0.006)	(0.014)
Age squared / 100	0.140***	0.0622***	0.141**	0.113***	0.0207*	0.0464	0.121***	0.0373***	0.0894***
	(0.016)	(0.024)	(0.059)	(0.012)	(0.012)	(0.031)	(0.010)	(0.007)	(0.018)
Hours worked	-0.00294	-0.00105	-0.00238	-0.00663***	-0.000281	-0.000648	-0.00517***	-0.000872	-0.00192
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Log of real household income	0.228***	0.0687***	0.149**	0.166***	0.0239	0.0571	0.190***	0.0440***	0.0950***
	(0.035)	(0.027)	(0.062)	(0.031)	(0.018)	(0.043)	(0.026)	(0.014)	(0.032)
Married or cohabiting	0.616***	0.193***	0.410***	0.576***	0.200***	0.466***	0.590***	0.206***	0.466***
	(0.045)	(0.042)	(0.091)	(0.038)	(0.029)	(0.069)	(0.032)	(0.021)	(0.049)
Number of children in household	-0.0656***	0.00432	-0.00344	-0.0392**	-0.00429	-0.0169	-0.0498***	-0.00959	-0.0308
	(0.020)	(0.022)	(0.051)	(0.017)	(0.013)	(0.032)	(0.015)	(0.009)	(0.021)
Saves regularly	0.314***	0.119***	0.287***	0.289***	0.0539***	0.138***	0.299***	0.0887***	0.216***
	(0.031)	(0.018)	(0.043)	(0.026)	(0.013)	(0.033)	(0.022)	(0.010)	(0.024)
University degree	-0.119**	-0.0702	-0.159	0.0172	0.0224	0.0454	-0.0273	0.0527	0.125
	(0.049)	(0.118)	(0.308)	(0.039)	(0.078)	(0.191)	(0.035)	(0.052)	(0.128)
Individuals	7076	7076	7076	8298	8298	8298	9930	9930	9930
Observations	23116	23116	23116	39670	39670	39670	62786	62786	62786

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.17: GHQ interacted with Female, by period

	1996-2000			2002-2008			1996-2008		
	(1) Pooled OL	(2) Linear FE	(3) BUC	(4) Pooled OL	(5) Linear FE	(6) BUC	(7) Pooled OL	(8) Linear FE	(9) BUC
Commuting time × Female	-0.624***	-0.746**	-0.321**	-0.422***	-0.366*	-0.156*	-0.495***	-0.367**	-0.158**
	(0.065)	(0.323)	(0.139)	(0.055)	(0.214)	(0.092)	(0.047)	(0.161)	(0.069)
Commuting time × Male	0.140***	-0.176	-0.103	0.180***	0.136	0.0774	0.164***	0.0135	0.00776
	(0.051)	(0.220)	(0.122)	(0.043)	(0.150)	(0.081)	(0.036)	(0.113)	(0.059)
Age	-0.0782***	-0.208**	-0.0949**	-0.0830***	-0.238***	-0.113***	-0.0809***	-0.172***	-0.0809***
	(0.010)	(0.087)	(0.045)	(0.008)	(0.047)	(0.024)	(0.007)	(0.026)	(0.013)
Age squared / 100	0.0849***	0.188*	0.0842	0.0904***	0.195***	0.0897***	0.0879***	0.156***	0.0732***
	(0.013)	(0.105)	(0.057)	(0.010)	(0.055)	(0.030)	(0.009)	(0.031)	(0.016)
Hours worked	0.00853***	-0.00652	-0.00298	0.00530***	-0.00569	-0.00286	0.00655***	-0.00793**	-0.00383**
	(0.002)	(0.007)	(0.003)	(0.001)	(0.005)	(0.002)	(0.001)	(0.003)	(0.002)
Log of real household income	0.0864***	0.232*	0.101	0.103***	0.168*	0.0761*	0.0968***	0.157**	0.0694**
	(0.031)	(0.128)	(0.062)	(0.027)	(0.088)	(0.043)	(0.022)	(0.065)	(0.031)
Married or cohabiting	0.152***	0.584***	0.236***	0.0879**	0.437***	0.173***	0.112***	0.382***	0.154***
	(0.041)	(0.194)	(0.084)	(0.035)	(0.147)	(0.064)	(0.029)	(0.100)	(0.044)
Number of children in household	-0.0311*	0.0210	0.00243	-0.00491	-0.0257	-0.0162	-0.0148	0.0143	0.00273
	(0.017)	(0.103)	(0.049)	(0.016)	(0.063)	(0.032)	(0.013)	(0.041)	(0.020)
Saves regularly	0.214***	0.428***	0.217***	0.160***	0.199***	0.101***	0.180***	0.331***	0.165***
	(0.027)	(0.083)	(0.042)	(0.024)	(0.060)	(0.031)	(0.020)	(0.047)	(0.023)
University degree	-0.0190	0.0934	0.0461	0.00512	0.502	0.262	-0.00132	0.274	0.144
	(0.047)	(0.499)	(0.263)	(0.037)	(0.331)	(0.174)	(0.033)	(0.227)	(0.108)
Individuals	7917	7917	7917	9273	9273	9273	11410	11410	11410
Observations	25269	25269	25269	42602	42602	42602	67871	67871	67871

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.18: Overall Life Satisfaction with mode interactions, by period

	1996-2000			2002-2008			1996-2008		
	(1) Pooled OL	(2) Linear FE	(3) BUC	(4) Pooled OL	(5) Linear FE	(6) BUC	(7) Pooled OL	(8) Linear FE	(9) BUC
Commuting time ×Car Driver	-0.212***	-0.0196	-0.0547	-0.0990**	0.0274	0.0762	-0.138***	-0.00151	-0.00420
	(0.063)	(0.041)	(0.099)	(0.045)	(0.024)	(0.066)	(0.040)	(0.020)	(0.050)
Commuting time × Car passenger	0.277**	0.0241	0.0793	-0.148	0.0186	0.0369	-0.00618	0.0225	0.0464
	(0.141)	(0.092)	(0.190)	(0.108)	(0.054)	(0.137)	(0.091)	(0.044)	(0.101)
Commuting time × Rail	-0.0539	-0.0770	-0.221	-0.0934	0.0251	0.0496	-0.0801	0.00534	0.00979
	(0.096)	(0.061)	(0.163)	(0.068)	(0.047)	(0.120)	(0.059)	(0.033)	(0.083)
Commuting time× Tube	-0.0668	0.000904	-0.0327	-0.167	0.0524	0.118	-0.137	-0.0321	-0.0898
	(0.146)	(0.112)	(0.263)	(0.126)	(0.074)	(0.185)	(0.108)	(0.060)	(0.142)
Commuting time × Bus	-0.0956	-0.00492	0.00922	-0.189**	-0.00832	-0.0320	-0.159**	-0.00517	-0.00767
	(0.112)	(0.067)	(0.159)	(0.091)	(0.049)	(0.114)	(0.079)	(0.037)	(0.084)
Commuting time × Motorbike	-0.226	-0.184	-0.489	-0.340	0.0530	0.0866	-0.311	-0.0460	-0.139
	(0.439)	(0.195)	(0.449)	(0.333)	(0.187)	(0.391)	(0.309)	(0.122)	(0.270)
Commuting time × Bicycle	0.0641	0.00768	0.0555	-0.228	0.171	0.363	-0.125	0.0124	0.0134
	(0.287)	(0.242)	(0.498)	(0.299)	(0.160)	(0.363)	(0.233)	(0.127)	(0.288)
Commuting time × Walk	0.0584	-0.121	-0.211	-0.401**	0.00252	-0.0209	-0.235*	-0.0287	-0.0825
	(0.190)	(0.123)	(0.265)	(0.158)	(0.087)	(0.212)	(0.131)	(0.065)	(0.152)
Age	-0.117***	-0.0757***	-0.176***	-0.100***	-0.0273***	-0.0640**	-0.105***	-0.0411***	-0.0986***
	(0.012)	(0.019)	(0.047)	(0.010)	(0.010)	(0.026)	(0.008)	(0.006)	(0.015)
Age squared / 100	0.139***	0.0620***	0.141**	0.115***	0.0204*	0.0460	0.122***	0.0373***	0.0896***
	(0.016)	(0.024)	(0.059)	(0.012)	(0.012)	(0.031)	(0.011)	(0.007)	(0.018)
Hours worked	-0.00265	-0.00111	-0.00252	-0.00714***	-0.000280	-0.000670	-0.00536***	-0.000888	-0.00196
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Log of household income	0.223***	0.0698***	0.153**	0.151***	0.0249	0.0591	0.171***	0.0448***	0.0968***
	(0.035)	(0.027)	(0.062)	(0.030)	(0.018)	(0.043)	(0.024)	(0.014)	(0.032)
Married or cohabiting	0.614***	0.192***	0.406***	0.573***	0.199***	0.463***	0.591***	0.206***	0.465***
	(0.045)	(0.042)	(0.092)	(0.038)	(0.029)	(0.069)	(0.032)	(0.021)	(0.049)
Number of children in household	-0.0646***	0.00503	-0.00163	-0.0425**	-0.00437	-0.0171	-0.0520***	-0.00955	-0.0307
	(0.020)	(0.022)	(0.051)	(0.017)	(0.013)	(0.032)	(0.014)	(0.009)	(0.021)
Saves regularly	0.315***	0.119***	0.288***	0.288***	0.0539***	0.138***	0.299***	0.0886***	0.216***
	(0.031)	(0.018)	(0.043)	(0.026)	(0.013)	(0.033)	(0.022)	(0.010)	(0.024)
] University degree	-0.117**	-0.0704	-0.156	0.0166	0.0229	0.0471	-0.0281	0.0526	0.125
	(0.049)	(0.118)	(0.309)	(0.039)	(0.078)	(0.191)	(0.036)	(0.052)	(0.128)
Individuals	7075	7075	7075	8298	8298	8298	9929	9929	9929
Observations	23111	23111	23111	39670	39670	39670	62781	62781	62781

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 5

Commuting and Life Satisfaction Within a Couple: Evidence from the BHPS

5.1 Introduction

In this chapter we build on the work of the previous chapter by considering members of a couple. Here a couple is defined as a man and a woman who live together. The terms couple and household are used interchangeably to define a dwelling in which a man and a woman live together, and are in a relationship with one another. In this work the term couple is used irrespective of the actual legal marital status of the two people, such that they need not be married. Due to the way the data is constructed for this analysis, it is not possible to look at same sex couples.

Commuting is often thought about as being the interaction of the labour market and the housing market. As housing location decisions are often taken at the household level (see, for example Alonso, 1964, Mills, 1967, Singell and Lillydahl, 1986, Mok, 2007), it would appear a natural progression from the last chapter to examine households in this chapter. Dual (or higher) residency properties allows for the possible scenario in which one member of the household is prepared to travel further such that the other member(s) of the household may benefit from shorter commutes. In the cases we study here, where a household is made up of a male and female member, it may be the case that the male sacrifices his own travel time such that the female does not have to. Madden (1981) found evidence of a similar phenomenon in America by analysing the 1976 Panel Survey of Income Dynamics (PSID). Her results show that women typically work closer to home to enable them, amongst other things, to partake in more household roles such as cleaning and cooking. Roberts et al. (2011) also list household responsibilities, such as childcare and domiciliary work, as factors why women seem to have shorter commutes than males.

Further to the above, Singell and Lillydahl (1986) use the 1980 US census to analyse household locations and commutes of people in two earner households. They find that in the majority of cases the household location decision is dominated by the head of household's job location, and that this head of household is usually the male partner. They find that female labour supply can be adversely affected by longer commutes induced by male-dominated household relocation decisions. As a robustness check they examine a subsample of couples who move house. They find that the household usually moves closer to the male's place of work but further away from the female's. They do note, however, that this perceived female disadvantage is likely to decrease as female earnings grow closer to males.

