Using the Academic Timetable to Influence Student Trip-Making Behaviour

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Abstract

The university academic timetable is the framework which defines the rhythm of the term-time student activities that occur on campus.

This thesis explores how the design of the academic timetable affects student trip-making behaviour to and from campus and is motivated by concerns around the environmental, social and economic sustainability of the campus-based university.

The thesis investigates the current understanding of student trip-making behaviour and shows that whilst it is informally generally accepted that students may plan their trips to campus around the demands placed on their time by the academic timetable, this appointment based approach is not generally recognised in student trip models.

The thesis demonstrates that it is the timetable which is the main driver of student travel demand, that changes to the timetable can influence trip-making behaviour, and that a policy of timetable compression, combined with a greater use of online resources could be employed to reduce student trips to/from campus and student presence on it, thereby making the university more environmentally sustainable.

However, students with compressed timetables appear to be less engaged with their studies, and exhibit a greater degree of variation in terms of their attainment level compared with students whose timetables force them to be on campus on an almost full-time basis.

Students appear to prefer timetables that limit the time they need to spend on campus, and the thesis suggests that addressing this mismatch between what students currently appear to want, and what seems to offer them the best potential academic outcome represents a major future challenge to the long term academic sustainability of the campus based university.

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Chapter 1 – Introduction

1.1 Introduction

The first chapter of this thesis contains an introduction to the subject that it is to be examined, namely the relationship between the academic timetable and student trip-making behaviour and consequences of this link.

The chapter begins with an outline of some of the themes discussed within the thesis, and this is followed by a rationale of the motivation for the study.

The aims and objectives of the study are identified, followed by the research questions to be answered and the hypotheses to be tested.

The chapter concludes with an outline of the structure of the rest of the thesis.

1.1.1 Students and the Academic Timetable

The experience of a student enrolled at Cambridge University in the early seventeenth century might seem, at first glance, to have little in common with that of the contemporary student. Their backgrounds, life experiences, and aspirations will be vastly different. However, there is one factor which unites them across the centuries, even if the contemporary student may own more portable electronic devices. For both the modern student and their scholarly ancestor, it is the academic timetable which regulates and schedules their learning experience.

The origins of the timetable can be traced back to the development of the lecture as the main pedagogical approach used to support the transfer of knowledge. In the early seventeenth-century, lectures at Cambridge University were to run:

> *“fower* [four] *days every week at the least in Term time, and two hours every day viz: from six to eight in the morning”*

while knowledge acquired by the students from the lectures was to be tested through a series of disputations (debates) which required them to:

> “*come to the Schools on every Monday, Tuesday, Wednesday, Thursday & Friday, at one of the Clock until 5*”

but simultaneously allowing for:

> “*every day at 3 of the clock all the Bachelors & Sophistors* [students] *… may goe out till 4, & refresh & recreate themselves*”

(Costello, 1958, p. 13-15).

From this account it would appear that the academic timetable, early starts and the need for breaks were as an integral a part of student life then as they are now.

The university academic timetable is in reality a simple planning tool, a chart of times, scheduling the meeting of groups of like-minded students and academics at arbitrary places and times to facilitate the transfer of knowledge and information around a topic of interest to them all. And it is the university timetable, or more precisely the impact that this timetable has on the trip-making behaviour of the students whose day-to-day lives it affects that is the subject of this thesis.

The thesis will aim to demonstrate that the relationship between a student's trip-making behaviour and their timetable is one about which many assumptions are made, whilst simultaneously being one that is not well understood in a formal sense.

1.1.2 Two Views of the Academic Timetable

Consider two possible alternative interpretations of what the academic timetable might represent to the student.

In the first interpretation the timetable is simply a guide, advising the student of WHERE they should be on campus at different times during the day. In the discussion that follows, this interpretation will be called traditional view of the timetable. However, an alternative interpretation is that rather than advising the student of where they should be on campus, it is instead advising them of WHEN they should be present on campus. This interpretation fundamentally changes the role the timetable plays in the student's day-to-day life, and will be labelled as being a contemporary view of the timetable and how it is used.

Under the traditional interpretation student trips to and from campus can be assumed to be conducted largely independently of the timetable, with students making a regular inbound trip in the morning before the start of their first session[1], and a return trip in the evening once all the activities for the day have been completed. However, the contemporary interpretation of the academic timetable suggests a very different type of trip-making behaviour. In this case the timetable represents a series of appointments at which attendance is required and the student will schedule their inbound and outbound trips around keeping these appointments. Under this interpretation the timing and frequency of student trips is determined to some extent by the timetable, meaning that trips may no longer be taken at the

[1] Within the thesis the generic term session will be used to describe any type of timetabled activity

same time each day, that on some days no trips might be taken, whilst on others multiple return trips may occur.

Although the traditional and contemporary views of the timetable imply very different trip-making behaviours, assumptions are often made about the actual behaviour of students. Ortuzar implies a traditional view of the timetable when he suggests that student trips are equivalent to mandatory work-based commuting (Ortuzar and Willumsen, 2011, p. 141), whilst many observers of on-campus student behaviour would argue that student attendance is partially discretionary and implies a contemporary view of the timetable.

This leads to the first research question (RQ):

RQ1 Do students hold a traditional or a contemporary view of their timetable?

1.1.3 The Campus and Urban Trip-Making

At the start of the 2012/13 academic year there were over 2.3 million students (1.8 million undergraduate) in higher education within the UK enrolled for courses at 163 British institutions (HESA, 2014). These students were taught by a community of over 181,000 academic staff and supported by approximately 197,000 non academic staff (HESA, 2014, staff figures for 2011/12). At the same time the UK resident population approached 63.7 million by mid-2012 (Office For National Statistics, 2013).

If the contemporary view of the timetable is at least partially correct then the term-time trip-making behaviours of over 3% of the total adult population of the UK will have been influenced by 163 institution specific academic timetables.

Whilst this number is small relative to the 30.9 million (48%) who were in employment in mid 2013 (Office For National Statistics, 2013, Labour Market Survey) and for whom the commute to work is a regular part of their daily lives, the high density of students in some urban areas suggests that the effect of student trips on the local network will be significant.

In Leeds undergraduate students make up about 10% of the total population of the city (City Populations, 2008), and whilst this not as high as elsewhere (Cambridge: 25%, Loughborough: 20%, Oxford: 18%. Delft-Holland: 14%, Heidelberg-Germany: 18%) it is typical of other university cities (Manchester: 11%, Southampton: 11%, Lincoln: 11%, Sheffield: 9%, Utrecht-Holland: 9%, Zurich-Switzerland: 10%).

Traffic congestion during peak periods is a major problem for many urban areas (Downs, 2004, p. 1, Banister, 2005, p. 15) whilst the scale of many university campus located within these areas means they are major generators of employee workplace commuting and student education trips (Tolley, 1996, p. 213), loading this demand onto the already congested urban network (Toor and Havlick, 2004, p. 3). Many student trips use active modes of travel (walking and cycling) and during peak times they may be exposed to elevated emissions levels and road safety risks.

If the contemporary view of the timetable is correct then the student calendar is made up of two types of days: those which contain at least one timetabled session, timetabled days (TTD) and those which don't, non-timetabled days (NTD), and that the link between timetable and trip-making provides an opportunity to influence both the frequency and timing of student trips relative to normal urban peak periods.

RQ2 Are students less likely to come to campus on non-timetabled days?

1.1.4 Students and Timetable Quality

The construction of a timetable can be described as "the allocation, subject to constraints, of given resources to objects being placed in space-time in such a way as to satisfy as nearly as possible a set of desired objectives" (Wren, 1995).

In the context of the university academic timetable 'resources' are usually taken to mean: a session, a room, a member of staff and a group of students, whilst constraints refer to the innate inability of any of these resources to be allocated more than once at any given point in time.

The quality of a timetable, as measured by any of the resources allocated within it will be judged in terms of how well it fits around the additional external constraints within which the resource must operate. For students these external constraints could be related to the any part-time work they undertake, household duties and caring responsibilities, or their travel time to/from campus.

RQ3 What constitutes a high quality timetable from a student point of view?

If students coordinate their trips making around the timetable, then the layout of the sessions within it may effect their trip-making in other ways. Extended breaks between sessions may encourage the students to leave campus and return home to wait for their next session, leave-and-return behaviour. Fewer sessions on any given day may discourage students from making a trip to campus at all. Under the contemporary view, student trip-making and the design of the timetable will interact, and the attributes of the timetable will partially describe the type of interaction that occurs.

RQ4 Do students exhibit leave-and-return behaviour?

1.1.5 Understanding Student Trip-Making Through Travel Plans

Travel plans aim to combat an over-dependency on cars through promotion of all possible alternatives to single occupancy vehicle (SOV) use (Department for Transport, 2008, p. 6).

Travel plans represent a delivery mechanism for a series of strategic measures for influencing travel behaviour towards more sustainable options (Enoch, 2012, p. 33), whilst workplace travel plans aim to manage the travel associated with commuting trips to and from an organisation's workplace (Department for Transport, 2008).

The adoption of a travel plan is a mandatory condition for any organisation seeking planning permission, this is currently the major source of UK travel plans (Enoch, 2012, p. 38), and many universities have adopted a travel plan for this reason (The University of Warwick, 2007, The University of Brighton, 2009, The University of Newcastle, 2009).

The development of a travel plan requires data to be gathered on existing trip-making behaviour through site audits and surveys (Department for Transport, 2008, Section 4), and within the university sector the movements of students, as well as staff, should be taken into account (Forum for the Future, 2003, p. 35).

Travel plans both capture existing trip-making behaviour through surveys, and define measures for mitigating or influencing these behaviours. Therefore the travel plans for campus-based universities should describe the relationship between student trip-making and their timetable, whilst at the same time providing some clues towards the degree to which either the traditional or contemporary view of the timetable is prevalent amongst students.

RQ5 How do university travel plans and their associated travel surveys represent student trip-making behaviour?

1.1.6 Timetable and Reducing the Need to Travel

The traditional and contemporary interpretations of the timetable and the trip-making behaviour they imply have parallels with workplace commuting.

Under the traditional view the student could be seen like an office-based commuter; arriving in the AM peak, departing in the PM peak, with the timetable being similar to a desk diary notifying them of when they should break off from whatever they are doing to attend a scheduled session. In the contemporary view the student can be seen like a hot-desking employee within a flexi-working/flexi-time regime, in which the sessions within the timetable represent the minimum core-hours for which attendance is required.

Student trip-making behaviour under the traditional and contemporary views can potentially be described by the metaphors of an office-based commuter and traveling salesperson. The flexible approach to work adopted by the salesperson, mixing time in the office, with working from home and other remote locations, echoes one of the main themes of the travel plan; reducing the need to travel (Department for Transport, 2008, section 13), and this has been developed more recently into a new policy area under the title 'Alternatives to Travel' (ATT) (Department for Transport, 2011). ATT incorporates home working, remote working, staggered hours, compressed hours, tele-conferencing, video-conferencing, web-conferencing (Department for Transport, 2012). A contemporary view of the timetable suggests that ATT measures can be adopted by students to provide flexibility in the way they learn, by staggering timetable start and finish times, compressing the timetable into fewer days and offering virtual alternatives to time spent on-campus. However, the use of ICT to reduce trip frequency in response to ATT may cause others changes in behaviour, perhaps increasing trip lengths (Banister, 2005, p. 171) if students respond by commuting from their parental home, rather than living closer to campus.

1.1.7 Timetable and Student Engagement

The traditional and contemporary views of the timetable present two alternative interpretations of the way a student perceives the campus and their presence on it. Students attend university to gain a qualification, attained partially through the acquisition of knowledge from staff who are already qualified in their chosen discipline. Therefore it is reasonable to assume that student-staff contact scheduled through the timetable represents the minimum hours for which student attendance on-campus might always be considered to be mandatory. The rest of the week is made up of non-contact hours in which students are expected to be engaged in self-study or group-work during (at least part of) this time.