Conversely, Blank (1988) looks at what happens to household where the female is the head of household. Her analysis is concerned with estimating the probability of moving into areas of the US with high and low welfare payments. She finds that, given that the female is the head of the household, the probability of leaving an area with low levels of welfare payments is 12 percentage points higher than leaving an area with high welfare payments. As we are not interested in household relocation decisions in this analysis we do not discriminate between male and female head of households.

5.1.1 Household Well-being

Given that aggregating 'household' or 'couple' satisfaction scores is relatively rare in the literature, there is no gold standard technique on how this aggregation should be carried out. The classical household bargaining model predicts that the person who has the highest income will be most influential in making household decisions, e.g Donkers and Van Soest (1999) for financial decisions, Leslie and Richardson (1961) for decisions on household relocation, etc.

Based on the above, it would therefore appear that the most common thing to do would be to weight people's life satisfaction scores by their contribution to the household income. However, as income has been found to be correlated with commuting time and distance (e.g. Mulalic et al., 2013, Manning, 2003, chapter 2) we wish to avoid this income weighting. We therefore propose to employ a simple aggregation technique; we intend to look at the sum of each partner's score.

Guven et al. (2012) examine data from the UK (BHPS), Germany (GSOEP) and Australia (HILDA) to look at the total and the average satisfaction score of a couples to predict the probability of divorce. They find that the probability of divorce increases when the female partner's satisfaction score is lower than the male's. Their main area of focus is predicting divorce, and not determining what impact one partner's characteristics has on the other's satisfaction. However, the fact that they use both the averaging and the totaling of satisfaction scores is in someway a validation of the totaling of scores we use here.

As mentioned above, Guven et al. (2012) further look at the average score of the couple. As the data we have here are ordinal, and hence by definition can only take positive integer values, and we plan to use the Blow-Up-and-Cluster (BUC) method of incorporating fixed effects into the ordered logit model (Baetschmann et al., 2011), we cannot look at average as this adds the possibility that the average couple score may not be an integer (*i.e.* the couple average of a male life satisfaction score of 5 and a female life satisfaction score of 6 would be 5.5). Because logit models require the dependent variable to be an integer we focus only on the total couple satisfaction score. In this case this is not a major issue as we focus only on couples, such that the average and the total are defined up to a scale factor of 2. However, if future research were to consider households with different numbers of people, then the average and the total would not be so well defined in terms of each other.

Manser and Brown (1980) argue that instead of households collectively aiming to maximise household utility, what is more common is individual members of given households engaging in bargaining with other household members in an attempt to maximise their own utility. A similar argument was put forward earlier by Gary

Becker (Becker, 1962, 1965), and other household bargaining literature include McElroy (1990), Lundberg and Pollak (1996), and Akerlof and Kranton (2000). Therefore instead of focusing solely on household level utility, we focus also on the utility of each member of the couple as functions of own and spousal covariates.

Mincer (1962) examined the labour force participation decision of married women when the consumption behaviour of the household (or couple) was the outcome of interest. Using American census data on the labour force participation rates of married women in the Northern Standard Metropolitan area from the 1950s (US Census of Population, 1950) and the Bureau of Labour Statistics, he shows that the labour force participation of married women had grown enormously. Akerlof and Kranton (2000) build on this work by examining what happens to household chores and other housework given that female labour supply had increased. This is further built upon in Brown and Roberts (2014), which is detailed below.

In a series of papers Booth and van Ours further examine female labour supply, with a particular focus on the impact that part-time work, especially for females, has on family happiness. Booth and van Ours (2008) use data from the BHPS to investigate the relationship between employment type (full or part-time) and three measures of satisfaction (working hours, overall job satisfaction, and overall life satisfaction). They restrict their analysis to members of a couple to allow them to examine the role that other family/household commitments have on the decision to work part-time, and then examine what impact this has on the satisfaction measures. They find that men have higher levels of satisfaction with work hours if they are employed full-time and do not partake in regular overtime, but that overall job and overall life satisfaction are not affected by hours worked. They get, what they term, 'puzzling' results when they consider female members of a couple: they find that married (or cohabiting) females prefer to work part time, when considering satisfaction with hours and satisfaction with job overall, yet overall life satisfaction is unexplained by the number of hours worked by the female. These results are robust to controlling for spousal covariates, and most importunately spousal labour market participation decisions.

Booth and van Ours (2009) then consider the same phenomenon for Australian couples by analysing the Household, Income and Labour Dynamic in Australia (HILDA) data. They find roughly similar results to above in that females are more satisfied with their hours worked if they work part-time, only they now show that female life satisfaction is higher if their partner works full-time. For men, consistent with Britain, they find that life satisfaction increases if the male is employed full-time, and again, the labour force status of their female partner plays an insignificant role on determining male life satisfaction. Finally, using data from the Netherlands, Booth and van Ours (2013) show that males report higher satisfaction scores if their female partner works part-time, but that this effect disappears if they control for family income. For women, they initially find no relationship between working hours and satisfaction, but after controlling for income they find that women prefer to work part time, but the working hours of their partner remains insignificant in determining female life satisfaction.

The concept of examining spousal covariate on own well-being has been employed in previous literature other than that concerned with own and spousal employment status. Clark and Etilè (2011) examine the impact that body mass index (BMI) has on own well-being, proxied by life satisfaction. They then go on to investigate the impact that partner's BMI has on own well-being. They show that own BMI is initially positively correlated with life satisfaction, but after a threshold this relationship becomes negative. Crucially the authors show that the threshold is found to be a function of the spouses BMI, especially so when the individual is overweight.

In a more recent working paper, Brown and Roberts (2014) use data from the BHPS to focus on the role that gender identity within a couple has on psychological well-being (proxied by the General Health Questionnaire (GHQ)). They follow the definitions of couple type first outlined in Ross et al. (1983)[1], and find that women in 'traditional' couples - couples where both the man and the woman think that the woman should not work - have improved GHQ scores. Conversely, the authors find that women in 'modern' couples - couples where the woman is the main breadwinner, yet still does the majority of household chores - report lower GHQ mental well-being scores. When considering the male member of the couple, the authors find that men who hold traditional views have lower well-being if their female partner is employed. For men who have more modern views on gender identity, the authors find that males report marginally higher well-being scores if their partner works, but this is stronger if the female works part time.

[1] These definitions are: (i) the wife is not employed (both partners approve) and she does the majority of the housework; (ii) the wife if employed (both partners disapprove) and she does the majority of the housework; (iii) the wife is employed (both partners approve) but she still does the majority of the housework; and (iv) the wife is employed (both partners approve) and housework is shared between the man and the wife. Definitions (i) and (ii) are termed 'traditional', whereas (iii) and (iv) are denoted 'modern'.

5.2 Data for Couples

Following on from the previous chapter we use data from the British Household Panel Survey (BHPS) here. As previously noted we focus on 1996-2008, but acknowledge that data is missing for 2001, and hence look at the whole period before considering the two sub-panels which make up the whole period in turn. More detail concerning the BHPS is presented in the previous chapter, and hence we refrain from presenting a detailed introduction to the data here. The outcome(s) of interest in this chapter are responses to the overall life satisfaction question, which we detailed in the previous chapter.

As we are interested in the effect that commuting time has on members of a couple, we initially restrict our analysis to the case where at least one member of the couple is employed. However, for completeness we also focus on the case where both the male and the female are in paid employment. We further impose a number of other restriction. There must be information for the couple for at least two waves of data, the age of the male and the female must be between 17 and 65[2], and finally there must be some change in couple life satisfaction in the period the couple are in the sample (to allow us to use fixed effects methodologies). Following these restrictions, we have information for 29,154 individuals across 4,378 couples (of which 2,058 are couples where only one member is in employment, and the remaining 2,320 are couples where both members are employed). Given that a couple has only one member employed, we have information on 1,117 couples where the male is employed

[2] We acknowledge that the retirement age of females is 60, but we impose this restriction to avoid losing data on couples where the female is over 60 but her male partner is still in employment.

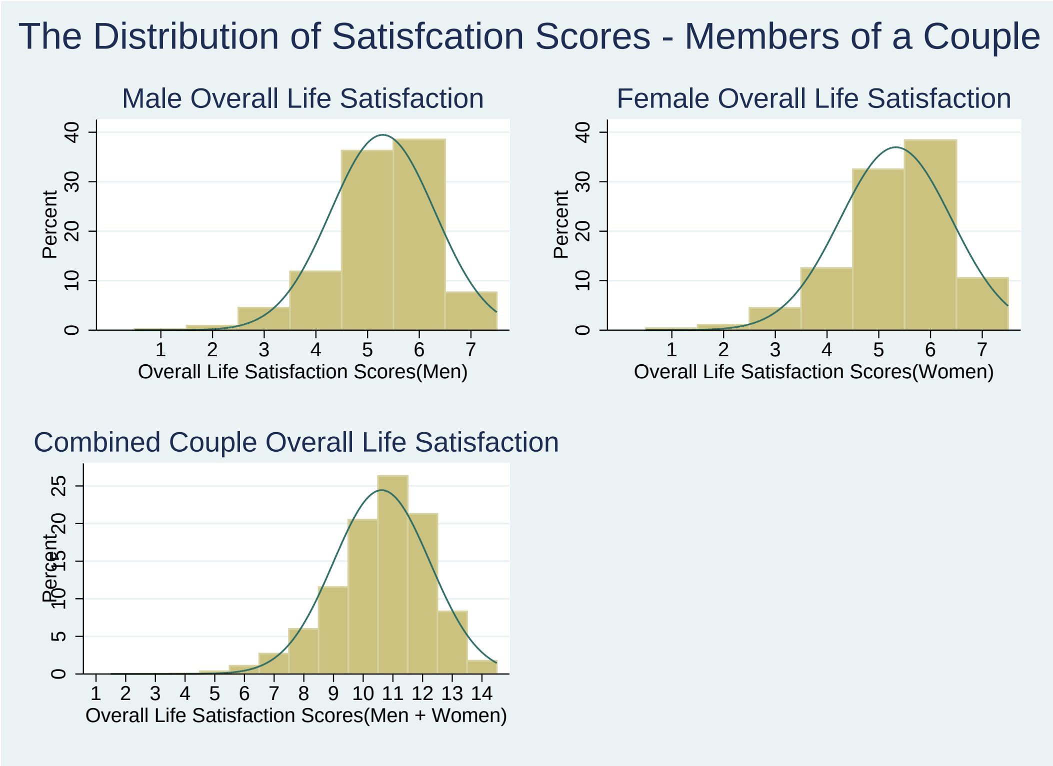
and the female is not, and information on 941 couples where the female is the only employee in the couple.

Consistent with Becker (1962) and Manser and Brown (1980) we will separately examine three independent variables in our analysis: (i) the satisfaction of the male member of the couple; (ii) the satisfaction of the female member of the couple; and (iii) the satisfaction of the couple as a whole. Obviously (i) and (ii) are straightforward; the BHPS directly asks each respondent how satisfied they are with their life overall, on a seven point scale. Figure 5.1 below shows the distribution of male and female satisfaction scores (assuming that the man and the woman are part of a couple). It can be seen that, consistent with literature on self-reported satisfaction, that the majority of the observations are in the higher end of the distribution - people are more likely to report higher levels of satisfaction. (iii) takes somewhat more consideration however. As mentioned above our starting point is to assume that each of the couple's life satisfaction scores is as important as the other. This way we can merely aggregate up to form a measure of couple satisfaction.

Figure 5.3, in the Appendix, looks at the make up of couples well-being by couple type. We can see that one worker couples have more observations in the tails of the distribution, especially the lower tail, whereas dual earner couples have more observations centered on 11 and 12 (out of 14).

Summary statistics of the key variables under consideration are presented in Table 5.1, from we can see that male and female life satisfaction scores are approximately equal. However, a paired t-test returns a test statistic of $t = -3.333$ such that we reject the hypothesis that they and equal and conclude that female members of a

Figure 5.1: Distribution of Satisfaction with Life Overall, given at least one member of the couple is in employment



couple have higher life satisfaction scores then males. For commuting time, we see that male travel for approximately 5 minutes more (each day, one way) per day, and that this difference is statistically significant. Table 5.1 further shows that males work more hours per week, consistent with the hypothesis that female often work part-time (e.g Mincer, 1962, Booth and van Ours, 2008, 2009, 2013).

Figure 5.2 shows how the commuting patterns of male and females within a couples has changed over time. There appears to be a gradual increase although this is relatively small over the 12 year period. What we can observe from Figure 5.2 is that both men and women in dual earner couples commute further than men and women where we stipulate that only one person must be employed. For example, we can see that women in a dual earner household commute for approximately the same time as men in single earner couples. This may be picking up the fact that

Table 5.1: Summary statistics for all couples

	Obs.	Mean	Std. Dev.	Min.	Max.
Couple Life Satisfcation (LS)	29154	10.57	1.76	2.00	14.00
Male LS	29154	5.27	1.07	1.00	7.00
Female LS	29154	5.30	1.16	1.00	7.00
Male commuting time (minutes)	29154	20.51	23.65	0.00	500.00
Female commuting time (minutes)	29154	15.76	18.22	0.00	453.00
Male age	29154	43.21	11.56	17.00	65.00
Female age	29154	41.16	11.31	15.00	65.00
Number in the couple employed	29154	1.60	0.49	1.00	2.00
Hours worked (male)	29154	31.69	17.06	0.00	99.00
Hours worked (female)	29154	22.25	15.28	0.00	99.00
Monthly household income ('000s)	29154	3.39	2.03	0.00	72.93
Number of children in household	29154	0.87	1.04	0.00	6.00
Male saves regularly	29154	0.48	0.50	0.00	1.00
Female saves regularly	29154	0.48	0.50	0.00	1.00

working hours are less in single worker couples.

Table 5.2 breaks the summary statistics down by couple type. For each variable the top row corresponds to couples where only one member is in employment, and the bottom row relates to couples where both members are working. For each of the variables considered the difference between the two group means is significant at the 1% level.

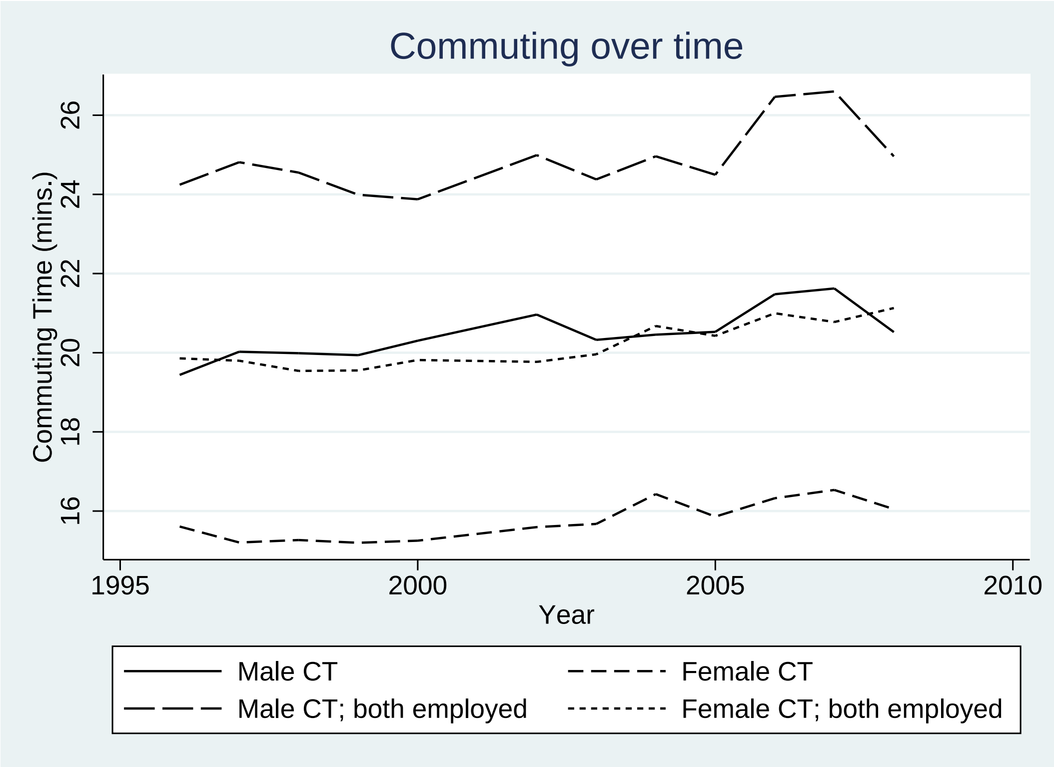
Table 5.2 shows that couples where both are employed are, on average, happier than couples where only one member works, with the same true for both male and female individual life satisfaction scores. Male and female commuting times in one earner households are smaller. One explanation for this is the fact that if a person is not working, their commuting time (and hours worked) are set to be zero. Single earner couples appear to be older than dual earners, and as expected household income is higher in the case where both members are employed.

Table 5.2: **Summary statistics by couple type**

	Obs.	Mean	Std. Dev.	Min.	Max.
Couple LS	11729	10.48	1.93	2.00	14.00
	17425	10.63	1.63	2.00	14.00
Male LS	11729	5.23	1.16	1.00	7.00
	17425	5.30	1.01	1.00	7.00
Female LS	11729	5.25	1.27	1.00	7.00
	17425	5.33	1.08	1.00	7.00
Male CT (minutes)	11729	14.04	21.49	0.00	300.00
	17425	24.87	24.04	0.00	500.00
Female CT (minutes)	11729	9.18	15.62	0.00	330.00
	17425	20.20	18.51	0.00	453.00
Male age	11729	45.72	12.74	17.00	65.00
	17425	41.51	10.35	17.00	65.00
Female age	11729	43.44	12.50	17.00	65.00
	17425	39.64	10.15	17.00	65.00
Hours worked (male)	11729	21.80	20.41	0.00	99.00
	17425	38.36	9.78	0.00	99.00
Hours worked (female)	11729	12.75	15.65	0.00	80.00
	17425	28.64	11.14	0.00	99.00
Monthly household income ('000s)	11729	2.91	2.06	0.00	33.69
	17425	3.71	1.95	0.01	72.93
Number of children in household	11729	0.94	1.11	0.00	6.00
	17425	0.82	0.99	0.00	5.00
Male saves regularly	11729	0.42	0.49	0.00	1.00
	17425	0.52	0.50	0.00	1.00
Female saves regularly	11729	0.39	0.49	0.00	1.00
	17425	0.55	0.50	0.00	1.00

Note: the top row refers to one earner couples, and the bottom row is for the case when both members of the couple are working.

Figure 5.2: **Changes in commuting time across time, by couple type**



To get more of an understanding of the make-up of single earner couples, summary statsitics are presented by whether it is the male or the female that is in employment. These statistics are presented in the Appendix, in Table 5.6. Consistent with the literature on unemployment and life satisfaction (e.g Clark and Oswald, 1994, Clark et al., 2008, Kassenboehmer and Haisken-DeNew, 2009), we see that when the male (female) is the only employee in the couple the male (female) reports a higher life satisfaction score than their unemployed partner, and this difference is statistically significant at the 1% level. When the female is the only breadwinner in a couple their commuting time is higher, on average, than female commuting times if both the male and the female are employed. Family income is higher if the male is employed, but this is likely to be due to the fact that male working hours (given they are employed) are higher than the female equivalent. The last two rows of Table 5.6 show that which ever member of the couple is employed is likely to save more.

5.3 Models for Couples

As mentioned in the previous section, we are considering three outcome variables: (i) the satisfaction of the male member of the couple; (ii) the satisfaction of the female member of the couple; and (iii) the satisfaction of the couple as a whole. The third can be estimated as a function of all male, female, and household characteristics:

$$LS_{it}^{Couple} = \beta_1 C_{it}^{M} + \beta_2 C_{it}^{F} + \beta_3 X_{it}^{M} + \beta_4 X_{it}^{F} + \beta_5 H_{it}^{Couple} + \varepsilon_{it} \tag{5.1}$$

where LS^{Couple} is the life satisfaction score of the couple i at time t, C is a vector of commuting information, X is a vector of individual level information where superscripts M and F refer to the male and female member, respectively. H^{Couple} is a vector of household level information. Information contained in the vectors X^j ($j = M, F$) and H^{Couple} is presented in Table 5.1. Finally ε is a random error term comprising a time invariant fixed effect and an individual time specific random component[3].

The first two outcome variables allow for four specifications (with one nested in another for both males and females). These are:

$$LS_{it}^{M} = \beta_1 C_{it}^{M} + \beta_2 C_{it}^{F} + \beta_3 X_{it}^{M} + \beta_4 X_{it}^{F} + \beta_5 H_{it}^{Couple} + \varepsilon_{it} \tag{5.2a}$$

$$LS_{it}^{M} = \alpha_1 C_{it}^{M} + \alpha_2 X_{it}^{M} + \alpha_3 H_{it}^{Couple} + \varepsilon_{it} \tag{5.2b}$$

[3] If we assume LS is ordinal, and impose the BUC methodology, then the random component is standard logistic (0,$\pi^2/3$). If we assume LS is cardinal and implement a FE Linear specification then the random component is standard normal (0,1).

and

$$LS_{it}^F = \beta_1 C_{it}^M + \beta_2 C_{it}^F + \beta_3 X_{it}^M + \beta_4 X_{it}^F + \beta_5 H_{it}^{Couple} + \varepsilon_{it} \tag{5.3a}$$

$$LS_{it}^F = \alpha_1 C_{it}^F + \alpha_2 X_{it}^F + \alpha_3 H_{it}^{Couple} + \varepsilon_{it} \tag{5.3b}$$

where in both equations (b) is obtained by setting $\beta_2 = \beta_4 = 0$ in (a).

A priori specifications (5.2b) and (5.3b) should replicate the results of the previous chapter, assuming that males and females who are members of couples are comparable to men and women who do not belong to a couple.

We estimate all model specification using three econometric methodologies: (1) the Pooled Ordered Logit (Pooled OL); (2) the linear fixed-effects model (Linear FE); and (3) the BUC FE-OL model (BUC). As the work in the previous chapter demonstrates, the choice between BUC and the Das and van Soest (1999) estimator is arbitrary, although the BUC model works better for smaller numbers of observations in the left hand tail. As documented in the previous chapter the F&F model has been shown to be inconsistent due to the endogenous choice of cut-off. For further detail on the fixed effects ordered logit methodology please see Baetschmann et al. (2011) and Dickerson et al. (2012).

5.4 Results

In this section we present the results from those individuals who are a member of a couple. We start by considering the satisfaction of the couple as a whole for various outcome measures, where initially at least one member of the couple is employed, and then do the same analysis for the case when both members are employed. We then look at the satisfaction scores of both members of the couple individually, and again repeat this for the case when at least one, and then both, members are employed.

5.4.1 The satisfaction of 'the couple'

Recall here that the satisfaction of the couple is defined as the sum of the satisfaction scores of the two members of the couple.

At least one member of the couple is employed

Table 5.3 shows the results from the satisfaction on the couple model using data from the whole sample. We can see that the commuting coefficients are only significant in the pooled ordered logit model. When we extend the models to incorporate individual fixed effects this significance disappears. We further observe that the age of both members of the couple impacts on the combined life satisfaction outcome as expected; that is the coefficient on age is negative whilst that on age squared is positive, although we do not always observe statistical significance as we would expect. Similar to the previous chapter, we attribute the difference in results from the pooled specifications vs. the FE specifications to the presence of an omitted individual specific effect in the pooled specification.