Under the traditional view of the timetable, in which on-campus arrival and departure times are relatively fixed, all non-contact hours can also be regarded as being mandatory. However, with the contemporary view these hours on-campus can be considered to be discretionary.

If the student holds a traditional view of the timetable, in which full-time attendance on-campus is seen as the norm, the student will require some other motivation to absent themselves from campus. Alternatively if the student has a contemporary view in which only attendance for timetabled sessions is considered mandatory, then they will instead require motivation to attend for the non-contact hours, and their attendance across the week will depend upon the value they place on spending discretionary non-contact time on campus.

The non-contact hours available to the student will be inversely proportional to their timetabled contact hours and when every available hour is timetabled then the traditional and contemporary views will converge since all hours will be considered mandatory.

This demonstrates one attribute of the timetable, timetabled contact hours, that may influence trip-making behaviour and suggests that students enrolled on lower contact hours courses have a greater degree of flexibility in terms of how they interpret their timetable when compared to those on higher contact hours courses.

The term student engagement is used to describe the strength of the relationship between a student and their studies, their peers and their university. It is believed that student educational outcomes are influenced by the relationship that exists between the student and their university and that the time spent on-campus studying, socialising, working or playing sports can strengthen this bond (Astin, 1984). If students hold a contemporary view of the timetable then their experience of university may be at risk of being marginalised as a series of appointments in the daily diary (Krause, 2005). An understanding of any links between student trip-making behaviour and their timetable may be important in order to minimise any negative effects on student engagement.

RQ6 Do certain timetable designs have a negative impact on levels of student engagement and attainment?

1.1.8 The University of Leeds

The main study area for the work described within this thesis is The University of Leeds (UoL), which is a traditional campus-based university located in the city of Leeds, within the country of West Yorkshire in the United Kingdom. The oldest and largest Yorkshire university, its roots can be traced back to Leeds School of Medicine (1831) and The Yorkshire College of Science (1874), being granted its Charter to award degrees from King Edward VII in 1904 (University of Leeds, 2014). More than 32,000 students were enrolled at The University in 2011/12, with over than 8,000 of these being postgraduates; they were taught by just under 3,000 academic staff and supported by over 4,000 non-academic staff (HESA, 2014). UoL was most recently ranked as the 139th best global higher education provider (Times Higher Education World, 2013).

UoL’s operations are concentrated on their large main campus located to the north west of the city centre and a ten minute walk from it. The University provides over 1,000 student places in halls directly on campus and is building more accommodation nearby. Many students live in privately rented accommodation within the Hyde Park area around 0.5 miles from campus, whilst further accommodation is provided along the congested Otley Road (Headingley) which follows in a north westerly axis away from the city.

Within the city peak time congestion is a major issue for car and bus users alike (West Yorkshire Local Transport Plan 3, 2011, Appendix F). Whilst the absolute level of peak hour traffic has not increased for 15 years, the duration of the peak periods is increasing, with more journeys starting earlier. In the morning peak over half the road network operates at below 70% of the speed limit, and a quarter at below 50% (ibid, p. 11). The city was an early adopter of high occupancy vehicle lanes and also has invested heavily in in bus-lanes and guided bus-ways (Powell, 2001, p. 95). The city has aspirations to build a 14.8 km trolleybus system (NGT) that will link areas to the north and south of the city and provide direct access to UoL’s campus (West Yorkshire Metro, 2014).

Within UoL, 38% (4%) of staff (student) commuting trips are undertaken by car with 20% (1%) being SOV trips. The campus provides parking spaces for 1605 vehicles, allocated through a permit system, although students, with the exception of blue-badge holders, are ineligible for these (University of Leeds, 2013). On-street parking in the immediate vicinity of the campus is restricted but unrestricted on-street parking can be found 0.5 miles from campus and many non permit holding car commuters park there.

1.1.9 The Campus and Travel Survey Methods

The traditional method for gathering data about individual trip-making behaviour is through the travel diary in which respondents specify the detail of all the trips they make over the study period (Stopher and Greaves, 2007).

The use of GPS technology potentially allows for a passive data collection technique (Bricka, 2005) but at the time when the survey methodology for this study was being chosen, 2010, GPS devices were standalone and power hungry (Bonsall, 2006). The positional accuracy of GPS devices drops when the device is used inside a building or in a built up area (Jun et al., 2006) and an alternative approach for a proximity tracking system in self-contained and enclosed environments utilises wireless router connection events (Athanasiou et al., 2009). The university campus typically offers comprehensive wireless network coverage allowing staff and students access to university systems from their own mobile devices. Student access to the wireless network and other on-campus resources, like the library, is arbitrated through electronic systems that are administered by the university and linked to each student's enrolment status. Logs of student resource usage provide a secondary data source that can be exploited to expose patterns of on-campus activity and infer student trip-making behaviour.

RQ7 Can secondary data-sources be used to devise an observational method to obtain longitudinal survey data about student trip-making behaviour?

1.2 Motivation

The motivation for this study is based around concerns regarding the ongoing sustainable development of the campus-based university.

The most common definition of the term sustainable development is that given in the Bruntland Report of 1987 that:

> *"Sustainable development meets the needs of the present without compromising the ability of future generations to meet their own needs"*

(United Nations, 1987, p. 15)

This widely quoted definition has led onto the recognition that thinking around sustainability must consider three components: environmental sustainability, economic sustainability and social sustainability.

The thesis will examine the effect of the academic timetable on all three aspects of sustainability; on the institution's environmental sustainability through goals that are explicitly stated through carbon reduction targets, and on the economic and social sustainability of the institution which is implicit to the student experience.

1.2.1 Timetable and Environmental Sustainability

The Stern report, published in 2006, highlighted the global risks resulting from a failure to introduce measures to reduce greenhouse gas emissions (Stern N, 2006), In response to this report, the UK government announced legally binding targets for the delivery of emissions reductions to tackle climate change (HM Government UK Committee on Climate Change, 2008). Along with other public sector organisations The Higher Education Funding Council for England (HEFCE) commissioned research to examine the carbon emissions caused by higher education (SQW Consulting, 2009). This found that 61% of all emissions came from burning of gas and coal for heating (scope 1), from electricity generation (scope 2), whilst a further 19% were accounted for through staff and student commuting (scope 3).

A strategy for reducing emissions levels was published in 2010 (Higher Education Funding Council England, 2010) committing the sector to a 34% reduction in scope 1 and 2 emissions by 2020, with an 80% reduction by 2050, and a commitment to set targets for a reduction in scope 3 emissions by 2013. The approach and measurement methodology for reporting scope 3 emissions (Higher Education Funding Council England, 2012) identifies that emissions data for both staff and student commuting should be obtained[2]. An earlier study into institutional sustainability conducted by Roy (Roy et al., 2005) compared the 'whole-system' emissions generated to produce one student credit via one of three study modes (full-time, part-time, distance learning), two residential locations (near campus, at-home), and two delivery methods (paper-based, electronic). It found that emissions from student transport were the most significant contributor at 46%, with buildings contributing a much smaller 22%. However, Roy's results may be skewed, as his methodology assumes a perfect utilisation of teaching accommodation and hence apportions a marginal emissions level to each student. Whilst the results of these two studies are inconsistent, both of identify transport and buildings as being major contributors to total emissions levels.

The HEFCE identified six policy measures to achieve the reductions required, with two of these interventions being: behaviour change/new ways of working and building energy and space management. If student trip-making is driven by a contemporary view of the timetable changes to timetable policy could help to partially achieve these goals through a compaction of student/staff timetables into fewer days, thereby encouraging a reduction in the total number of commuting trips to the institution. At the same time, more efficient timetabling could result in the improved utilisation of teaching space, reducing the energy wasted spent heating, cooling and lighting empty rooms.

The future requirement for the creation of a sustainable university potentially moves timetabling policy to centre-stage as an enabler of institutional sustainability. To ensure that accurate predictions can be made of the effect of such policy changes it is important that the campus based university has accurate student trip models.

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[2] Only student commuting trips between their term-time address and campus are to be included in scope 3 targets, with trips from the student's home address to the institution excluded. In an era in which institutions are globally competitive the likely impact of including the emissions from many thousands of student air-miles within scope 3 emissions, and the consequent need for reduction, would represent an economic challenge to many institutions.

1.2.2 Timetable and Economic/Social Sustainability

In a broader sense the term sustainability can also be applied when considering the future of the campus based university as an organisational entity.

In this context, if the contemporary view of the timetable as being the main driver behind student presence on campus is correct, then the long term health of the campus university depends to some extent upon the development of timetable designs that encourage students to spend a greater proportion of their time engaged in their studies and in the company of other students on campus.

The study is motivated by a concern that higher education institutions are unaware of the effect that timetable design may have on student trip-making and that by ignoring this factor and instead focusing on other targets, such as improving the utilisation of on-campus resources, the institutions risk making themselves a less attractive study destination for students.

Institutional targets for emissions reduction are being created during a period in which UK universities find themselves increasingly operating within a globally competitive market, in which potential students can now choose between many campus-based universities across the world and also new and evolving delivery methods, referred to as massive open online courses (MOOCs) (BBC News, 2013b). MOOC's represent an emerging educational market and are typically characterised by similarly high levels of uptake and attrition, with up to 95% of students dropping out before completion (BBC News, 2013a). At the same time the direct cost of higher education in the UK has risen through the introduction of loan-based tuition fees payable at the point of entry, whilst the value of the degree in terms the employability it bestows on the holder is falling (Barber et al., 2013, p. 14). Both of these trends present challenges to campus-based universities with their traditional teaching methods, large estates, and high maintenance costs.

The campus itself represents the unique selling point of the campus-based university offering the ideal of a collegiate student experience that should be easily differentiable from those for other delivery channels. Measures that aim to reduce the time students need to spend on-campus may potentially marginalise the student experience of the campus-based university.

RQ8 What are the potential impacts of timetable design decisions on the environmental, economic and social sustainability of the campus-based university?

1.3 Aims and Objectives

The introduction suggests that the relationship between student trip-making behaviour and their academic timetable is not well understood. If the timetable is a key determinant in student decisions regarding the timing and frequency of their trips to and from campus then attention to the design of the timetable will have a bearing on the sustainability of the university. Therefore the three broad aims of this work are:

A1 To investigate the current understanding of the relationship between student trip-making behaviour and the academic timetable, and to identify opportunities to improve institutional environmental sustainability presented by this relationship.

A2 To identify the factors which contribute towards a timetable design perceived by students as being of high quality and examine how student timetable preferences influence and are influenced by their trip-making behaviour.

A3 To examine the impact of the academic timetable on longer term student trip making behaviour and the effect of timetable design policy on progress towards the sustainable development of the campus-based university, from an economic/social perspective.

These three aims will be achieved through the following seven objectives:

O1 To identify previous work into student trip-making and which links the areas of the academic timetable to student trip-making behaviour, student engagement, student attendance and attainment.

O2 To conduct a review of the travel plans developed by UK universities to examine if practitioners in the area of university travel planning acknowledge links between the academic timetable and student trip-making, and to investigate the measures implemented at UK universities which mitigate the impact of student trips and contribute towards the environmental sustainability of the hosting institution.

O3 To design and conduct a survey of student timetable preferences to identify the attributes within the timetable that students value, and which examines self-reported student trip-making relative to the student timetable.

O4 To develop an observational survey method utilising secondary data-sources describing student on-campus activity to generate a dataset which describes student presence on-campus and from which trip-making behaviour can be inferred.

O5 To model the trip-making behaviour of undergraduate students using the observational survey data at an aggregate and disaggregate level and to determine the effect of their timetable and demographic characteristics on this behaviour.