Following on from the previous chapter, we disaggregate these results by examining

Table 5.3: Couple Satisfaction with Life Overall, 1996-2008: At least one member in employment

	(1) Pooled OL	(2) Linear FE	(3) BUC
Male commuting time (hours)	-0.0673***	-0.00615	-0.00851
	(0.024)	(0.032)	(0.052)
Female commuting time (hours)	-0.0879**	0.0164	0.0322
	(0.044)	(0.041)	(0.068)
Male age	-0.0978***	-0.0289	-0.0531
	(0.019)	(0.028)	(0.044)
Male age squared / 100	0.114***	0.0259	0.0456
	(0.021)	(0.032)	(0.050)
Female age	-0.0515***	-0.0830***	-0.126***
	(0.019)	(0.028)	(0.043)
Female age squared / 100	0.0611***	0.0733**	0.111**
	(0.023)	(0.033)	(0.052)
Hours worked (male)	0.00184	0.00307***	0.00473***
	(0.001)	(0.001)	(0.001)
Hours worked (female)	0.00101	0.000676	0.00110
	(0.001)	(0.001)	(0.002)
Monthly household income ('000s)	0.0523***	0.0138**	0.0212**
	(0.010)	(0.006)	(0.010)
Number of children in household	-0.0134	0.0282	0.0316
	(0.022)	(0.020)	(0.032)
Male saves regularly	0.262***	0.0847***	0.137***
	(0.033)	(0.021)	(0.034)
Female saves regularly	0.199***	0.104***	0.172***
	(0.033)	(0.021)	(0.033)
Male has university degree	0.0176	0.0984	0.170
	(0.061)	(0.107)	(0.184)
Female has university degree	0.0395	-0.00316	-0.0129
	(0.059)	(0.098)	(0.163)
Number of Couples	4378	4378	4378
Observations	29163	29163	29163

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the two sub-panels available to us. These results are presented in Table 5.7 in the Appendix. From this we can see that initially the combined satisfaction of the couple decreased as the female's commuting time increased. However, in the later period the converse is true; the satisfaction was an increasing function of the female commute. However, these results are not significant at the 10% level (with the exception of column (6)). The net results in an insignificant impact for the whole period. The commuting distance of the male member of the couple always has an insignificant role when fixed effects are included, independent of which time period is under consideration.

Both members of the couple are employed

We now impose the constraint that both the male and the female member of the couple must be employed, and repeat the above analysis. Table 5.8, in the Appendix, shows these results by period. It is clear that the same pattern is present for the case when both members are employed - that is the commuting time of the female member fluctuates between negative and significant and positive and insignificant, with the net result of statistical insignificance. Further, the commuting time of the male, in the fixed effects models, is always insignificant.

We conclude from this that the choice of studying couples with at least one, or both, members in employment is irrelevant as both give the same results when analysing the outcome of choice for the couple. In the commuting context we are interested in here, we deduce that females who are a member of a couple initially suffered disutility from longer commutes, but interestingly this changed to positive utility between 2002 and 2008, although this was significant in only one specification (BUC for the case where at least one member was employed - column (6) of Table 5.3). This finding of a positive relationship between female commuting time and aggregated household well-being between 2002 and 2008 is, as far as we are aware, unique in the sense that it is usually a negative relationship (Stutzer and Frey, 2008 and Roberts et al., 2011 for women) or statistically insignificant (Dickerson et al., 2012, Roberts et al., 2011 for men). However, we are aware that simply summing the individual's life satisfaction scores to obtain the life satisfaction score of the couple is not an ideal measure, and we further concede that this relationship is only significant at the 10% level.

To shed more light on spousal commuting we now look at the life satisfaction scores of male and female members of couples separately, to enable us to examine possible bargaining models within a couple (e.g. Manser and Brown, 1980, McElroy, 1990, Akerlof and Kranton, 2000).

5.4.2 The satisfaction of male and the female

In this subsection we focus on the individual scores of the two members - *i.e.* we estimate Eq.'s (5.2a), (5.2b). (5.3a), (5.3b). Again, we believe it is possible that couples where at least one and both members are employed may differ, so we estimate models for both couple type.

As we run 3 different models for both members of a couple over three different time periods it is not possibly to include them in one table to compare. We therefore estimate the model for the whole period first, before focusing on the earlier and later component years afterwards. In all of the tables and discussion which follow, columns (1) to (6) show the results for the males, and columns (7) through (12) show the results for females. In all cases odd columns have the model estimated when all of the controls are included, whereas the even columns have the results when only the individual level controls are included. The tables for the whole sample period are presented in the main body of the text, and the tables for the two sub-panels are presented in the Appendix.

At least one member of the couple is employed

The results for the whole period, presented in Table 5.4, show that the commuting time of both males and females is only ever significant in the pooled ordered logit regressions. In the models that incorporate fixed effects the results drop out. This is consistent for the effect of female commuting on male well-being, and *vice-versa*. Interestingly, in the pooled models it is only ever the own commute that is significant never that of the partner. Again, the controls all behave as expected but it is usually own characteristics that are more important than spousal characteristics. For example, male age is an important factor in determining male life satisfaction, but not their female partner's life satisfaction. When looking at the hours worked variables, we see that female life satisfaction is an increasing function of male hours of work, consistent with Booth and van Ours (2009), yet own female hours worked is insignificant, which appears to contradict Booth and van Ours (2013) as we do control for family income in all of our models.

The presence of savings for both males and females significantly increases both own and spousal well-being here. This result is robust to removing income from our analysis (results omitted here). However, we do concede that there is likely to be an endogeneity between working and savings, with couples in employment having access to more money to be able to save. This result is not as striking for the case where both the male and female are employed, so this possible endogeneity may not be such a problem. If the relationship was completely endogenous we would expect to observe greater significance for the case where both members are employed than the case where at least one member is in employment, but this is not the case here.

Table 5.4: Male and Female Satisfaction with Life Overall, 1996-2008: At least one member in employment

	Male Satsifaction with Life Overall						Female Satsifaction with Life Overall					
	(1) Pooled OL	(2) Pooled OL	(3) Lin. FE	(4) Lin. FE	(5) BUC	(6) BUC	(7) Pooled OL	(8) Pooled OL	(9) Lin. FE	(10) Lin. FE	(11) BUC	(12) BUC
Male commuting time (hours)	-0.119***	-0.120***	0.00975	0.0114	0.0246	0.0296	-0.0113		-0.0159		-0.0695	
	(0.045)	(0.045)	(0.018)	(0.018)	(0.057)	(0.057)	(0.044)		(0.020)		(0.053)	
Female commuting time (hours)	-0.0182		0.0328		0.0940		-0.128**	-0.126**	-0.0163	-0.0193	-0.0148	-0.0279
	(0.065)		(0.025)		(0.075)		(0.062)	(0.061)	(0.027)	(0.027)	(0.070)	(0.069)
Male age	-0.114***	-0.116***	-0.0454***	-0.0592***	-0.131***	-0.164***	-0.0438**		0.0165		-0.0833*	
	(0.020)	(0.012)	(0.014)	(0.007)	(0.046)	(0.025)	(0.018)		(0.015)		(0.048)	
Male age squared / 100	0.139***	0.138***	0.0485***	0.0540***	0.139***	0.150***	0.0480**		-0.0226		0.0325	
	(0.022)	(0.014)	(0.015)	(0.008)	(0.052)	(0.028)	(0.020)		(0.016)		(0.053)	
Female age	-0.00294		-0.0151		-0.0352		-0.0849***	-0.117***	-0.0680***	-0.0545***	-0.0616	-0.137***
	(0.020)		(0.013)		(0.044)		(0.020)	(0.014)	(0.014)	(0.007)	(0.049)	(0.025)
Female age squared / 100	0.000315		0.00669		0.0128		0.102***	0.138***	0.0666***	0.0454***	0.0816	0.104***
	(0.024)		(0.016)		(0.054)		(0.023)	(0.016)	(0.017)	(0.008)	(0.057)	(0.028)
Hours worked (male)	0.00232*	0.00207	0.00120**	0.00121**	0.00299*	0.00298*	0.000846		0.00187***		0.00529***	
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)		(0.001)		(0.002)	
Hours worked (female)	0.000750		-0.000373		-0.00105		0.000462	0.0000886	0.00105	0.000923	0.00227	0.00212
	(0.001)		(0.001)		(0.002)		(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Monthly household income ('000s)	0.0445***	0.0486***	0.0102***	0.0104***	0.0260**	0.0267**	0.0379***	0.0432***	0.00362	0.00641	0.0104	0.0164
	(0.010)	(0.010)	(0.004)	(0.004)	(0.010)	(0.011)	(0.010)	(0.010)	(0.004)	(0.004)	(0.012)	(0.012)
Number of children in household	-0.0408*	-0.0488**	0.0153	0.0141	0.0350	0.0326	0.00893	0.000928	0.0129	0.0133	0.0222	0.0203
	(0.022)	(0.020)	(0.010)	(0.010)	(0.035)	(0.033)	(0.022)	(0.022)	(0.011)	(0.011)	(0.033)	(0.033)
Male saves regularly	0.245***	0.271***	0.0447***	0.0491***	0.127***	0.139***	0.176***		0.0400***		0.0952**	
	(0.033)	(0.033)	(0.013)	(0.013)	(0.038)	(0.037)	(0.034)		(0.014)		(0.037)	
Female saves regularly	0.103***		0.0280**		0.0818**		0.218***	0.264***	0.0765***	0.0840***	0.182***	0.201***
	(0.033)		(0.013)		(0.036)		(0.034)	(0.033)	(0.014)	(0.014)	(0.038)	(0.037)
Male has university degree	-0.00636	0.00731	0.0469	0.0476	0.150	0.164	0.0274		0.0515		0.116	
	(0.060)	(0.056)	(0.083)	(0.083)	(0.208)	(0.207)	(0.059)		(0.090)		(0.213)	
Female has university degree	0.0437		0.0608		0.170		0.0368	0.0551	-0.0639	-0.0659	-0.0201	-0.0256
	(0.061)		(0.054)		(0.165)		(0.058)	(0.055)	(0.059)	(0.058)	(0.187)	(0.186)
Number of Couples	4378	4378	4378	4378	4378	4378	4378	4378	4378	4378	4378	4378
Observations	29163	29163	29163	29163	29163	29163	29163	29163	29163	29163	29163	29163

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.9 examines the same relationships as above, but we now focus on the early data from 1996-2000. As is the case with individuals in the same time period, we see that there are no statistically significant relationships between any commuting and well-being variables. For male commuting time we observe positive, but insignificant, coefficients on both own well-being and on their partner's. For female commuting time we observe a positive relationship with male life satisfaction scores, and a negative relationship with their own SWB. Again, however, these coefficients are not significant even at the 10% level. The remaining covariates act as expected.

When we focus on the later period (2002-2008) in Table 5.10 we obtain almost identical results to those presented above. From this we deduce that the period under consideration does not impact upon our findings here. For all time periods we observe an insignificant relationship between both own commuting time and own SWB and spousal commuting time and own SWB, and that this result is robust irrespective of gender.

To see if it matters how many people in the couple are in paid employment, we now turn our attention to the case where both the male and the female are employed.

Both members of the couple are employed

As is the case with the aggregate couple satisfaction analysis we now re-estimate all of our models for those couples where both the male and the female are employed. These results are presented in table 5.5. Consistent with the case where at least one member is employed, we find no evidence of spousal commuting time affecting own life satisfaction in a fixed effects framework, nor do we find evidence of own commute affecting own satisfaction. As previously mentioned, we find no evidence of a relationship between saving (of either male or female) and male SWB here, which is inconsistent with the case above where we allowed for one member of the couple to be unemployed. All other covariates act as previously documented.

Table 5.5: Male and Female Satisfaction with Life Overall, 1996-2008: Both members in employment

	Male Satsifaction with Life Overall						Female Satsifaction with Life Overall					
	(1) Pooled OL	(2) Pooled OL	(3) Lin. FE	(4) Lin. FE	(5) BUC	(6) BUC	(7) Pooled OL	(8) Pooled OL	(9) Lin. FE	(10) Lin. FE	(11) BUC	(12) BUC
Male commuting time (hours)	-0.167***	-0.162***	0.0191	0.0201	0.0617	0.0641	0.00239		-0.0323		-0.101	
	(0.053)	(0.053)	(0.022)	(0.022)	(0.072)	(0.072)	(0.050)		(0.024)		(0.068)	
Female commuting time (hours)	-0.00569		0.0316		0.0934		-0.204***	-0.198***	-0.0305	-0.0330	-0.0423	-0.0557
	(0.075)		(0.029)		(0.087)		(0.073)	(0.072)	(0.032)	(0.032)	(0.089)	(0.089)
Male age	-0.159***	-0.120***	-0.0644***	-0.0509***	-0.197***	-0.149***	-0.0415		-0.00341		-0.177***	
	(0.028)	(0.019)	(0.019)	(0.010)	(0.070)	(0.036)	(0.027)		(0.020)		(0.066)	
Male age squared / 100	0.194***	0.145***	0.0679***	0.0435***	0.203***	0.126***	0.0394		-0.0104		0.0754	
	(0.034)	(0.022)	(0.021)	(0.011)	(0.078)	(0.041)	(0.033)		(0.023)		(0.086)	
Female age	0.0544*		0.0167		0.0586		-0.0373	-0.0677***	-0.0474**	-0.0499***	0.0139	-0.137***
	(0.029)		(0.018)		(0.070)		(0.028)	(0.018)	(0.020)	(0.011)	(0.066)	(0.036)
Female age squared / 100	-0.0719*		-0.0300		-0.0949		0.0428	0.0705***	0.0519**	0.0410***	0.0549	0.106**
	(0.037)		(0.022)		(0.083)		(0.036)	(0.023)	(0.024)	(0.013)	(0.090)	(0.044)
Hours worked (male)	0.000285	-0.0000470	-0.00119	-0.00119	-0.00345	-0.00345	0.00497**		0.000597		0.00264	
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)		(0.001)		(0.003)	
Hours worked (female)	-0.00167		-0.000642		-0.00171		-0.00938***	-0.00942***	-0.00188*	-0.00185*	-0.00377	-0.00348
	(0.002)		(0.001)		(0.003)		(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Monthly household income ('000s)	0.0267**	0.0293**	0.00767	0.00774	0.0177	0.0183	0.0269**	0.0321***	-0.00312	-0.00403	-0.00918	-0.0119
	(0.012)	(0.012)	(0.005)	(0.005)	(0.014)	(0.014)	(0.012)	(0.012)	(0.006)	(0.006)	(0.016)	(0.017)
Number of children in household	-0.0852***	-0.0705***	0.00486	0.00900	0.00747	0.0209	-0.0865***	-0.0920***	-0.0167	-0.0163	-0.0495	-0.0558
	(0.028)	(0.026)	(0.013)	(0.012)	(0.046)	(0.044)	(0.027)	(0.027)	(0.014)	(0.014)	(0.042)	(0.043)
Male saves regularly	0.188***	0.213***	0.0190	0.0191	0.0605	0.0602	0.123***		0.0273		0.0574	
	(0.041)	(0.041)	(0.016)	(0.016)	(0.050)	(0.049)	(0.041)		(0.018)		(0.049)	
Female saves regularly	0.0885**		0.00239		0.00534		0.290***	0.321***	0.0861***	0.0907***	0.222***	0.239***
	(0.042)		(0.016)		(0.049)		(0.042)	(0.041)	(0.018)	(0.017)	(0.052)	(0.051)
Male has university degree	0.0278	0.0463	0.0710	0.0697	0.249	0.237	0.0472		0.0480		0.349	
	(0.075)	(0.068)	(0.108)	(0.108)	(0.267)	(0.267)	(0.071)		(0.118)		(0.256)	
Female has university degree	0.0387		0.0823		0.262		0.00689	0.0196	-0.0773	-0.0983	-0.0481	-0.0769
	(0.076)		(0.074)		(0.219)		(0.069)	(0.066)	(0.081)	(0.080)	(0.289)	(0.280)
Number of Couples	2320	2320	2320	2320	2320	2320	2320	2320	2320	2320	2320	2320
Observations	17434	17434	17434	17434	17434	17434	17434	17434	17434	17434	17434	17434

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When we consider the relationship by period, in Table 5.11 (1996-2000) and Table 5.12 (2002-2008) in the Appendix, we do observe evidence of a relationship between commuting behaviour and life satisfaction. In the early period we observe that an increase in (own) female commuting time lead to a reduction in (own) female life satisfaction, and this is robust to including fixed effects. However, the impact of (male) spousal commuting on female life satisfaction remained insignificant. For male life satisfaction in this period we observe statistical insignificance on all commuting variables. In both cases the rule appears to be female commuting time is negatively related to both male and female SWB (although insignificant for male SWB), whereas male commuting time is positively, albeit insignificantly, related to both male and female SWB.

In the latter period we observe something different again. Here there appears to be a statistically significant negative relationship between male commuting time and female life satisfaction. This result holds for the fixed effects specifications, but interestingly not for the pooled ordered logit specification. Again, this difference between pooled and FE results is likely attributable to omitted variable bias, although in the opposite direction to the previous results. From the FE models we deduce that females were worse off as a result of an increase in their partner's daily commuting time. In this period we observe insignificance between female commuting time and female life satisfaction and between both male and female commuting times and male life satisfaction.

For the other controls, we observe no relationship between hours worked and life satisfaction for wither partner in either time period considered when considering the fixed effects specifications. This is to be expected as we do stipulate that both partners must already be in employment, whereas the majority of the existing literature look at transitions in and out of employment type. In both time periods we observe that it is the presence of own savings that is more highly correlated with own well-being, and not the presence of savings for the partner. This result is stronger for females in the later time period. In the earlier time period age does not appear as significant as it usually is, although this is not true for the later period.

5.5 Conclusion

In this chapter we have built on the work of the previous chapter by examining the role that each member of a couples commuting time has on overall couple satisfaction, and each member of the couple's individual satisfaction scores. Consistent with the literature for women, we find that in the earlier period the commuting time of the female partner negatively effected her own SWB (Roberts et al., 2011 who use GHQ, and Dickerson et al. (2012) who use overall life satisfaction). This result appears stable across women who live in single and dual worker households.

When we examine later waves of the data and consider dual earner households we observe that employed females are negatively impacted upon by longer commuting times of their male partner. This is the only occasion in which we observe statistical significance between commuting and well-being in our data. One possible explanation for this the result that when the male is the head of the household, household relocation decisions tend to be geared towards reducing the male commuting time (Singell abd Lillydahl, 1986), and this, in turn, will lower the burden that the male commute places on female life satisfaction. This explanation is only speculative however.

The choice of studying couples where only both members are employed compared to the case where at least one is employed seems an arbitrary choice in most cases, based on these results. However, the result documented in the previous paragraph is only true for when both male and female members of a couple are employed, and hence there might exist subtle differences between the two couple types.

The vast majority of our results here would tend to imply that household bargaining, with respect to commuting decision, is efficient. If neither member of the couple is affected by their own or their partner's commute, then we can infer that household location decisions are optimally made (as documented by, for example, Alonso, 1964, Mills, 1967).

We have refrained from considering GHQ as a proxy for well-being in this analysis. This alternative proxy could provide scope for further research. Based on the previous chapter, and Roberts et al. (2011), there does appear to exist differences in the overall conclusions obtained, depending on which proxy for SWB is employed by the researcher.

Consistent with the methodological literature, we again find no difference between employing FE Linear methodologies over FE Ordered Logit methodologies.

Appendix 5A: Additional Tables and Figures

Table 5.6: Summary Statistics by the gender of the employed member of the couple, given only one member is employed

	Obs.	Mean	Std. Dev.	Min.	Max.
Couple LS	6666	10.46	1.93	2.00	14.00
	5063	10.50	1.93	2.00	14.00
Male LS	6666	5.25	1.08	1.00	7.00
	5063	5.21	1.26	1.00	7.00
Female LS	6666	5.21	1.33	1.00	7.00
	5063	5.30	1.17	1.00	7.00
Male commuting time (minutes)	6666	23.97	23.26	0.00	300.00
	5063	0.00	0.00	0.00	0.00
Female commuting time (minutes)	6666	0.00	0.00	0.00	0.00
	5063	18.30	17.77	0.00	330.00
Male age	6666	43.14	12.25	17.00	87.00
	5063	49.12	12.59	17.00	91.00
Female age	6666	41.69	12.79	16.00	88.00
	5063	45.75	11.71	17.00	80.00
Hours worked (male)	6666	37.35	11.44	0.00	99.00
	5063	0.00	0.00	0.00	0.00
Hours worked (female)	6666	0.00	0.00	0.00	0.00
	5063	26.29	12.21	0.00	80.00
Monthly household income ('000s)	6666	2.97	1.97	0.06	30.84
	5063	2.82	2.17	0.00	33.69
Number of children in household	6666	1.15	1.15	0.00	6.00
	5063	0.66	0.99	0.00	6.00
Male saves regularly	6666	0.46	0.50	0.00	1.00
	5063	0.38	0.48	0.00	1.00
Female saves regularly	6666	0.32	0.47	0.00	1.00
	5063	0.48	0.50	0.00	1.00

Note: the top row refers to couples where the male is working and the female is not, and the bottom row refers to the case where the female is working and the male is not.

Figure 5.3: Distribution of Satisfaction with Life Overall: by couple type

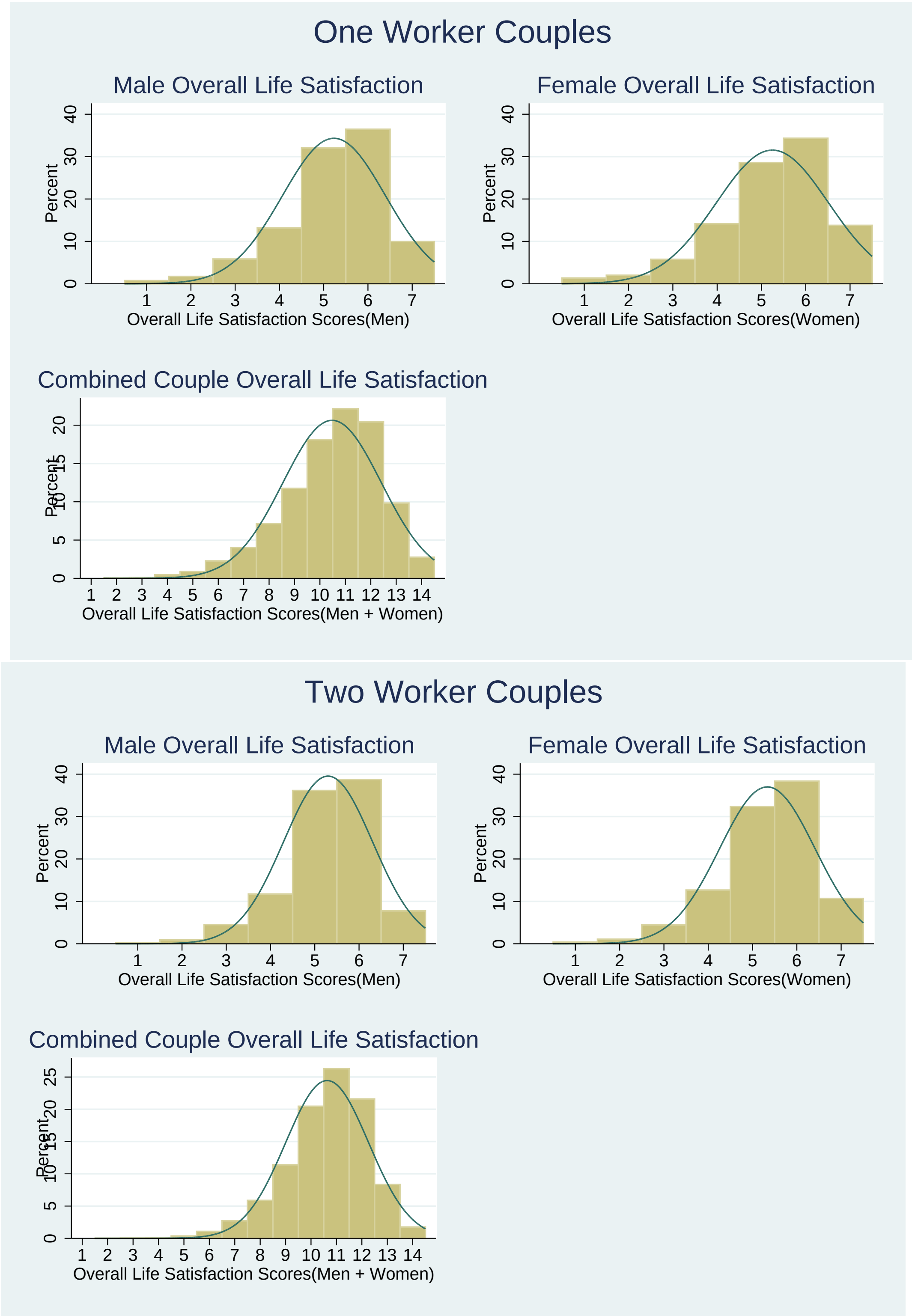


Table 5.7: Couple Satisfaction with Life Overall, By Period: At least one member in employment