O6 To examine the impact of student trip-making behaviour on academic outcome and indicators of student engagement and to explore the impact that timetable has on this behaviour

O7 To discuss the implications of any findings identified through objectives O1-O6 on the sustainable development of the campus-based university and to make recommendations in terms of future policy towards academic timetable design and student trip-making.

1.4 Research Questions and Hypotheses

Eight research questions were raised in the introductory sections of this thesis, and are summarised below together with a list of the research objectives that will be used to answer each question :

RQ1 Do students hold a traditional or a contemporary view of their timetable?
(O1, O2, O3, O5)

RQ2 Are students less likely to come to campus on non-timetabled days?
(O1, O2, O3, O5)

RQ3 What constitutes a high quality timetable from a student point of view?
(O1, O3, O5)

RQ4 Do students exhibit leave-and-return behaviour?
(O1, O2, O3)

RQ5 How do university travel plans and their associated travel surveys represent student trip-making behaviour?
(O1, O2, O3, O5)

RQ6 Do certain timetable designs have a negative impact on levels of student engagement and attainment?
(O1, O5, O6)

RQ7 Can secondary data-sources be used to devise an observational method to obtain longitudinal survey data about student trip-making behaviour?
(O1, O4, O5, O6)

RQ8 What are the potential impacts of timetable design decisions on the environmental, economic and social sustainability of the campus-based university?
(O1, O2, O6, O7)

Based on these research questions, aims and objectives the hypotheses to be tested in this thesis are listed below, together with the relevant research question applicable to each:

H1 That student trip-making behaviour tends towards the contemporary view of the timetable, rather than the traditional view (RQ1).

H1a That students are less likely to attend campus on NTDs and that as a consequence it is the number of timetabled days in the timetable, which is the main determinant of trip-making behaviour (RQ2).

H1b That students exhibit leave-and-return behaviour (RQ4).

H2 That that there is little recognition of the contemporary view of the academic timetable in the operational documents (travel plans) used by universities to describe and mitigate student trip-making behaviour (RQ5).

H2a That current university travel planning practice, does not represent an optimal response to the challenges set by institutional carbon reduction targets (RQ8).

H3 That student preferences for a quality timetable differ fundamentally from the timetable that they currently receive (RQ3).

H4 If H1 is correct then that this new understanding of the relationship between timetable and trip-making can be used to improve the environmental sustainability of the institution by controlling and perhaps reducing the level of student trip-making (RQ6, RQ8).

No hypothesis is given for RQ7 (can an observational survey method be devised?) as this is question is outcome based rather than research based.

1.5 Novelty and Original Contribution

The work reported in this thesis makes an original contribution to the understanding of the link between the academic timetable and student trip-making.

It will be demonstrated that no other research project has been found which links the academic timetable to student trip-making in UK universities and whilst many assumptions are made about the nature of this relationship, it has never been formally investigated.

The comprehensive review of the travel plans in place at UK universities is also unique in that it highlights a limited understanding of the link between timetable and trip-making held by practitioners at UK universities.

Although previous studies have examined the effect of the academic timetable on attendance most have been more limited in nature and none have asked the respondents to specify the features present in a high quality timetable and instead have focused on the negative aspects of the timetable. No other survey has explicitly attempted to identify the links between timetable preferences and trip-making.

The study uses a novel observational survey method, that borrows estimation techniques from the field of ecology and which can successfully replicate the findings of a more traditional survey method at both the aggregate and disaggregate level.

1.6 Thesis Outline

The remaining chapters of this thesis are organised as follows.

Chapter 2 contains a literature review of the areas related to the work described in this thesis. The literature review provides some background material on university timetables and timetabling, student engagement, and urban trip-making. A review of work on university travel behaviour and student trip-making is conducted. Student attendance is examined in relation to attainment and the literature which links timetable and attendance is discussed, whilst limited examples of the use of timetable to influence student travel behaviour are identified.

Chapter 3 describes the methodology adopted to meet the objectives and answer the research questions and hypotheses raised by this study. Three analysis streams are introduced relating to a review of UK university travel plans (UTR), a timetable quality survey (TQS) and an observational student survey technique (OSS).

Chapter 4 reports on the results of a desktop review of UK university travel plans and their associated travel surveys (UTR),

Chapter 5 outlines an analysis into the effect of different travel plan measures on institutional environmental sustainability (using data from UoL), and includes an assessment of the environmental impact of using timetable design as a travel plan soft measure.

Chapter 6 reports on the design and execution of an online survey to obtain data on student timetable preferences, the timetable quality survey (TQS), to determine the attributes of the academic timetable which students regard as being of high quality and reviews qualitative and quantitative data captured through the survey.

Chapter 7 contains an analysis of further data taken from the TQS examining the links between the timetable and student trip-making behaviour.

Chapter 8 outlines an observational student survey (OSS) dataset for capturing longitudinal data about student trip-making. A large body of electronic data recording student activity on-campus is introduced and evidence of links between student activity on-campus and student engagement are explored.

Chapter 9 introduces the development of a novel method for estimating aggregate levels of attendance on-campus and for inferring individual student trip rates. Models of student trip-making behaviour are constructed and the results compared to those identified in Chapter 7. The efficacy of the method itself is reviewed.

Chapter 10 explores links between individual student trip rates and measures of student engagement, disengagement and attainment. The applicability of using timetable as a means for controlling student commuting is discussed and a series of recommendations around future timetabling policy are outlined.

Chapter 11 discusses the limitations and applicability of the study, identifies opportunities for further work, summarises the work conducted and outlines some general conclusions for the thesis as a whole.

Chapter 2 – Literature Review

2.1 Introduction

This chapter contains a review of previous work in the areas related to this study, and demonstrates the gaps in the existing research highlighted by the questions raised in Chapter 1.

It begins with some background material on academic timetables, timetable quality, factors that constraint the university timetabling process and introduces a sample timetable from UoL. The chapter continues with a discussion of the effect of student attendance at timetabled sessions on attainment and around the need to encourage student engagement with their studies.

The impact of traffic congestion on the urban environment is established and measures to reduce the effects of congestion, specifically through the use of travel plans, are introduced and discussed.

The significance of the campus as a destination for commuting trips is identified and studies that have investigated how to mitigate the effect of these trips are introduced, followed by a review of further studies that have examined student trip-making behaviour.

Work examining the effect of the design of the university timetable on student attendance is outlined, and the few studies that have attempted to use timetable to influence student travel behaviour are identified.

The literature review presented within this chapter delivers research objective O1 (identify previous work).

2.2 The University Timetable

2.2.1 Background and Primer

Within the university context there are two major types of timetabling problem; the construction of the semester-long academic teaching timetable and the development of the semester-end examination timetable (Burke et al., 1997) whilst the most common objectives against which a timetable is measured are feasibility and quality (Lewis, 2008).

A timetable is feasible if all sessions are allocated to timeslots and assigned objects (students/lecturers) and resources (rooms) such that no object or resource is allocated to more than one activity at any time (a clash) and no resource exceeds its specific capacity. The feasibility objective is discrete, it can either be met or not met, and is usually defined in terms of a set of hard (mandatory) constraints.

The quality of a timetable is determined through measures which describe how usable it is and how closely it meets the external requirements of the objects (students/lecturers) that it allocates activities to. The quality objective is a continuous, and to some extent a subjective, measure and is specified through a set of soft (discretionary) constraints. Academic institutions define quality through a combination of space utilisation and staff/student satisfaction (McCollum, 2007).

2.2.2 Student Timetable Quality

Whilst the academic community has devoted considerable time and energy to developing algorithms and techniques to create timetables, little research has been conducted in the area of assessing academic timetable quality (Burke et al., 1997, Lewis, 2008). Academic timetable quality is defined as being a combination of institutional resource utilisation, staff satisfaction and student satisfaction (McCollum, 2007). Resource utilisation is largely synonymous with teaching space usage, as this can easily be measured, however the definition of staff and student quality is more subjective.

Generally staff are perceived to desire timetables in which their teaching duties are clumped or bunched together (Pryzililla, 2010, Pongcharoen et al., 2008, McCollum, 2007) or alternatively to have an input into the timetabling process allowing them to specify the times when they want to teach (Schimmelpfeng and Helber, 2007).

Birbas suggests that compactness is similarly important for students (Birbas et al., 2009), although a privately commissioned student survey listed teaching/session balance as the most desirable attribute (Algonquin College of Applied Arts and Technology Ottawa, 2004). Another important factor will be the need to maximise the choice of courses/modules available to the student (McCollum, 2007).

Research studies typically list the needs of students last when describing the stakeholders affected by the timetable generation process, and this may reflect an institutional bias against including measures of student timetable quality in the timetable design process; the timetable is served up to students on a take-it or leave-it basis. In a real-world timetabling model developed for a German University no student related soft constraints were included because "*the powerful position of the professors determines the schedule to a large extent"* (Schimmelpfeng and Helber, 2007). However, it may also be a recognition to incorporate the diverse preferences of a large group of students can considerably increase the difficulty of generating a timetable (Burke et al., 1997).

Pongcharoen conducts a short review of the hard and soft constraints used in ten other timetable models (Pongcharoen et al., 2008) . Of the 43 instances of 18 different constraint types listed, 22 had an impact on student timetable quality, whilst 33 were related to either staff timetable quality or optimising resource utilisation, suggesting that student timetable quality has less importance than either institutional of staff requirements.

An alternate method for assuring student timetable quality is through a service level agreement approach. A timetable system proposed for Algonquin College (Algonquin College of Applied Arts and Technology Ottawa, 2004) is an example of this approach, explicitly stating an acceptable range for contact hours/day, and maximum allowable values for consecutive teaching hours and the gaps between classes. This approach mirrors the way constraints are specified in staff rostering problems and it could be argued that the accepted academic timetabling paradigm, based on a view of individual students as being part of a homogenous cohort, predates the current modular-based pedagogical approach in which students have more freedom to define their own study pathway. As such, the rostering approach to solving the academic timetabling problem may be more applicable in a modern institution.

2.2.3 Timetable Assignment – A Random Process

The timetable allocated to an individual student will take no account of that student's individual circumstances, their residential distance, family commitments or their need to work whilst studying will have little impact on the timetable they receive.

In some cases the needs of a particular group may be recognised in the timetable. For example part-time students, may find that the main parts of their course are scheduled over one or two days per week rather than over five, whilst another strategy is for students to be offered a number of alternative timings for a particular session, with students then self-selecting the most appropriate one on a first-come first-served basis.

2.2.4 Timetable and Institutional Considerations

The property portfolio of any higher education institution is a key asset, but also represents major capital expenditure and a significant ongoing revenue cost. To the administrators, academics and students who work within the spaces the property contains, it has traditionally been "*regarded as a 'free good', something which is* *always there*” As a result administrators have tended to over-book and hoard space. (Shove, 1993)

The Pearce report (Pearce, 1992) identified low utilisation rates and significant surplus space within higher education institutions and suggested that organisations took a more aggressive role in managing this space, including the introduction of charging regimes. To assist in this process the National Audit Office created a standard measure for calculating the utilisation rate for teaching space (National Audit Office, 1996).

Most HEIs collect some data on space utilisation with the main focus being on teaching space. The Estate Management Statistics (EMS) project collates and publishes reports for the sector on the global utilisation of teaching space. Between 2001 and 2006 median weekly utilisation rates for the core teaching day (09:00-17:00) rose from 24% to 27%. (Estates Management Statistics, 2008). Nearly three quarters of all teaching space/hours are not used across each teaching week.

The Higher Education Space Management Group (SMG) was established in 2003 to identify policies and practices for improving space utilisation and linked these to improvements in timetabling practice (Chiddick, 2003).