	1996-2000 ($n = 3098$)			2002-2008 ($n = 3242$)			1996-2008 ($n = 4378$)		
	(1) Pooled OL	(2) Lin. FE	(3) BUC	(4) Pooled OL	(5) Lin. FE	(6) BUC	(7) Pooled OL	(8) Lin. FE	(9) BUC
Male commuting time (hours)	-0.0709	0.0283	0.0473	-0.0736	-0.0334	-0.0601	-0.0673***	-0.00615	-0.00851
	(0.063)	(0.056)	(0.097)	(0.055)	(0.047)	(0.077)	(0.024)	(0.032)	(0.052)
Female commuting time (hours)	-0.0769	-0.0549	-0.0923	-0.0826	0.0867	0.178*	-0.0879 **	0.0164	0.0322
	(0.103)	(0.094)	(0.154)	(0.074)	(0.053)	(0.103)	(0.044)	(0.041)	(0.068)
Male age	-0.111***	-0.159*	-0.251*	-0.0865***	-0.130**	-0.227**	-0.0978***	-0.0289	-0.0531
	(0.025)	(0.087)	(0.134)	(0.024)	(0.060)	(0.097)	(0.019)	(0.028)	(0.044)
Male age squared / 100	0.131***	0.128	0.191	0.0988***	0.119*	0.205*	0.114***	0.0259	0.0456
	(0.028)	(0.106)	(0.163)	(0.026)	(0.068)	(0.112)	(0.021)	(0.032)	(0.050)
Female age	-0.0434	0.0293	0.0430	-0.0717***	-0.0277	-0.0461	-0.0515***	-0.0830***	-0.126***
	(0.028)	(0.085)	(0.132)	(0.024)	(0.059)	(0.094)	(0.019)	(0.028)	(0.043)
Female age squared / 100	0.0545	-0.0546	-0.0810	0.0852***	0.0187	0.0333	0.0611***	0.0733**	0.111**
	(0.034)	(0.109)	(0.172)	(0.028)	(0.071)	(0.115)	(0.023)	(0.033)	(0.052)
Hours worked (male)	0.00350**	0.000988	0.00180	0.00130	0.00566***	0.00927***	0.00184	0.00307***	0.00473***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Hours worked (female)	-0.000641	0.00220	0.00337	0.00252	-0.000769	-0.00148	0.00101	0.000676	0.00110
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
Monthly household income ('000s)	0.0619***	0.00999	0.0173	0.0524***	0.00572	0.00815	0.0523***	0.0138**	0.0212**
	(0.018)	(0.009)	(0.017)	(0.011)	(0.009)	(0.017)	(0.010)	(0.006)	(0.010)
Number of children in household	-0.0597**	0.0220	0.0229	0.0368	0.0316	0.0398	-0.0134	0.0282	0.0316
	(0.029)	(0.047)	(0.075)	(0.027)	(0.032)	(0.053)	(0.022)	(0.020)	(0.032)
Male saves regularly	0.281***	0.148***	0.246***	0.244***	0.0302	0.0501	0.262***	0.0847***	0.137***
	(0.045)	(0.037)	(0.058)	(0.042)	(0.031)	(0.053)	(0.033)	(0.021)	(0.034)
Female saves regularly	0.212***	0.144***	0.241***	0.197***	0.0666**	0.121**	0.199***	0.104***	0.172***
	(0.045)	(0.036)	(0.059)	(0.042)	(0.030)	(0.052)	(0.033)	(0.021)	(0.033)
Male has university degree	-0.00764	0.0783	0.142	0.0561	0.195	0.363	0.0176	0.0984	0.170
	(0.079)	(0.222)	(0.369)	(0.069)	(0.222)	(0.360)	(0.061)	(0.107)	(0.184)
Female has university degree	-0.0511	0.0134	0.0284	0.0739	-0.165	-0.329	0.0395	-0.00316	-0.0129
	(0.084)	(0.229)	(0.357)	(0.065)	(0.155)	(0.278)	(0.059)	(0.098)	(0.163)
Observations	11062	11062	11062	15281	15281	15281	29163	29163	29163

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.8: Couple Satisfaction with Life Overall, By Period: Both members in employment

	1996-2000 ($n = 1328$)			2002-2008 ($n = 1824$)			1996-2008 ($n = 2320$)		
	(1) Pooled OL	(2) Lin. FE	(3) BUC	(4) Pooled OL	(5) Lin. FE	(6) BUC	(7) Pooled OL	(8) Lin. FE	(9) BUC
Male commuting time (hours)	-0.0550	0.0467	0.0810	-0.118*	-0.0497	-0.0796	-0.0907*	-0.0132	-0.0197
	(0.076)	(0.064)	(0.121)	(0.065)	(0.061)	(0.100)	(0.051)	(0.039)	(0.066)
Female commuting time (hours)	-0.180	-0.209**	-0.395**	-0.110	0.0965	0.198	-0.138*	0.00109	0.0000153
	(0.120)	(0.095)	(0.181)	(0.087)	(0.061)	(0.132)	(0.076)	(0.046)	(0.082)
Male age	-0.158***	-0.0979	-0.161	-0.0846**	-0.0606	-0.120	-0.119***	-0.0678*	-0.122*
	(0.036)	(0.125)	(0.212)	(0.037)	(0.082)	(0.150)	(0.028)	(0.038)	(0.064)
Male age squared / 100	0.181***	0.0385	0.0378	0.0956**	0.0262	0.0571	0.136***	0.0575	0.102
	(0.043)	(0.140)	(0.244)	(0.043)	(0.094)	(0.175)	(0.033)	(0.043)	(0.072)
Female age	0.0164	-0.00494	0.00673	-0.00786	-0.0655	-0.116	0.0100	-0.0307	-0.0463
	(0.036)	(0.124)	(0.207)	(0.039)	(0.082)	(0.149)	(0.028)	(0.037)	(0.063)
Female age squared / 100	-0.0160	0.00348	0.0000716	0.00237	0.0830	0.147	-0.0162	0.0219	0.0311
	(0.045)	(0.141)	(0.250)	(0.048)	(0.100)	(0.184)	(0.036)	(0.045)	(0.076)
Hours worked (male)	0.000759	-0.00460*	-0.00862*	0.00550**	0.00277	0.00509	0.00332*	-0.000595	-0.000940
	(0.003)	(0.003)	(0.005)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)
Hours worked (female)	-0.00490*	-0.000114	-0.000358	-0.00959***	-0.00455*	-0.00828*	-0.00695***	-0.00253	-0.00402
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.002)	(0.002)	(0.003)
Monthly household income ('000s)	0.0550**	0.0114	0.0202	0.0231	-0.0134	-0.0238	0.0332***	0.00455	0.00646
	(0.023)	(0.012)	(0.023)	(0.015)	(0.015)	(0.026)	(0.012)	(0.008)	(0.014)
Number of children in household	-0.102***	0.0357	0.0541	-0.0949***	-0.0280	-0.0533	-0.103***	-0.0118	-0.0334
	(0.037)	(0.063)	(0.106)	(0.035)	(0.041)	(0.071)	(0.027)	(0.024)	(0.040)
Male saves regularly	0.153***	0.0773*	0.138*	0.194***	0.0271	0.0484	0.189***	0.0463*	0.0824*
	(0.057)	(0.047)	(0.079)	(0.053)	(0.039)	(0.071)	(0.040)	(0.027)	(0.045)
Female saves regularly	0.235***	0.0859*	0.143*	0.245***	0.0842**	0.151**	0.235***	0.0885***	0.148***
	(0.058)	(0.047)	(0.082)	(0.053)	(0.038)	(0.069)	(0.041)	(0.027)	(0.045)
Male has university degree	0.0768	0.339	0.588	0.0911	0.302*	0.592**	0.0597	0.119	0.236
	(0.099)	(0.315)	(0.516)	(0.089)	(0.170)	(0.296)	(0.075)	(0.135)	(0.241)
Female has university degree	-0.0928	0.466	0.756	0.0577	-0.234	-0.490	0.0206	0.00503	0.0219
	(0.104)	(0.416)	(0.644)	(0.082)	(0.207)	(0.388)	(0.072)	(0.129)	(0.223)
Observations	6602	6602	6602	9137	9137	9137	17434	17434	17434

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.9: Male and Female Satisfaction with Life Overall, 1996-2000: At least one member in employment

	Male Satsifaction with Life Overall						Female Satsifaction with Life Overall					
	(1) Pooled OL	(2) Pooled OL	(3) Lin. FE	(4) Lin. FE	(5) BUC	(6) BUC	(7) Pooled OL	(8) Pooled OL	(9) Lin. FE	(10) Lin. FE	(11) BUC	(12) BUC
Male commuting time (hours)	-0.130*	-0.129*	0.0161	0.0174	0.0454	0.0471	0.00255		0.0122		0.0257	
	(0.070)	(0.071)	(0.036)	(0.035)	(0.117)	(0.117)	(0.060)		(0.039)		(0.095)	
Female commuting time (hours)	-0.00206		0.0319		0.0873		-0.114	-0.111	-0.0869	-0.0876	-0.214	-0.219
	(0.106)		(0.052)		(0.168)		(0.094)	(0.094)	(0.057)	(0.057)	(0.157)	(0.156)
Male age	-0.110***	-0.105***	-0.0887**	-0.0696***	-0.255*	-0.192**	-0.0654***		-0.0707		-0.143	
	(0.029)	(0.019)	(0.045)	(0.024)	(0.141)	(0.078)	(0.021)		(0.049)		(0.165)	
Male age squared / 100	0.130***	0.129***	0.0657	0.0456*	0.173	0.118	0.0777***		0.0624		0.0507	
	(0.034)	(0.022)	(0.055)	(0.027)	(0.175)	(0.090)	(0.023)		(0.061)		(0.182)	
Female age	0.00436		0.0220		0.0664		-0.0837***	-0.131***	0.00728	-0.0486*	-0.0143	-0.146*
	(0.029)		(0.043)		(0.136)		(0.025)	(0.019)	(0.047)	(0.025)	(0.164)	(0.076)
Female age squared / 100	-0.00152		-0.0248		-0.0637		0.101***	0.160***	-0.0298	0.0194	0.0288	0.0719
	(0.036)		(0.057)		(0.180)		(0.031)	(0.024)	(0.062)	(0.030)	(0.191)	(0.093)
Hours worked (male)	0.00298*	0.00309*	0.0000665	0.000111	0.000218	0.000374	0.00260		0.000921		0.00301	
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)		(0.001)		(0.003)	
Hours worked (female)	-0.00122		-0.000295		-0.00103		-0.000321	-0.00100	0.00249**	0.00245**	0.00517	0.00499
	(0.002)		(0.001)		(0.003)		(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)
Monthly household income ('000s)	0.0413***	0.0423***	0.00398	0.00456	0.00974	0.0108	0.0511***	0.0569***	0.00601	0.00668	0.0179	0.0217
	(0.014)	(0.014)	(0.007)	(0.007)	(0.020)	(0.019)	(0.018)	(0.017)	(0.008)	(0.007)	(0.018)	(0.018)
Number of children in household	-0.0763**	-0.0765***	0.0250	0.0247	0.0662	0.0634	-0.0284	-0.0408	-0.00299	-0.00380	-0.0475	-0.0528
	(0.030)	(0.028)	(0.026)	(0.025)	(0.080)	(0.078)	(0.029)	(0.029)	(0.029)	(0.029)	(0.081)	(0.081)
Male saves regularly	0.286***	0.313***	0.116***	0.121***	0.331***	0.348***	0.161***		0.0326		0.0642	
	(0.046)	(0.045)	(0.023)	(0.023)	(0.065)	(0.065)	(0.046)		(0.025)		(0.066)	
Female saves regularly	0.0966**		0.0428*		0.127**		0.244***	0.287***	0.101***	0.107***	0.265***	0.274***
	(0.046)		(0.022)		(0.064)		(0.046)	(0.045)	(0.025)	(0.024)	(0.067)	(0.066)
Male has university degree	-0.0380	-0.0250	0.140	0.142	0.431	0.433	0.00196		-0.0620		-0.0744	
	(0.079)	(0.071)	(0.156)	(0.156)	(0.418)	(0.429)	(0.077)		(0.171)		(0.390)	
Female has university degree	0.0310		-0.0347		-0.125		-0.0832	-0.0815	0.0481	0.0465	-0.197	-0.203
	(0.084)		(0.139)		(0.451)		(0.082)	(0.076)	(0.152)	(0.152)	(0.405)	(0.405)
Observations	11062	11062	11062	11062	11062	11062	11062	11062	11062	11062	11062	11062