The SMG calculated that the cost of operating and maintaining $1m^2$ of teaching space was £162 (2004 figures), but when an opportunity cost of capital was added to represent the low utilisation rate, this figure rose to £215 per m^2 (UK HE Space Management Group, 2006b).

The SMG identified a number of timetabling factors as contributing to the low utilisation rates. These included a resistance to timetabling teaching sessions at the start and end of the day or on Friday afternoons, traditionally teaching at certain times, such as 10:00-12:00 on Tuesdays and Thursdays and due to assumptions made about what students want and when they want to attend (UK HE Space Management Group, 2006b).

The group found that institutions which timetabled their teaching space centrally used on average 17% less floor space than institutions which timetabled at a faculty or department level (UK HE Space Management Group, 2006c).

The work of the SMG predates the institutional sustainability agenda outlined in section 1.2.1. Consequently the pressure on universities to design the timetable to optimise the use of teaching space for both economic and environmental reasons will only increase in the future.

However, the complexity of the timetabling process means that optimising for space may result in a poorer quality in other dimensions.

2.2.5 Complexity and Multiple Constraints

The solution of the timetabling problem is computationally difficult (Burke et al., 1996) and institutionally challenging (McCollum, 2007), with the number of constraints determining the complexity of the problem and the relative tightness of the resultant timetable.

Wesson examines this problem qualitatively through a comparison of academic timetabling with industrial production scheduling problems. He suggests that since constraints interact, the reduction in timetable flexibility resulting from the introduction of a new constraint is greater than the effect of the constraint on its own. This leads to the concept of a threshold of rigidity (Wesson, 1995). This is the point at which no further activities may be allocated to the timetable without violating one or more of the hard constraints defined on the timetable. Although each resource within the timetable may all have spare capacity, this capacity is functionally inaccessible.

Schimmelpfeng examined the effect of varying the number and type of rooms available and found that feasible timetables could be produced at varying levels of resource provision but that a temporal objective function (measuring how well lecturers preferences were met by the timetable) increased (got worse) as the number of rooms were reduced (Schimmelpfeng and Helber, 2007).

Wesson's hypothesis is supported by quantitative work conducted by Beyrouthy (Beyrouthy et al., 2009) which demonstrates that timetabling constraints have the potential to explain low space utilisation rates. This study also confirms the existence of the threshold of rigidity (in terms of space utilisation rates) through the identification of a timetable specific critical (space) utilisation level below which requests are almost always totally satisfied and above which they are almost always never totally satisfied. Optimising the timetable in one dimension (for example room usage) reduces the flexibility for optimisation in any of the opposing dimensions.

These conclusions have important implications in terms of institutional sustainability policy, and for this study:

- Resource utilisation rates are a function of the timetabling process and not a result of it.
- Resource utilisation rates above a critical level are not achievable given the current academic timetabling model, meaning that institutional efforts to improve resource utilisation rates may not yield the increase envisaged.

- Scope for improving the quality of an individual academic timetable may be limited by the need to optimise the utilisation of resources in other timetable dimensions.

The need for institutions to improve the utilisation of their fixed assets, combined with the combinatorial complexity of the timetable generation problem means that universities may be overlooking the impact of the academic timetable on other aspects of their overall sustainability. No work has been identified in this area, thereby justifying the inclusion of research question RQ8 (what are the impacts of timetable design on university sustainability).

2.3 Student Attendance

Student attendance at timetabled sessions would appear to be a prerequisite for academic success, and many studies have examined the link between attendance and attainment (Schmidt, 1983, Dolton et al., 2001, Kirby and McElroy, 2003, Vanblerkom, 1992). As Lipscomb et al reports "*Studies from multiple disciplines link attendance with performance or course success*" and that "*a positive relationship is generally cited*" (Lipscomb and Snelling, 2010). This conclusion is supported by a meta-analysis of attendance studies (Crede et al., 2010), which finds that class attendance levels are the best individual predictor of likely grades.

The work by Crede et al is based on studies undertaken in the USA and might not be completely relevant in the UK context, However, a similar conclusion was found in a small scale study in the UK (Colby, 2004). Newman-Ford reports on the results of a large-scale attendance study that analysed data captured from an electronic attendance monitoring system, UniNanny (Newman-Ford et al., 2008). This study replicated the results of Colby's earlier work with both studies also finding that once a student misses one session the likelihood of them missing subsequent session's increases.

However, there is some disparity between the studies on the specific relationship between attendance and the grade obtained. In the UK studies of Newman-Ford and Colby a linear relationship is proposed, whereby the probability of achieving a high grade increases in direct proportion, whereas Crede's work suggests a curve-linear effect, with the highest performing students having either very good or very poor attendance, and poor students exhibiting average levels of attendance.

Establishing a causal link between attendance and attainment is difficult as unobserved differences between students may be contributing to both higher attendance levels and improved grades. Crede et al examined four possible models linking attendance and individual difference factors to attainment and found best support for a unique effects model, suggesting that class attendance and student characteristics both make unique contributions towards overall academic performance (Crede et al., 2010). This conclusion supports the argument that all students benefit from attendance on campus, and at timetabled sessions, irrespective of their background or ability level.

2.4 Student Engagement

If an individual's academic outcome can be enhanced through improving attendance and increasing study time, then why don't all timetabled sessions have 100% attendance, and why aren't students spending all of their spare time in private study? Frank makes an analogy between a university and a health club, in which "*membership of the club does not automatically bestow fitness; it requires an individual's commitment and long term engagement with exercise to achieve some level of fitness*" (Frank, 2009). Similarly, in a university context some students will be more motivated to learn than others, and these students are more likely to attend and spend a greater on their time on study related activities.

Motivation may be related to ability, and "*clever students may work harder because they tend to enjoy their subject*" (Stevens and Weale, 2004), but do institutional factors play a part in determining levels of student motivation? Student motivation and their desire to learn is explained by two largely similar theories: Astin's theory of involvement (Astin, 1984) and Tinto's theory of student persistence (Tinto, 1997).

Astin's theory, which was motivated by a desire to explain student development whilst at university, defines involvement as *"the amount of physical and psychological energy that the student devotes to the academic experience*", Astin identifies a series of behaviours that increase levels of involvement including; living on-campus, subject interest, time on task, student-college interaction, participation in extra curricula activities and membership of student committees, and proposes that the greater the level of involvement the greater the amount of student learning and development that will take place.

Tinto's theory was developed out of work examining why students fail to persist at college and instead decide to dropout. He proposes that "*the more academically and socially involved individuals are, and the more they interact with other students and* [the college], *the more likely they are to persist*" (Tinto, 1998).

The theories of involvement and persistence are represented in the literature under the generic term of student engagement and operationalised in the USA and

Australia through national annual student surveys to measure engagement levels; the NSSE in the US (since 1998) and the AUSSE in Australia (since 2007). Both surveys encapsulate the principles of good practice in undergraduate education proposed by Chickering et al (Chickering and Gamson, 1989) and measure levels of engagement through the same series of benchmarks: academic challenge, active learning, student and interactions, enriching educational experiences and the construction of a supportive learning environment (NSSE - National Survey Of Student Engagement, 2010, AUSSE - Australian Survey of Student Engagement, 2009).

In the UK no equivalent exists, although data on final year student perception of their educational experience is collected through the National Student Survey (NSS), established in 2005, (NSS - UniStats, 2010). The survey instrument is much less comprehensive than either the NSSE or the AUSSE and focuses more on the administrative aspects of the student's course, as opposed to the level of engagement attained.

Many researchers have used the data collected through the NSSE and the AUSSE to analyse the factors affecting levels of student engagement and these studies have largely been supportive of the theories proposed by Astin and Tinto.

Higher levels of student engagement improve academic outcomes in general and this is particularly true for socially disadvantaged and lower ability students (Kuh et al., 2008). Similarly, students admitted to their first choice institution are more likely to graduate, than those who were denied access to their first choice (Jones-White et al., 2009).

Living away from campus increases the likelihood of leaving in the first year (Bozick, 2007), whilst students living on-campus have a greater likelihood of graduating (Jones-White et al., 2009) and exhibit a higher level of engagement (AUSSE - Research Briefing, 2009).

Students in paid employment spend significantly fewer days on-campus, and spend less time in private study, whilst those students who spend the most time on-campus are more likely to feel they belong to a learning community. Students who spent the least time on-campus were also the least likely to ask questions in class (Krause et al., 2005). Students who work, enrol part-time or live away from campus report lower levels of learning (Lundberg, 2003) and are at a greater risk of dropping out (Bozick, 2007).

However, work reported by Brint suggests that activities which link students with the campus do not all contribute positively to the level of academic engagement, and that some behaviours might instead be integrating students into on campus 'party' cultures (Brint and Cantwell, 2008).

The theories of involvement and persistence provide persuasive explanations of student behaviour, with multiple sources supporting the view that factors which increase levels of student engagement are to be encouraged.

Timetable design has a potentially major influence on levels of student engagement, in terms of the number of days students are required to be on campus to attend scheduled sessions. If students are only required to be on campus two days a week they may be likely to feel less engaged with their institution than if they were required to attend every day. Astin recognises this and identifies "*class schedules*" and "*regulations on class attendance*" as having an impact on involvement (Astin, 1984), whilst Tinto suggests that *"every institutional action and decision will affect retention rates in unintended or unexpected ways"* (Tinto, 1993, p. 205).

This review demonstrates that no work has been conducted into links between engagement/attainment and the academic timetable, thereby justifying the inclusion of research question RQ6 (do certain timetable designs have a negative impact on engagement and attainment?).

2.5 Urban Trip-Making in the UK and Travel Plans

The ability to travel is an essential prerequisite of life within any modern economy (Banister, 2005, p. 11), in which demand for travel is matched by the supply of transport capacity to meet that demand.

In classical economic theory transport is regarded as a derived good in that demand for travel occurs solely to attain some other benefit and travel is only undertaken when the value of the benefit derived exceeds the generalised cost of the travel (Powell, 2001, p. 96), whilst transport supply is taken as being a service since it must be consumed where and when it is produced otherwise its benefit is lost (Ortuzar and Willumsen, 2011, p. 4).

The aim of the transport planner is to balance the demand for transport within a society with a matching supply of transport opportunities (Enoch, 2012, p. 6) subject to the constraints of a national policy framework that should aim to maximise societal utility and enable the optimum quantity of travel to take place using the most cost effective mode (Powell, 2001, p. 19)

Within the UK prior to the advent of mass car ownership in the early 1950's, life was centred around the local community and trips outside the local area were rare (Banister, 2002, p. 1). However, between 1953 and 1998 absolute levels of passenger travel in the UK more than tripled growing from 139 to 443 billion miles, whilst in the same period the number of households owning at least one car rose from 17% to 73% resulting in a modal transfer of trips away from bus and rail in favour of the car (Powell, 2001, p. 83-84).

The increase in demand for car travel was met in the UK through a series of government transport policies summarised by the maxim ‘predict and provide’ whereby urban transport supply was improved through an increase in road capacity (Banister, 2002, p. 25). However, this approach has been shown to induce trips not previously taken, with new capacity being consumed by a latent demand for more travel within the population (Banister, 2002, p. 211).

When the demand for travel exceeds the supply of transport capacity congestion in the network can occur. Congestion represents a method for allocating scarce transportation capacity among competing consumers (Downs, 2004, p. 5), but as a policy for controlling travel demand it is economically inefficient since each trip added to a system already at capacity imposes an additional marginal generalised cost on all trips already in the system (Powell, 2001, p. 98).

Measures to reduce levels of congestion attempt to balance supply with demand by increasing or decreasing either transportation supply or demand through a variation in transport capacity or in the application of incentives or penalties (Enoch, 2012, chapter 1).