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.10: Male and Female Satisfaction with Life Overall, 2002-2008: At least one member in employment

	Male Satsifaction with Life Overall						Female Satsifaction with Life Overall					
	(1) Pooled OL	(2) Pooled OL	(3) Lin. FE	(4) Lin. FE	(5) BUC	(6) BUC	(7) Pooled OL	(8) Pooled OL	(9) Lin. FE	(10) Lin. FE	(11) BUC	(12) BUC
Male commuting time (hours)	-0.112**	-0.116**	0.0367	0.0373	0.100	0.102	-0.0241		-0.0408		-0.115	
	(0.051)	(0.051)	(0.024)	(0.024)	(0.074)	(0.075)	(0.054)		(0.026)		(0.073)	
Female commuting time (hours)	-0.0245		0.0330		0.0997		-0.140**	-0.135*	-0.00516	-0.00805	0.0242	0.0134
	(0.071)		(0.032)		(0.091)		(0.071)	(0.071)	(0.035)	(0.035)	(0.099)	(0.098)
Male age	-0.114***	-0.125***	-0.0373	-0.0565***	-0.105	-0.158***	-0.0285		-0.0199		-0.148*	
	(0.023)	(0.014)	(0.026)	(0.013)	(0.092)	(0.045)	(0.024)		(0.028)		(0.077)	
Male age squared / 100	0.141***	0.147***	0.0402	0.0496***	0.109	0.137***	0.0279		0.00736		0.114	
	(0.025)	(0.016)	(0.029)	(0.014)	(0.101)	(0.050)	(0.027)		(0.032)		(0.087)	
Female age	-0.0146		-0.0206		-0.0575		-0.0956***	-0.117***	-0.0358	-0.0513***	-0.0109	-0.137***
	(0.023)		(0.025)		(0.088)		(0.025)	(0.016)	(0.027)	(0.014)	(0.079)	(0.044)
Female age squared / 100	0.0109		0.0107		0.0323		0.115***	0.136***	0.0340	0.0367**	-0.00270	0.0880*
	(0.026)		(0.030)		(0.101)		(0.029)	(0.019)	(0.032)	(0.016)	(0.094)	(0.051)
Hours worked (male)	0.00194	0.00152	0.00254***	0.00255***	0.00678***	0.00677***	-0.0000977		0.00219***		0.00645***	
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)		(0.001)		(0.002)	
Hours worked (female)	0.00215		-0.000806		-0.00248		0.00122	0.000907	0.000731	0.000750	0.00197	0.00193
	(0.002)		(0.001)		(0.003)		(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Monthly household income ('000s)	0.0493***	0.0552***	0.0102*	0.00972*	0.0291*	0.0278*	0.0348***	0.0407***	-0.000419	0.00174	-0.00250	0.00588
	(0.012)	(0.011)	(0.005)	(0.005)	(0.016)	(0.016)	(0.011)	(0.011)	(0.006)	(0.006)	(0.017)	(0.017)
Number of children in household	-0.0146	-0.0296	0.0144	0.0152	0.0362	0.0374	0.0386	0.0343	0.0178	0.0190	0.0584	0.0575
	(0.026)	(0.023)	(0.016)	(0.016)	(0.050)	(0.049)	(0.028)	(0.028)	(0.017)	(0.017)	(0.050)	(0.049)
Male saves regularly	0.218***	0.245***	0.00632	0.00624	0.0162	0.0164	0.188***		0.0351*		0.0945*	
	(0.040)	(0.039)	(0.017)	(0.016)	(0.051)	(0.050)	(0.040)		(0.018)		(0.051)	
Female saves regularly	0.106***		0.00202		0.00665		0.197***	0.247***	0.0573***	0.0638***	0.165***	0.182***
	(0.040)		(0.017)		(0.050)		(0.041)	(0.040)	(0.018)	(0.018)	(0.051)	(0.050)
Male has university degree	0.0126	0.0226	-0.0448	-0.0493	-0.213	-0.219	0.0461		0.191		0.594*	
	(0.068)	(0.063)	(0.130)	(0.130)	(0.362)	(0.362)	(0.066)		(0.139)		(0.330)	
Female has university degree	0.0459		0.0559		0.172		0.0915	0.117**	-0.205**	-0.219**	-0.193	-0.199
	(0.066)		(0.086)		(0.278)		(0.063)	(0.059)	(0.092)	(0.091)	(0.353)	(0.345)
Observations	18101	18101	18101	18101	18101	18101	18101	18101	18101	18101	18101	18101

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.11: Male and Female Satisfaction with Life Overall, 1996-2000: Both members in employmentt

	Male Satsifaction with Life Overall						Female Satsifaction with Life Overall					
	(1) Pooled OL	(2) Pooled OL	(3) Lin. FE	(4) Lin. FE	(5) BUC	(6) BUC	(7) Pooled OL	(8) Pooled OL	(9) Lin. FE	(10) Lin. FE	(11) BUC	(12) BUC
Male commuting time (hours)	-0.156*	-0.152*	0.0100	0.00682	0.0138	0.00953	0.0715		0.0366		0.0989	
	(0.083)	(0.084)	(0.042)	(0.042)	(0.135)	(0.134)	(0.073)		(0.046)		(0.134)	
Female commuting time (hours)	-0.0291		-0.0517		-0.167		-0.262**	-0.235**	-0.158**	-0.157**	-0.428**	-0.418**
	(0.130)		(0.064)		(0.209)		(0.106)	(0.105)	(0.069)	(0.069)	(0.190)	(0.189)
Male age	-0.175***	-0.121***	-0.0771	-0.0727**	-0.229	-0.197	-0.0774**		-0.0208		-0.234	
	(0.037)	(0.025)	(0.064)	(0.034)	(0.215)	(0.120)	(0.034)		(0.069)		(0.213)	
Male age squared / 100	0.209***	0.150***	0.0541	0.0541	0.135	0.133	0.0817**		-0.0156		0.0838	
	(0.045)	(0.030)	(0.079)	(0.041)	(0.268)	(0.147)	(0.041)		(0.085)		(0.257)	
Female age	0.0740**		0.00367		0.0279		-0.0510	-0.108***	-0.00861	-0.0246	0.156	-0.0571
	(0.038)		(0.060)		(0.200)		(0.036)	(0.026)	(0.065)	(0.035)	(0.212)	(0.105)
Female age squared / 100	-0.0871*		0.000498		0.00208		0.0639	0.125***	0.00299	-0.0163	-0.134	-0.0623
	(0.048)		(0.080)		(0.261)		(0.045)	(0.034)	(0.086)	(0.044)	(0.269)	(0.134)
Hours worked (male)	-0.00210	-0.00224	-0.00246	-0.00246	-0.00783	-0.00789	0.00255		-0.00214		-0.00583	
	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)		(0.002)		(0.005)	
Hours worked (female)	-0.00244		-0.000547		-0.00146		-0.00612**	-0.00618**	0.000433	0.000281	0.000906	0.000902
	(0.003)		(0.002)		(0.006)		(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)
Monthly household income ('000s)	0.0339**	0.0350**	0.00971	0.00950	0.0233	0.0230	0.0514**	0.0551**	0.00165	0.000972	0.00473	0.00145
	(0.014)	(0.015)	(0.008)	(0.008)	(0.023)	(0.023)	(0.024)	(0.023)	(0.009)	(0.009)	(0.021)	(0.021)
Number of children in household	-0.0884**	-0.0678*	0.0710**	0.0741**	0.219*	0.229**	-0.0841**	-0.0919**	-0.0354	-0.0329	-0.0914	-0.0943
	(0.040)	(0.036)	(0.035)	(0.034)	(0.115)	(0.113)	(0.036)	(0.036)	(0.037)	(0.037)	(0.111)	(0.110)
Male saves regularly	0.203***	0.228***	0.0905***	0.0907***	0.266***	0.265***	0.0369		-0.0132		-0.0466	
	(0.057)	(0.056)	(0.029)	(0.029)	(0.085)	(0.084)	(0.059)		(0.032)		(0.091)	
Female saves regularly	0.0849		0.00124		0.00449		0.297***	0.303***	0.0846***	0.0816***	0.208**	0.199**
	(0.058)		(0.029)		(0.088)		(0.059)	(0.058)	(0.031)	(0.031)	(0.091)	(0.089)
Male has university degree	0.0210	0.0237	0.200	0.199	0.579	0.559	0.0617		0.139		0.388	
	(0.098)	(0.088)	(0.197)	(0.197)	(0.574)	(0.566)	(0.091)		(0.212)		(0.579)	
Female has university degree	0.0204		0.146		0.470		-0.162	-0.136	0.320	0.307	0.306	0.285
	(0.106)		(0.226)		(0.752)		(0.102)	(0.097)	(0.244)	(0.243)	(0.784)	(0.777)
Observations	6602	6602	6602	6602	6602	6602	6602	6602	6602	6602	6602	6602

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5.12: Male and Female Satisfaction with Life Overall, 2002-2008: Both members in employment

	Male Satsifaction with Life Overall						Female Satsifaction with Life Overall					
	(1) Pooled OL	(2) Pooled OL	(3) Lin. FE	(4) Lin. FE	(5) BUC	(6) BUC	(7) Pooled OL	(8) Pooled OL	(9) Lin. FE	(10) Lin. FE	(11) BUC	(12) BUC
Male commuting time (hours)	-0.174***	-0.171***	0.0388	0.0409	0.125	0.130	-0.0422		-0.0779**		-0.191**	
	(0.062)	(0.061)	(0.030)	(0.030)	(0.097)	(0.097)	(0.061)		(0.033)		(0.096)	
Female commuting time (hours)	0.00865		0.0462		0.135		-0.176**	-0.177**	0.00386	-0.000848	0.0322	0.0252
	(0.081)		(0.038)		(0.105)		(0.087)	(0.086)	(0.041)	(0.041)	(0.123)	(0.123)
Male age	-0.148***	-0.126***	-0.0340	-0.0446**	-0.106	-0.135**	-0.0242		-0.0292		-0.234**	
	(0.036)	(0.023)	(0.037)	(0.019)	(0.121)	(0.065)	(0.035)		(0.040)		(0.097)	
Male age squared / 100	0.184***	0.149***	0.0284	0.0405*	0.0904	0.122*	0.0202		0.0149		0.203	
	(0.041)	(0.027)	(0.043)	(0.021)	(0.142)	(0.074)	(0.042)		(0.047)		(0.130)	
Female age	0.0342		-0.0122		-0.0334		-0.0303	-0.0461**	-0.0235	-0.0469**	0.0601	-0.132**
	(0.037)		(0.035)		(0.117)		(0.037)	(0.023)	(0.039)	(0.020)	(0.102)	(0.066)
Female age squared / 100	-0.0527		0.0140		0.0373		0.0319	0.0429	0.0289	0.0394*	-0.0619	0.101
	(0.046)		(0.043)		(0.145)		(0.046)	(0.027)	(0.047)	(0.023)	(0.140)	(0.079)
Hours worked (male)	0.00182	0.00149	0.0000762	0.00000847	0.000261	0.0000568	0.00661***		0.00213		0.00752*	
	(0.003)	(0.003)	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)		(0.001)		(0.004)	
Hours worked (female)	-0.00109		-0.00125		-0.00389		-0.0115***	-0.0117***	-0.00167	-0.00153	-0.00426	-0.00393
	(0.003)		(0.001)		(0.004)		(0.003)	(0.003)	(0.001)	(0.001)	(0.004)	(0.004)
Monthly household income ('000s)	0.0246	0.0285*	0.00520	0.00410	0.0133	0.0104	0.0132	0.0200	-0.0153*	-0.0162*	-0.0404	-0.0396
	(0.017)	(0.016)	(0.008)	(0.008)	(0.028)	(0.027)	(0.015)	(0.015)	(0.009)	(0.009)	(0.026)	(0.026)
Number of children in household	-0.0801**	-0.0692**	-0.00221	0.000779	-0.00711	0.00128	-0.0860**	-0.0912***	-0.0147	-0.0125	-0.0206	-0.0248
	(0.034)	(0.031)	(0.021)	(0.021)	(0.071)	(0.070)	(0.034)	(0.034)	(0.023)	(0.023)	(0.068)	(0.068)
Male saves regularly	0.182***	0.206***	-0.00346	-0.00615	-0.0105	-0.0182	0.173***		0.0382*		0.110	
	(0.051)	(0.050)	(0.021)	(0.021)	(0.069)	(0.068)	(0.049)		(0.023)		(0.068)	
Female saves regularly	0.0914*		-0.0194		-0.0656		0.289***	0.334***	0.0904***	0.0973***	0.261***	0.279***
	(0.051)		(0.022)		(0.067)		(0.051)	(0.049)	(0.024)	(0.023)	(0.070)	(0.069)
Male has university degree	0.0405	0.0618	0.0292	0.0236	0.0636	0.0654	0.0497		0.170		0.581*	
	(0.086)	(0.080)	(0.164)	(0.163)	(0.517)	(0.524)	(0.082)		(0.179)		(0.315)	
Female has university degree	0.0422		0.00348		0.00391		0.0789	0.0866	-0.193	-0.221*	-0.182	-0.229
	(0.084)		(0.111)		(0.367)		(0.076)	(0.072)	(0.122)	(0.119)	(0.492)	(0.477)
Observations	10832	10832	10832	10832	10832	10832	10832	10832	10832	10832	10832	10832

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 6

Conclusions

This thesis has studied the impact that commuting behaviour specifically, and travel more generally, has on a number of outcome measures in the UK. As previously documented, commuting is an important and increasing use of time for an employed individual in the UK, with the average employee commuting for 56 minutes per day according to the Department of Transport (DfT), National Travel Survey (NTS), 2013. Hence the effect(s) that commuting have on an individual is a key area for economic analysis. We add to this literature by considering a possible benefit of longer commutes (higher wages), a possible negative aspect of commuting (increased social exclusion and a reduction is social capital) and then go on to examine the net effect by considering subjective well-being (SWB) as a proxy for overall individual utility.

In the first empirical chapter, chapter 2, we show that there is a relationship between commuting distances and wages when we consider data obtained from the Annual Survey of Hours and Earnings (ASHE). To account for the endogeneity in the wage-commuting relationship we focus our analysis on a subset of individuals who experience an exogenous shock to their commuting distance. This shock was brought about by a workplace relocation. We stipulate that an individual must keep the same job and the same household location, such that the change in commuting distance following the workplace relocation can be viewed as exogenous to the employee (Mulalic et al., 2010, 2013).

By employing linear fixed effects (FE) regressions to data that meet the above criteria, we show that there exists a positive and statistically significant relationship between commuting distance and income. By employing a double logarithmic specification, we show that a 1% increase in commuting distance is compensated by a 0.006% increase in annual gross pay. When we evaluate these figures at their respective sample means, we find that a 50% increase in commuting distance (equivalent to a 15km increase) is compensated by, on average, a £7,558 increase in annual pay. When we look at basic weekly pay the corresponding figure is an increase in weekly pay of around £184 per week. These are both sizable sums of money. Our results are robust to considering different sectors of employment, although the public and private sectors do better than government and local authority workers (when the latter two are excluded from the public sector). Non-managerial staff benefit from greater percentage increases in pay after changes to commuting, when compared to those employed in managerial roles. We find evidence to suggest that even employees who benefit from a reduction in commuting distance also benefit from an increase in their pay, although this is a a smaller increase in pay than those employees whose commute increases.

Chapter 2 is potentially limited in a number of ways. Firstly the ASHE does not contain a great deal of socio-economic information. Ideally we would have preferred more detail here, but this may not be too big of a limitation due to the fact we employ fixed effects techniques and so control for any time-invariant socio-demographic factors. A second potential drawback is that our commuting distance variable is an approximation based upon Euclidean geometry. Ideally we would have liked to have more precise commuting information. However there is a literature in the urban economics field that shows that the relationship between true distance (T) and the Euclidean approximation (E) is roughly $T = 1.2E$ (Newell, 1980, Ballou et al., 2002).

The second empirical chapter, chapter 3, takes a step back from commuting *per se*, and considers travel behaviour in a wider sense. In this chapter we analyse unique data (which, to our knowledge, has not been used in an econometric context before) to examine the impact that congestion charging has on social capital. This *ex post* study is quite unique to our knowledge, as the majority of the existing work on the relationship between congestion charging and social capital had been *ex ante* predictions (e.g. Rajé, 2003, Bonsall and Kelly, 2005).

By focusing on the western extension zone (WEZ) of the London Congestion Charging (LCC) zone, we are able to analyse the frequency of visits to friends and family both before and during the WEZ. Following Putnam (2000), we use these visits as a proxy for social capital. By employing difference-in-difference (D-i-D) techniques we explore what impact the congestion charging policy had on the frequency of these visits, and hence on social capital. We find evidence to suggest that social capital stocks fell as a result of this policy, as people made significantly fewer visits after the introduction of the WEZ.

The main limitation to chapter 3 is the absence of a 'true control group'. We have information on three types of trip ((i) those made by WEZ residents to other WEZ residents; (ii) those made by WEZ residents to non-WEZ residents; and (iii) those made by non-WEZ residents to WEZ residents). The true control group would be trips made by non-WEZ residents to other non-WEZ residents, as these trips are not affected the WEZ policy in any way. However, as this information is not available, we use a less econometrically robust version of D-i-D and set (iii) as the control group. While our empirical results suffer from this omission, they are still insightful in that we find evidence to suggest that congestion charging policies reduce social capital, and hence increase social exclusion.

Chapter 4 contributes to an emerging strand of literature that examines the role that commuting has on subjective well-being. In previous work, Stutzer and Frey (2008) document evidence of a so called 'commuting paradox' in which workers are not suitably compensated for their longer commutes. Using German data the authors find that there is a negative relationship between commuting and well-being, which should not exist if individuals were fully compensated for partaking in longer commutes. Similarly, when considering British data, Roberts et al. (2011) find evidence of a negative relationship between commuting and well-being. By examining the role that gender plays in this relationship, they find that women are negatively affected by longer commutes, but that men are not.

Our main body of analysis is concerned with overall life satisfaction (consistent with Stutzer and Frey, 2008), but we also examine the General Health Questionnaire (GHQ) score as an alternative proxy for well-being (as used by Roberts et al., 2011). As both outcome measures are strictly speaking ordinal, we employ fixed effects ordered logit (FE OL) models which allow us to control for time-invariant personal characteristics (such as personality and strength of preferences etc.). However, our results appear to be consistent with Ferrer-i-Carbonell and Frijters (2004) in that we find very little difference between assuming ordinality (and hence using FE OL models) or cardinality (and hence employing fixed effect linear models).

When considering life satisfaction, we can find no evidence of a relationship between commuting and SWB for either gender in any period of data we consider. This is robust to controlling for occupation, part-time status, and exogenous shocks to commuting. We do find a relationship between commuting and life satisfaction if we consider individuals who move home and/or job, with movers reporting higher SWB scores. We note, however, that this is likely to be endogenous as household and job relocation decisions are influenced, at least in part, by commuting behaviour.

In contrast, we can replicate the results of Roberts et al. (2011) when we look at the GHQ score as a proxy for SWB in that we show there exists a negative relationship for women, but that men are unaffected by longer commutes. From this we conclude that the choice of which proxy of SWB is important in the commuting-SWB relationship.

The final empirical chapter, chapter 5, examines commuting behaviour in a household bargaining model framework. We consider three outcome measures, (i) aggregated couple life satisfaction; (ii) the satisfaction of the male partner; and (iii) the satisfaction of the female partner, and examine the impact that both partner's commuting times have on the three outcomes. For completeness we focus on the case where only at least one member of the couple must be in paid employment and the case where both members of the couple are employed. The results for both cases are remarkably similar.

We find evidence to suggest that household bargaining, with respect to commuting behaviour, is efficient. Neither partner is affected either by own or by spousal commuting times in the majority of cases we examine.

In chapters 4 and 5 we support the findings of Ferrer-i-Carbonell and Frijters (2004) in that the choice of assuming ordinality or cardinality appears insignificant. We do advise caution however, and recommend that researchers employ both methodologies in future work. We propose that the 'life-satisfaction' approach developed by Simon Luechinger and colleagues (Luechinger, 2009, Luechinger and Raschky, 2009, Frey et al., 2009) be applied to the coefficients from the FE-OL models, to allow sensible interpretation of these coefficients.

The empirical studies documented in this thesis have explored the relationship between commuting, or travel behaviour more generally, against a number of outcome measures. We have shown that there are monetary benefits in the form of higher wages from longer commutes, but that commuting may lead to an increase in social exclusion. When considering commuting against well-being we, on the whole, find an insignificant relationship. This statistical insignificance would tend to suggest that the positives (higher salary, better housing, etc.) are suitable compensation for the negatives (high opportunity cost, social exclusion, etc.), such that the net effect on SWB (which may be viewed as a proxy for utility) is insignificant.

The results presented here seem inconsistent with a comment made by Alois Stutzer in an interview for the New Yorker newspaper (The New Yorker, 2007), in which he states that, based on his paper with Bruno Frey[1], individuals seem to put more emphasis on the perceived benefits of commuting than the possible negative consequences. He argues that people tend to overvalue benefits (higher wages, better housing etc.) and undervalue the consequences (sleep, leisure time, etc.). This result holds true if there is a negative impact of commuting on well-being, as in Stutzer and Frey (2008), but disappears if there is no statistical relationship between commuting and SWB. From this it may be possible to deduce there exist certain differences between commuters in the UK (our analysis) and commuters in Germany (Stutzer and Frey, 2008), such that commuters in the UK are more able to accurately weigh up all positive and negative implications associated with a longer commute when compared with German commuters. This argument is at best speculative, but it does present a possible reason why there appears to be differences between German and UK commuters, when considering the commuting/well-being relationship.

The UK government have recently planned to go ahead with the planned HS2 rail infrastructure. The intense media debate surrounding this decision illustrates that travel related policies can be controversial, as they have a direct impact on people's everyday life. Hopefully this thesis has added to the body of literature that documents the possible effects that commuting can have on an individual.

[1] Stutzer and Frey (2008), although it was the working paper version that was referred to in the interview.

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