The publication of “A New Deal for Transport” in 1998 marked a departure from previous thinking on transport policy with a commitment to sustainable transport (Powell, 2001, p. 33), and defining a new orthodoxy that has been paraphrased by some as ‘predict and prevent’ (Owens, 1995). Policy instruments for implementing a sustainable transport system include: technological solutions, achieving behaviour change, adjustments in land use policy and planning, the selective provision of new infrastructure, traffic management, and pricing (May, 2013).

Within this context travel plans emerged as sustainable transport policy instrument and represent an alternative to further increases in road capacity as a means to tackle congestion reduction (Enoch, 2012, p. 33), with one of the major aims being to reduce the over-dependency on cars, by identifying all possible alternatives to single occupancy vehicle (SOV) trips (Department for Transport, 2008, p. 6). They can be seen as a response to congestion that aims to reduce the external costs associated with making each trip. The aim of the plan is to encourage change towards more sustainable behaviour at the level of the individual, and the measures included in a plan are often thought of as ‘soft’ measures in that they address the trip taker’s psychological motivation for specific travel choices (Cairns et al., 2008).

Different types of plan have been developed to address the distinct patterns of travel associated with specific categories of organisation: workplaces, schools, planned events, attractions, retail outlets, transport interchanges and residential developments (Enoch, 2012, p. 65, Cairns et al., 2008). Workplace travel plans aim to manage the travel associated with commuting trips together with the business travel of the employees within the organisation (Department for Transport, 2008) and provide an organisation with a mechanism to allow it to develop a collection of measures that influence both the supply of and demand for travel resources and which encourages employees (and visitors) to travel in more sustainable ways (Roby, 2010). Considerable success has been reported for the effect of workplace travel plans (Cairns et al., 2010), and their intensive application combined with car sharing and teleworking may reduce trips by at an organisation level by up to 26% (Cairns et al., 2008).

The workplace travel plan is the model most commonly adopted by organisations in the public sector, by hospitals and by universities (Enoch, 2012, p. 72). A university travel plan must cater for four distinct types of travel users: employees, students, visitors and suppliers whilst considering the regular trips taken by each type of user, plus any additional types of trip that might be undertaken intermittently. For example staff may be involved in travel for work (business) trips, whilst students will typically undertake longer distance trips from and to their (parental) home at the start and end of each university term.

If students hold a contemporary view of their timetable then the workplace travel plan model might be an inappropriate model for representing their trip-making behaviour. This justifies the inclusion of research question RQ5 (how do university travel plans represent student trip-making behaviour).

2.6 The University Campus and Student Travel Behaviour

The size and diversity of a modern university campus means that it can potentially have a major impact on both traffic and congestion levels within its hosting city.

Big universities have been likened to small cities in their own right (Brown et al., 2003), with high employment and residential densities (Toor and Havlick, 2004, p. 4) and are unique due to their distinct roles as: places of learning, major businesses and as leaders within their hosting communities (Forum for the Future, 2003, p.8).

Universities attract a mixed population that operates to irregular schedules resulting in a continual movement on and off campus throughout the day (Balsas, 2003) and include a higher proportion active travellers compared to the general population

(Whalen et al., 2013). University students tend to exhibit unique and complex travel behaviours (Limanond et al., 2011a) but this is not well understood and only sporadically researched (Khattak et al., 2011, Wang et al., 2012).

The motivation for most of the published research on university travel behaviour appears to come from the realisation that the university campus is not immune from the negative effects of an excess of car trips. Although the traditional campus was designed around the pedestrian (Toor and Havlick, 2004, p. 18), commuting, typically by car, now represents a university's largest environmental impact (Tolley, 1996, Miralles-Guasch and Domene, 2010) negatively affecting the quality of the on-campus environment (Toor and Havlick, 2004, p. 2) through poor air quality, increased congestion (Balsas, 2003) and which can be due in part to a mismatch in the supply of and demand for car parking (Barata et al., 2011). On-campus parking is an issue that can provoke strong emotions (Balsas, 2003) with existing parking users jealously guarding their own provision against strong demand from new users (University of Surrey, 2012, p. 6).

Most of the research into university travel behaviour has been focused in the area of travel demand management (TDM), and specifically around staff and student mode choice.

In the UK the problems associated with an excessive reliance on motorised transport for university student and staff commuting were first raised by Tolley whose prescient warnings about the environmental impacts of such behaviour predates both the adoption of travel plans by universities and much of the subsequent discussion around institutional sustainability (Tolley, 1996). He proposes an alternate view of campus travel in which bicycles are the favoured mode for student trips.

In the US, Toor has published extensively on university TDM (Toor and Havlick, 2004, Toor and Poinsatte, 1999), being motivated by a focus on the land-use, environmental and sustainability problems associated with the unconstrained growth of parking supply and by a desire to create more liveable on-campus environments through measures to control car use and to encourage the uptake of the more sustainable modes.

From Australia, Shannon reports on a travel survey based approach to identify potential opportunities to allow staff and students to switch to active commuting modes (Shannon et al., 2006). They identify the need to subsidise public transport, increase the cost of parking on campus, improve journey times, and encourage the development of student housing close to campus.

A similar study at the University of Barcelona (Miralles-Guasch and Domene, 2010) presents descriptive statistics for current mode, preferred mode and the barriers preventing to change. The main barriers identified are site specific and include poor service provision and extended journey times (public transport), commuting distance (walking and cycling) and lack of means (cycling). The study identifies one interesting difference between staff and student behaviour, in that students cite external factors as being key in preventing them from changing to their preferred mode (lack of PT services, no driving licence, car-sharing not appropriate) whilst staff tend to cite factors intrinsic to the travel experience (convenience, safety, travel time).

In a questionnaire based study at the small and self-contained University of Idaho students travel mode is shown to vary according to the season (Delmelle and Delmelle, 2012), with cycling being favoured in place of both the car and walking trips during warm and dry weather.

A travel diary approach, supplemented by a stated preference questionnaire was used to identify policy measures to encourage better patronage of public transport by student and staffs attending the University of Burgos, Spain (Gonzalo-Orden et al., 2012). The study concludes that a combination of supply-side measures (improved bus frequency, bus lanes) and demand-side measures (parking charges and traffic calming to increase vehicle journey times) can result in a greener and safer urban environment around the university campus.

Lavery studied the modality (a count of regularly used modes) of students at McMaster University, Canada (Lavery et al., 2013) finding that as residential distance increases fewer modes are seen as being available and feasible, whilst in a similar study Zhou found that telecommuting among students increases with residential distance (Zhou, 2012).

The links between active travel and health were explored in a study of the mode choice behaviour of staff and students attending a university campus in Sydney, Australia (Rissel et al., 2013). The study found that although 41% of the sample were sufficiently physically active, a further increase in this level through the promotion of active commuting would require students to transfer away from public transport.

No examples of similar studies in a UK context have been found. However, many of the papers describing these non UK based studies largely duplicate the type of research methodology associated with the development of a UK-style travel plan, and it could be that in the UK this research is conducted by the operational staff (travel planners) within an institution rather than academic staff, and consequently less emphasis is placed on the academic publication of the results of this work.

The focus in the academic literature on studies around mode choice and measures to achieve mode change is not matched by similar studies into student travel demand, although a few examples have been found.

The travel diary approach adopted by Gonzalo-Orden et al reveals a commuting pattern with four peak periods; two on-campus arrival peaks (morning and afternoon) and two departure peaks (lunchtime and evening) (Gonzalo-Orden et al., 2012). Although it is tempting to suggest that this might be evidence of leave-and-return behaviour, it is probably more likely to be due to the Spanish cultural tradition of taking an extended lunch-break/siesta.

Kamruzzaman used travel diaries collected from 130 students in Northern Ireland to examine the use of GIS to visualise travel and activity behaviour and measures of accessibility (Kamruzzaman et al., 2011).

Limanond describes a travel diary approach to examine student travel behaviour at a rural university in Thailand. This found that daily trips were evenly distributed around a midday peak and that trip rates and trip distances were higher than expected given the length of a single mandatory return trip between the residential accommodation and lecture halls (Limanond et al., 2011a). Limanond offers no explanation for these extra trips. A follow up study examines the effect of vehicle ownership on study time, and finds that whilst vehicle owners spent the same amount of time in class as non vehicle owners, they spent significantly less time on private study (Limanond et al., 2011b).

Wang employed a travel diary to obtain rates for student trips to campus and made whilst on-campus, and then used a Poisson-negative binomial approach to model personal demographic characteristics as predictors (Wang et al., 2012). The study found that students who live closer to campus are more likely to walk or cycle and make more overall trips compared to those living far from campus. A descriptive analysis of the same study (Khattak et al., 2011) shows that on-campus trips account for around 40% of the total of all trips for all students. These trips must partially be a function of class scheduling, but no mention is made of this, with differences in trip rates being explained solely through student demographic attributes.

The theoretical basis underpinning the studies by Khattak and Wang views the university campus as a special trip generator within a traditional four stage transport model. An alternative view of trip-making behaviour is the activity based approach.

Trips are examined at the discrete level and the spatial reach of any actor in the system is limited by their current position and the time available. Actors move from their current location to satisfy a desire to take part in activities occurring at another location. Hagerstrand's seminal work on space-time prisms proposes an activity based approach towards individual trip-making behaviour and suggests that trip-making is limited through constraints (Hagerstrand T, 1970). He proposes three types of constraint: capability constraints, coupling constraints and authority constraints. Capability constraints refer to the physical limits imposed on an individual by their need to sleep, eat, whilst authority constraints define the time slots within which certain activities can be performed, for example shop opening hours. Coupling constraints define the requirement for an individual to be in a certain place at a certain time in order to meet with other individuals for a prearranged task. The activity based approach of viewing trip-making at an individual level, combined with the constraint based approach proposed by Hagerstrand, corresponds very closely with the contemporary view of the timetable as a schedule of appointments.

Eom describes using a travel diary approach, to create student activity profiles for a typical study-day (Eom et al., 2009), and he develops this work further to produce an activity-based student trip model for commuting trips to campus and for trips on-campus between buildings/zones (Eom et al., 2010). The on-campus model is validated against the number of students scheduled to be in each building according to the academic timetable Eom's on-campus destination choice model assigns trips to buildings in proportion to their floor area, taking little account of the proportion of sessions scheduled within the building, whilst ignoring the effect of NTDs. The model overstates the trip demand suggested by the timetable. Chen describes a similar analysis and finds similar results to Eom using the data from the Khattak study described above (Chen, 2012).

If the timetable has an effect on student trip-making then attempting to understand the behaviour of students without reference to their timetable or daily schedule is analogous to trying to explain the apparently spontaneous and simultaneous demand for trips to a football stadium on a match-day without reference to the fixture list. The characteristics of each trip can be partially described by the demographic factors of those making the trips, but nothing can explain a trip demand which is apparently skewed towards alternate Saturday afternoons.

Nevertheless no examples were found of peer reviewed reports of studies that investigate the relationship between student travel behaviour and their timetable. Huismann proposes using Haggerstrad's time geographic model to represent the constraints placed on student space-time prisms by their timetable (Huisman and Forer, 1998) but no results from their proposed study appear to have been published.

The lack of research in this area provides a justification for research questions RQ1, and RQ2. None of the existing research can indicate if students hold a traditional or a contemporary view of the timetable (RQ1), whilst no research has been identified which links the number and duration of timetabled sessions on a given day with the probability of on-campus attendance on that day (RQ2).

2.7 University Timetable and Student Behaviour

The literature related to links between the university timetable and student behaviour is limited and appears to be concentrated in three areas: the links between timetable and lecture attendance, student perceptions of timetable quality and reports of timetabling measures that have been suggested to influence student trip-making behaviour.

2.7.1 Timetable and Attendance

Attendance at lectures has been shown to contribute to higher levels of academic attainment (section 2.22.2.5). Given this positive relationship some studies have examined the effect of specific timetable attributes on student attendance at timetabled sessions.

Attributes which describe a timetable can be thought of as belonging to one of two classes: within-day attributes and between-day attributes. Within-day attributes describe those features of the timetable that can be explained by examining a single day from the timetable, whilst between-day attributes refer to the features that can only be understood when the timetable for a whole week (or longer) is examined.

Within-day attributes describe features of the timetable such as the timing of sessions (start and finish times), the duration of sessions without a break, the length of any breaks, and the total number of contact hours delivered across the day. Between-day attributes describe features like the ratio of TTDs to NTDs during the week, the placing of sessions on particular days of the week, the balance between the number of contact hours delivered on each timetabled day and any weekly variability in the timetable.

The studies identified in the literature use a variety of methods: questionnaires, surveys, focus groups/interviews and observation to examine timetable attitudes and behaviour of students. These students were studying a range of disciplines: Accounting, Agriculture, Biochemistry and molecular biology, Economics, English, Health Sciences, Pharmacy and Psychology at different stages in the academic process: 1st year, 2nd Year, 3rd Year. The institutions studied were around the world: Australia, England, Egypt, Ireland, Turkey, and the United States. This diversity suggests that attendance issues associated with timetabling concerns is a common theme for many students world-wide.

Class timing is the most frequently cited timetable attribute that has been found to influence student attendance rates (Kelly, 2011, Persky et al., 2013, Ghenghesh and Nakhla, 2011, Kottasz, 2005, Devadoss and Foltz, 1996, Lang et al., 2008, Hunter, 1999, Arulampalam et al., 2012, Davis et al., 2012). Studies typically suggest that sessions scheduled within a time window focused around the middle of the day, for example 10:00-15:00 (Devadoss and Foltz, 1996), will be better attended than those scheduled at either end of the day. Lang suggests that the attendance of those students who achieve marks within the middle of the range will be most affected by variations in session timing (Lang et al., 2008).

Arulampalam et al report on a longitudinal study of the relationship between session timing and attainment over 3 cohorts. They identify some session times which result in a lower attendance and show that the groups with lower attendance then perform more poorly when assessed. They suggest that perhaps session timing may affect tutor performance (Arulampalam et al., 2012) in addition to student attendance but are cautious in their findings and resist claiming that the academic timetable has a direct impact on attainment, even though they have strong evidence to support this.

The day of the week is influential (Van Blerkom, 2001, Lang et al., 2008, Devadoss and Foltz, 1996, Newman-Ford et al., 2008), with Friday in particular being regarded as causing higher than average rates of absenteeism at scheduled sessions.

Other timetable attributes considered in studies included days containing a single timetabled session (Kelly, 2011, Persky et al., 2013) those which include an extended break between sessions (Fjortoft, 2005) and those suggesting session duration may influence attendance rates (Ghenghesh and Nakhla, 2011, Devadoss and Foltz, 1996).

Kelly’s study of Irish students showed that when a student day contains a single timetabled session attendance rates are lower compared to days containing two or more timetabled sessions (Kelly, 2011).

Fjortoft who used a focus group approach with American Pharmaceutical students to identify the factors which alternatively encourage or discourage lecture attendance, found that a break of two hours before or after a timetabled session causes a reduction in attendance rates (Fjortoft, 2005). She attributes this reduction to students leaving campus during the break and then not returning. She notes that student perceive these longer breaks in the academic day as wasted time, and that they prefer to go home despite study space being available on-campus.

A comparative study into the causes of student absenteeism as perceived by staff and students in the US (Persky et al., 2013) showed that students ranked course timetabling issues as the 2nd most important cause after the availability of course materials online. In terms of the specific timetable attributes considered within the study, students indicated that having one session on a given day was the most influential, followed by sessions at the end of a long day, those at the start of the day or those that occurred before or after a break of two hours or more. Staff underestimated the effect of timetabling issues on student absenteeism, and regarded them as being significantly less important.

Fjortoft suggests that different factors motivate students to attend sessions, and prevent attendance (Fjortoft, 2005). Issues associated with poor timetabling were found to have a disabling influence on attendance, but conversely a good timetable was never recognised as being responsible for encouraging attendance.

Students are poor time managers and they are often absent simply because they are undertaking academic or course work for another subject (Hunter, 1999, Ghenghesh and Nakhla, 2011, Persky et al., 2013). This leads to attendance declining as the academic semester progresses and as assignment deadlines become more frequent (Van Blerkom, 2001).

Some studies report that session timing interacts with transport issues to reduce attendance (Bati et al., 2013, Hunter, 1999, Kottasz, 2005) whilst Kirby et al suggest that those who live further away attend more frequently (Kirby and McElroy, 2003) although their results don't show a consistent trend across all distance categories.

Two authors, Kelly and Davis, both recommend that attention to the design of the academic timetable is adopted as a policy for improving attendance.

However, not all the evidence linking poor timetables to poor attendance is conclusive. In an Australian study of the factors affecting absenteeism amongst final year commerce students, classes timed at the extremes of the day did not appear to be consistently less well attended than those scheduled during the main part of the day, despite the presentation of anecdotal evidence to the contrary (Massingham and Herrington, 2006). Similarly although Devadoss and Foltz's study identifies that sessions scheduled between 10:00-15:00 will see a 2.4% increase in attendance over those outside this window (Devadoss and Foltz, 1996), but this finding is only significant at the 10% level and as such is not as conclusive as it could be.

The evidence presented in these studies suggests that a student's academic timetable can be a malign influence on their study behaviour, and that all timetables are not equally as good (or as bad).

The studies identified in this section focus largely on within-day timetable attributes; specifically session timing, the number of contact hours in the day and the duration of breaks. They ignore the potential effect of the between-day attributes; contact hours per day, session balance between days and timetable variability. Similarly the relationship between timetable and the amount of discretionary time spent by students on-campus has been overlooked.

A chain link fence is as an effective barrier as a brick wall and yet for the most part it consists of fresh air. Similarly the academic timetable is made up of a mixture of scheduled sessions and breaks before, after or between these sessions. It seems that when considering the effect of timetable on attendance, academics have to date largely focused on the scheduled sessions, and ignored the effect of the gaps between them even though, like the chain link fence, they must both contribute to the overall effect.

This approach towards considering a wider range of timetabling affects mirrors the approach taken by researchers who have studied the beneficial effect of interactions between students and staff that occur outside of the classroom (Pascarella et al., 1978, Cox and Orehovec, 2007, Lundberg and Schreiner, 2004), instead of simply focusing on attendance at taught sessions.

The piecemeal nature of the existing research into student timetable quality justifies research question 3: what constitutes a high quality timetable from a student point of view? (RQ3), whilst the effect of timetabled breaks on student leave-and-return behaviour is hinted at but has not been formally investigated justifying research question RQ4 (do students exhibit leave-and-return behaviour?).

2.7.2 Timetable and Travel Behaviour

There are limited examples of studies around attempts to use the timetable to influence student trip-making, and all that have been identified mainly focus on varying the daily start time for sessions.

Toor suggests that the start time of classes might be staggered to allow student commuter demand for parking to be dispersed (Toor and Poinsatte, 1999, p. 46). A practical example of this approach occurred in 2001 when the University of British Columbia faced a problem of excess demand for their AM peak bus services to campus. They addressed this through an alteration to their timetabling policy so that instead of having a fixed morning start time for all students, sessions were staggered across an hour long window. (Toor and Havlick, 2004, p. 189-190). This change redistributed demand across the peak resulting in an increase in bus ridership by 12%, with no change in service frequency.

Daniels and Mulley describe a similar problem of supressed peak-time demand for public transport services into central Sydney, where students travelling to the university compete with workers for places on bus services (Daniels and Mulley, 2012). They investigate a solution that involves rescheduling academic sessions timetabled for the early morning in order to shift student travel demand into the off peak. However, they reject this approach on the grounds that it might simply redistribute the problem into the evening peak, and also because the capacity released by students would immediately be taken by other commuters who are currently crowded off these services.

Toor imagines a future scenario in which sophisticated types of distance learning techniques are combined with learning modes designed to fit around students' work, school and family commitments and which deliver trip reduction benefits (Toor and Poinsatte, 1999, p. 45). It could be argued that what Toor is imagining in this scenario is something akin to the emerging MOOC delivery channel for higher education.

The lack of reported studies in this area further justifies the inclusion of research questions RQ1, RQ2 and RQ4.

2.8 Summary

This chapter contained a review of the existing literature around the themes to be developed within this thesis.

The review established that university timetabling is a complex process, that when designing timetables institutions are encouraged to prioritise teaching space utilisation over other concerns and that this reduces the optimality of the timetables produced for other stakeholders; staff and students.

The literature shows that student attendance at lectures and on-campus is important, resulting in increased levels of engagement and attainment and demonstrates that timetable design could exert a malign influence by reducing the attendance of those students who are randomly assigned poor quality timetables.

The limited work examining perceptions of student timetable quality was reviewed and it was demonstrated that studies have focused on the effect of within-day timetable quality attributes and largely ignored the effect of between-day attributes such as the ratio of TTDs to NTDs within the timetable.

The potential impact of large scale staff and student commuting on the campus and the containing urban network was established and the review showed that whilst some work has been conducted examining how to mitigate its effects, limited research of the factors behind student trip generation has been conducted and none has attempted to investigate any link with the academic timetable.

The literature review has identified that the relationships between the academic timetable and student trip-making, student engagement, student attainment and institutional sustainability are all potentially important but have generally been overlooked in existing research work. This creates the research gap which justifies the development of the research questions outlined in Chapter 1 and summarised in section 1.4.

Chapter 3 – Methodology

3.1 Introduction

The aims of this study are as follows. Firstly, to explore the current understanding of the relationship between the student timetable and trip-making behaviour and to investigate the opportunities to improve institutional environmental sustainability presented by this relationship (A1). Secondly, to identify student preferences towards timetable design, to determine how these preferences are shaped by/influence student trip-making (A2), and thirdly, to examine the effect of the timetable on longer-term student trip making behaviour and to investigate the impact of timetable design policy on the social/economic sustainability objectives of the campus-based university (A3).

To achieve these aims a three stream approach is taken to data collection and analysis consisting of:

- Stream 1 (UTR) – a review of UK university travel plans,
- Stream 2 (TQS) – a timetable quality survey,
- Stream 3 (OSS) – a longitudinal observational survey technique for examining student trip-making behaviour and presence on-campus.

A roadmap for the different approaches taken and the elements discussed within the thesis is shown in Figure 1. The road map shows how one element leads onto the next and highlights how the results from one analysis stream are used to validate or to support the evidence collected through the other streams.

Much of the work in this thesis, its aims, objectives and research questions is focused around gaining an understanding of whether students trip-making behaviour is informed by a traditional or the contemporary view of their timetable (RQ1) and this question is addressed in each of the three streams. The review of UK university travel plans highlights current understanding, the travel behaviour elements of the TQS (stream 2) allow this relationship to be quantified using a traditional survey methodology, whilst the OSS (stream 3) provides an alternative longitudinal approach to delivering the same information. The final element of the thesis, the review of evidence, synthesises the results obtained through each analysis stream into a single set of study-wide conclusions and recommendations.

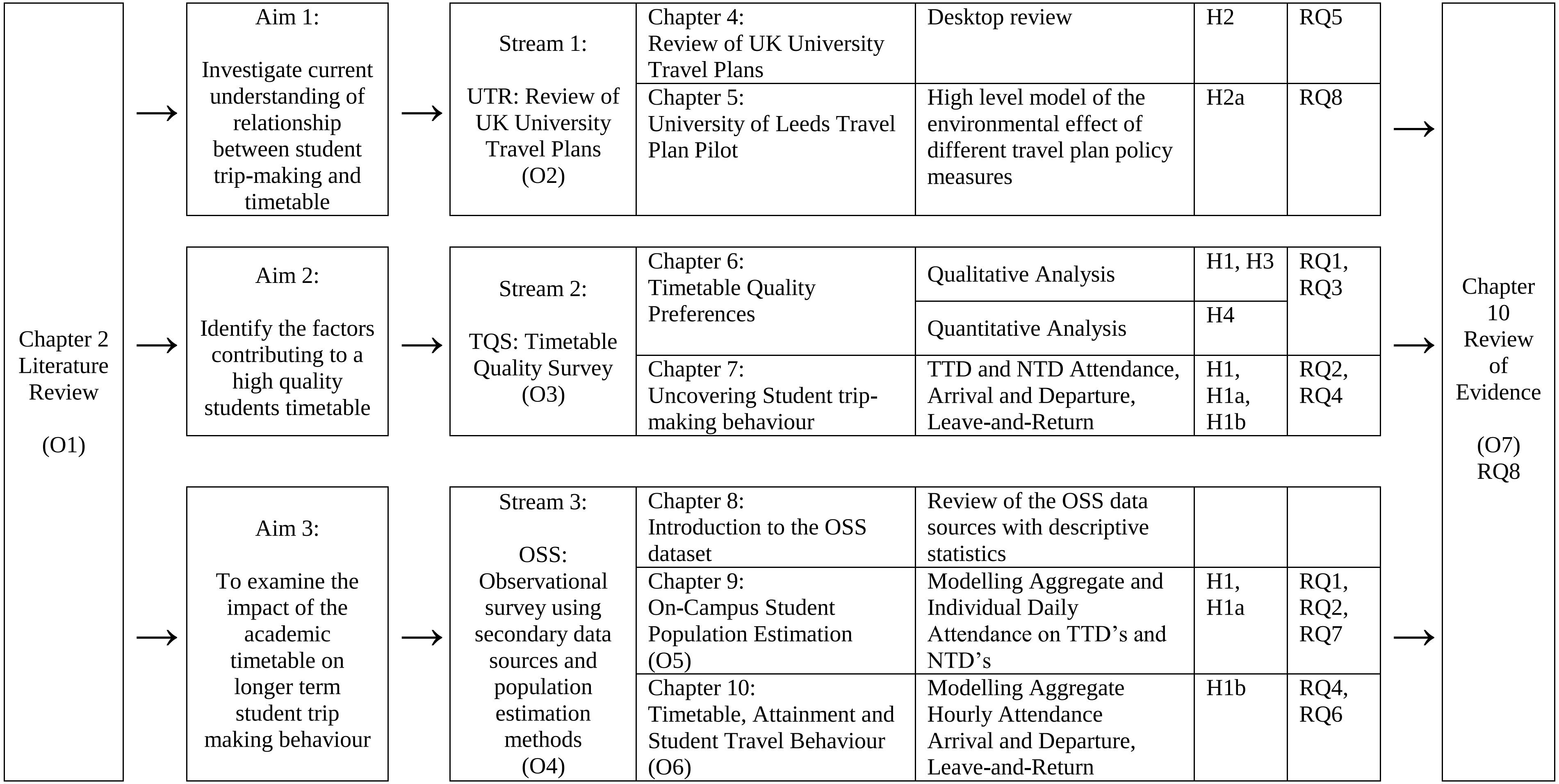

Figure 1 – Thesis Roadmap

The roadmap demonstrates that most of the research questions are addressed by more than one of the streams within the study, whilst the alternative methodological approaches used in each stream allow each question to be examined from a different angle thereby cross-validating the results.

The justification for and approach taken within each stream will now be described.

3.1.1 Review UK University Travel Plans

The first analysis stream within this thesis performs a UK university travel plan review (UTR). Chapter 2 described a review of the published literature on student travel behaviour. This showed that only limited work has been conducted in this area, that it provides little insight into real student trip-making behaviour and that no previous work has attempted to systematically investigate the potential links between timetable and travel behaviour.

Travel planning practitioners working within UK universities, undertake non-academic work using similar approaches to those described in the studies reported in section 2.6. This work is conducted as part of the efforts within universities to create staff and student travel plans and involves executing travel surveys to provide data to facilitate both the development of a travel plan and to measure progress towards the targets set out in the plan. The aim of a travel plan is to influence individual travel behaviour towards the choice of more sustainable alternatives, and to achieve this aim a proper understanding of existing travel behaviour is required. Therefore any link between timetable and student trip-making should be apparent either directly within these plans, or from an analysis of the survey methodologies or travel behaviour data on which they are based. Furthermore if student trip-making can be shown to be linked to a contemporary view of the timetable, and if this is not recognised within university travel plans then this in itself would represent an important finding, in that it identifies an area of travel planning practice which is as odds with real travel behaviour. This analysis stream encompasses a systematic literature-search approach to the collection of travel plan data, followed by an analysis and commentary on the collective content of the plans obtained, Chapter 4.

The second part of the review, Chapter 5, involves assessing the impact of academic timetable design on the environmental sustainability targets now being set for universities and examines the effectiveness of using intelligent timetable design as a travel plan measure. This element uses a simple quantitative modelling approach suggested by Potter (Potter, 2007), employing real-world data obtained from the UoL travel plan and other complementary sources.

3.1.2 The Timetable Quality Survey

The timetable quality survey (TQS) is used to explore student preferences towards their timetable in order to determine the features that are to be found in a high quality student-centred timetable.

The aims of this analysis stream are as follows. Firstly to discover what constitutes a high quality timetable for students, which attributes they value in their timetable and what features they dislike. Secondly, to identify what student timetable preferences suggest about student trip-making behaviour and thirdly to determine the extent to which student timetable preferences are influenced by a student's home to campus travel time. This stream is important because as identified in section 2.2.2 little research has been conducted in the area of student timetable quality. Similarly there is no consensus in terms of the timetable attributes valued by students, although some potential candidate attributes are suggested in work linking timetable to session attendance, see section 2.7.1.

The timetable quality survey (TQS) represents a traditional questionnaire survey-based approach to data collection, obtaining responses from a random sample of the total student population and then after for checking for bias in the sample taking the responses as being representative of the population. The data elicited through the TQS is divided into two categories. The first section of the survey obtains data around student timetable preferences using an unstructured approach that makes no assumptions around what timetable attributes students may either value or dislike. Both qualitative and quantitative preference data is collected, thereby further broadening the scope of the survey. The second part of the survey obtains information around student trip-making behaviour through the use of questions that define each student's trip-making relative to their timetable on any given day, as an alternative to the use of direct questions about the characteristic of all trips made within a specific period of time. This approach differs to that used within the travel surveys typically conducted as part of the development of a university travel plan.

A thematic analysis approach is applied to the qualitative data obtained through the survey, whilst standard parametric statistical tests, and linear regression and ordered logistic modelling techniques are used for processing the quantitative data.

The results from the TQS allow the main characteristics of student trip-making behaviour to be quantified whilst at the same time providing a consistent view of student timetable preferences.

3.1.3 The Student Trip Making Observational Survey

The main analysis stream of the thesis focuses around the development of a novel and repeatable observational survey (OSS) technique for examining student behaviour on-campus and student trip-making to and from campus. The justification for the development and inclusion of this technique is given below.

Studies of student behaviour usually require that students provide information for a 'typical' day' or week either directly (Eom et al., 2009) or through a diary based approach (Kamruzzaman et al., 2011, Gonzalo-Orden et al., 2012, Limanond et al., 2011a, Khattak et al., 2011).

This approach presupposes that either student behaviour does not vary or that students can efficiently aggregate any variation in behaviour into a response for the 'typical' day or week. The evidence suggests that student behaviour changes over time and that in this context there is no such thing as 'typical'. Lecture attendance varies across days of the week (Devadoss and Foltz, 1996, Newman-Ford et al., 2008) and reduces as the semester progresses (Colby, 2004, Van Blerkom, 2001) whilst Crede identifies variation in attendance by year of study reporting that students in the later years of their course are less likely to attend at classes (Crede et al., 2010). A time-use survey uncovered that some respondents adjusted the study time-use value they reported for a specific day as it was *'not typical for them'* (Stinebrickner and Stinebrickner, 2004). Babcock reports on a meta-analysis of American student time-use studies covering a period of fifty years which demonstrates a consistent and continuing decline in students' study time over that period (Babcock and Marks, 2008).

Student behaviour exhibits variation within-day, within-week, within-semester, between year of study and by chronological year, and therefore it is reasonable to assume that their trip-making behaviour may also exhibit some degree of variation. At the same time, as shown in section 5.2.1 many individual timetables also evolve/change over a semester and this may also affect behaviour patterns.

The traditional method for gathering data about individual trip-making behaviour is through the travel diary in which respondents specify the detail of all the trips they make over the study period (Stopher and Greaves, 2007). Student diary-based surveys that focus on a specific day or one week risk failing to capture the full extent of student behaviour variation. Longer study periods are often not possible due the higher respondent burden meaning that longer term changes in behaviour are difficult to observe (Stopher et al., 2008), or result in sample sizes that are unrepresentatively small.

For the purposes of this study the OSS technique needs to be: comprehensive – so that it covers all undergraduate students, repeatable – so that it can be applied more than once and sensitive – to within-day, within-week and within-semester variation.

A secondary data source is one in which data is captured for some purpose unrelated to the survey, but from which useful information about the object being surveyed can be obtained, derived or inferred. Information Communication Technology (ICT) devices present a rich potential secondary data source, as they are ubiquitous, and have capacity for data capture, storage and retrieval.

There has been significant research interest in this field, particularly into the possibility of using data from mobile phone records in transport modelling; for example in deriving origin and destination trip pairs (Caceres et al., 2007), to determine travel times (Bar-Gera, 2007), to impute transport mode (Reddy et al., 2008), to derive vehicle flow characteristics on inter-urban highways (Herrera, 2010), to reveal daily trip patterns (Ahas et al., 2009) and to infer and predict user activity patterns (Papliatseyeu and Mayora, 2009).

Techniques have been investigated for inferring individual movement patterns from device activity on wireless (Wi-Fi) networks (Athanasiou et al., 2009) and through the logging of Bluetooth enabled devices within the proximity of fixed monitoring stations (Hay and Harle, 2009, Van de Weghe, 2009, Fernandez et al., 2007). Both Wi-Fi and Bluetooth devices represent themselves to the network using a fixed unique identifier (MAC address) that does not identify the owner of the device. Therefore detecting the same device in different locations over time allows the partial movement pattern of the owner to be discovered, without any personal details related to the owner being revealed.

A similar approach is adopted in this study using information recorded in the usage logs of student interaction with university IT systems; the library and sports centre turnstile entry systems, the campus fixed PC network, the campus wireless network and the refectory prepayment meal-card system. Soria proposes a similar method, albeit more limited in scope, to study the effect of library usage on student retention and attainment (Soria et al., 2013).

The purpose of the OSS technique is to obtain an estimate of the number of students on-campus on any given day or any hour within a day and from this to make inferences about student trip-making behaviour.

The OSS dataset represents only a partial record of student activity on-campus and the method used to process this data shares characteristics with the problem of 'imperfect detection' which occurs in an ecological context and where the function E(x), equation 3-1, can be used to define the abundance of a species (Kery and Schmidt, 2008).

$$E(n) = N * a * p \tag{3-1}$$

where:

N	The total species population
n	The sampled population count
a	The probability that a member of the population is available for detection
p	The probability that the member of the population will be detected given that it is detectable

In the context of the OSS, a represents the probability that any student will come to campus on a given day and p the probability that any student will be detected given they are on-campus. To derive the number of trips it is necessary to calculate $\hat{n}$, the number of students on-campus at any time, equation 3-2.

$$\hat{n} \approx \frac{n}{p} \approx N * a \tag{3-2}$$

The results obtained through processing the OSS dataset using estimation techniques applicable to animal populations are then analysed using ordered logistic regression models.

The OSS technique allows research questions around student trip-making and presence on-campus to be answered using a method that is comprehensive, repeatable and sensitive to variation. The results provided through the OSS can be partially validated against similar results provided through the TQS.

Chapter 4 – UK University Travel Plans

4.1 Introduction

This chapter contains a desktop review of UK university travel plans (UTR) and their associated travel survey methodologies, partially delivering research objective O2 (conduct a review of university travel plans) and addressing RQ5 (how do university travel plans represent student trip-making behaviour?).

The primary aim of the review is to determine the degree to which the academic timetable is recognised by university transport planners as being a contributory factor in determining student travel behaviour, given that guidance on the preparation of university travel plans indicates that timetabling should be considered when developing a travel plan (Forum for the Future, 2003, p. 9).

A secondary aim is to look for evidence of student leave-and-return behaviour in the travel plans. This behaviour was informally identified in a study of timetable and attendance (Fjortoft, 2005) and dependant upon the number of breaks in the timetable could represent a major source of trips.

The review will examine the commuting trip data collected from students through university travel surveys, investigate the methods used to represent student trip-making patterns, and describe how this data is used to measure progress against travel plan targets.

The chapter will question whether university travel planners see student travel behaviour as being distinct from staff workplace commuting.

The background to the use of travel plans within the UK was explored in section 2.5, whilst the impact of the university campus on its hosting transport network was discussed in section 2.6.

Within the university sector the travel plan can potentially have a major impact on travel behaviour, whilst their unique demographic composition and the need for proactive planning together make them great laboratories for testing and implementing various alternative transportation strategies (Balsas, 2006). At the same time the travel choices made by a student whilst at university, and any exposure they gain of active modes may influence their future travel choices (Toor and Havlick, 2004) meaning that a planned approach to university travel provision can have an immediate effect on the short-term behaviour of the university population and longer-term effects on the future travel behaviour of university alumni within the wider community.

Although many universities have adopted a travel plan, within the UK as a whole workplace travel plans have had a limited take up with only 6% of businesses adopting a formal written plan (Enoch, 2012, p. 53) whilst being perceived by organisations as burdensome and non-essential (Enoch, 2012, p. 56).

It could be argued that by discouraging SOV trips, the travel plan provides societal benefits, reducing the external costs associated with congestion and that these savings are being offset by additional costs incurred by participating organisations to develop and operate the travel plan. In this sense the travel plan could be seen as an optional congestion reduction business charge levied on the businesses which decide, or are coerced through planning conditions, to participate. However in larger organisations which typically provide workplace parking, like universities, the balance between travel plan costs and benefits can change in favour of the organisation.

The provision and maintenance of workplace parking is expensive (Toor and Havlick, 2004, chapter 3). This means that organisations providing workplace parking have more to gain from the implementation of a travel plan, in that it offers them a mechanism to reduce both the supply of parking spaces and demand for them. The plan itself provides external leverage for implementing unpopular policies, whilst revenue generated from parking charges can be used to sustain the operation of the travel plan and provide a revenue stream to support other travel plan measures. At UoL, for example, the cost of a parking permit covers the true economic cost of the parking provision (University of Leeds, 2013). In this scenario the external costs saved by encouraging users to switch away from SOV trips are transferred through parking fees onto those who still wish to drive, potentially making the travel plan cost-neutral to the organisation itself.

As a consequence, and as will be shown in section 4.2, over half of all universities have a travel plan and that in most cases the measures contained in each plan are being implemented and actively developed, making this review both representative and relevant.

4.2 Methodology

The approach used for the UTR has parallels with the methodology adopted in a standard academic literature search.

The rationale for this methodological choice is based on the belief that institutional travel plans will embody a deep understanding of student trip-making behaviour given their development by travel planning professionals. As has been suggested in section 2.6 the context, background research, policy measures, survey methodologies and survey results contained within UK university travel plans embody a rich collection of non-academic work around staff and student travel behaviour and as such is potentially as valuable a reference source as academic papers which discuss student travel behaviour.

Evidence was found of two previous systematic reviews of UK university travel plans (Selby et al., 2009, Tilbury, 2010) suggesting that other researchers also regard these documents as being valuable sources.

To perform the review a full list of higher education establishments in the UK was obtained from the Higher Education Statistics Agency (HESA). This list was filtered to remove the smaller institutions, the majority of the institutions in central London and those institutions that were effectively part of a larger university via a franchising arrangement. The website for each institution was located and the section dealing with travel planning visited. This was usually found under the Estates Management section, particularly for the older universities. The latest travel plan, and travel survey results (if available) were downloaded. It was found that some institutions did not list a travel plan but included an alternative travel related document, and in these cases this was downloaded instead. This method appeared to be a reasonable approach since the HESA require universities to declare in their annual environmental monitoring return that a travel plan is accessible via their website. When no document was found a chasing email was sent to the institution’s travel coordinator (if listed) or the general enquiries email address (if not). However, few responses were received to these requests and none of them delivered any further plans.

The survey took place between the 7th and 26th September 2012, with 116 institutions being surveyed across the UK (91 in England). A travel plan, or equivalent document, was found for 82 (71%) of them. A full list of all the institutions referenced and the documents retrieved for each is given in Appendix A. Of the documents identified 7 were found to contain a single page statement of travel plan objectives which was more of a placeholder rather than a fully worked out plan, and consequently these were discarded leaving 75 documents of various types for analysis, Table 1.

Document Title (n=75)	count (%)
Travel Plan	42 (56%)
Sustainable Travel Plan	7 (9%)
Travel Plan Update	7 (9%)
Green Travel Plan	4 (5%)
Transport Policy	3 (4%)
Workplace Travel Plan	2 (3%)
Travel Plan Guide	2 (3%)
Other Title	8 (11%)
Total	75 (100%)

Table 1 – UTR: University Travel Behaviour Document Titles

The average age of these documents was around 2.5 years from the date of access. The oldest was from 2001 (Manchester Metropolitan) with Glasgow Caledonian, Plymouth, Reading and York all having updated their plans in 2012. As would be expected the age of the most recent travel survey referenced in each of the plans was slightly older than the plan itself at approximately 3 years. The oldest travel survey was from 2004 (Bath Spa), whilst both Glasgow Caledonian and Reading had completed surveys in 2012.

Analysis of the travel plans entailed reading each one and identifying/classifying any evidence of:

- the travel reduction/behaviour change measures adopted by each institution (sub divided into mode specific and non mode specific measures),
- explicit references to the academic timetable as being a factor in determining student travel behaviour or of measures which use timetable to influence student travel behaviour
- the survey methodology adopted by the travel plan to obtain evidence of actual student travel behaviour.

4.3 Review of UK University Travel Plans

This section summarises the evidence of travel plan measures, the influence of timetable on student trip and of the survey methodologies found within each of the reviewed travel plans.

4.3.1 Review of Mode Specific Travel Plan Measures

As stated in section 1.1.5 the aim of a travel plan is to reduce the share of SOV trips through the promotion of measures to support other modes. Collectively the UK university travel plans represent an impressive collection of good practice in this regard and identify a variety of unique measures, while other measures are common to many institutions confirming the approach of Toor (Toor and Havlick, 2004) who proposes universities should mix and match measures from a TDM toolbox.

The aim of this section is not to provide a definitive list of all types of mode specific travel plan measure currently adopted by UK universities, after the approach taken by Selby et al in their review of university plans (Selby et al., 2009, section 5.0). Instead the purpose of this review is to present evidence of an apparent bias within the focus of travel plans towards mode specific measures.

In the following examples one institution is cited against each measure (as evidenced through their travel plan), although in most cases multiple institutions may have implemented each measure.

Traditional approaches to control and influence the mode share of SOV trips are implemented through a series of supply-side and demand-side traffic management measures.

The control and charging for workplace parking is often essential to the overall success of a travel plan (Cairns et al., 2010), but the introduction of parking charges at workplaces is difficult and are only usually accepted for large trip generators and in those places where visitors also come to site, for example universities and hospitals (Rye and Ison, 2005).

University travel plans contain measures to reduce the supply of existing on-campus parking spaces or to develop new facilities with a reduced employee/parking space ratio, matched with by complementary policies to limit demand.

Parking charges (Bath) that represent the real cost of parking provision (Derby) and/or permits are typically used to restrict access to parking spaces. Sophisticated schemes have been developed to ration the provision of permits by assessing residential distance (Plymouth), vehicle emissions band (Exeter), salary level (UCL, Manchester), or through a multi-criteria points system (East Anglia). Often the provision of the permit does not guarantee a daily parking space, just the right to search for one. Typically students are banned from applying for permits for on-campus parking (Plymouth), or are limited to the number of times per year that they may park on campus (Surrey) and often have access to parking spaces at halls of residence restricted (Sussex). A low annual permit cost plus a daily parking charge is preferable to a higher fixed annual cost, as this forces users to confront the personal economic impact of car use whenever they drive to campus, and allows for other modes to be used for some part of the week (Exeter, Aberdeen). Other parking demand reduction measures include the removal of a parking permit application form from the new employee induction pack so that the car is no longer seen as the primary commuting mode (Derby) and pool cars being provided for business meetings to reduce the need to specifically bring a car to work for this purpose (Cumbria).

A significant life event (house move, new job) offers the individual the opportunity to re-evaluate their travel choices (Ampt et al., 2006). Some institutions target the induction process, offering new staff the option of a personal travel planning service (Highlands and Islands) or comprehensive travel information and support (Brighton).

Car or lift sharing schemes are used by most of the institutions although limited take-up appears to be a problem for some (Leeds Metropolitan). Many universities have joined county-wide (Exeter) or national (Southampton, Newcastle, Leeds Metropolitan) schemes to increase the pool of potential sharers.

Car-sharing and parking policy are linked by some with priority being given to parking permit applications from car-sharers (Plymouth), reserved spaces being made available to those who share (Hull), new permit holders automatically being enrolled into the car-sharing scheme (UCLAN), one parking permit being allocated to two cars in a share arrangement but with only one being used on any given day (Manchester), permit cost rebates for car-sharers (Derby), hosted coffee mornings to introduce employees living in the same areas (Derby). Most car-share schemes are complemented by measures to provide a guaranteed ride home in case of emergencies.

Walking is regarded as the most sustainable mode and all university travel plans contain measures to encourage the uptake of walking, including: the development walking routes (UCLAN), provision of information and maps (Highlands and Islands), improved pedestrian on-campus infrastructure with dropped crossings, tactile pavements, signage, seating (Hull), and priority maintenance of footways (Northampton). Some measures highlight the health benefits that accrue from walking and these include: self-guided walking tours of campus, and guided lunchtime health walks (Exeter), loan scheme for pedometers, with prizes for most miles walked in one month (Brighton), and a weekly running group (Plymouth). Personal safety is regarded as an issue by some and measures designed to reduce risk are mentioned: provision of personal attack alarms for students (Leeds Metropolitan), working with the police on the development of safe walking routes (Huddersfield), walking warden available for anyone who feels unsafe (Kent). Practical problems associated with walking are also addressed: walk-buddy scheme (Leicester), provision of luggage trolleys at a subsidised cost for those with lots of papers (Derby), loan umbrellas (Essex), and links to weather forecasts available through the university IT portal (Huddersfield).

Active travel through cycling is promoted at many institutions and measures include: high quality showers (Leeds Metropolitan), changing facilities and drying rooms (Brighton), supply-side measures to increase the provision of cycle parking (Portsmouth) or to replace car parking with cycle storage (UCL), secure cycle storage with CCTV monitoring (Derby), improved on-campus cycle paths and signage (Bournemouth), on-campus bike hire schemes (East Anglia), pool bikes available to staff for short trips off-campus (Essex), bike recycling and recovery (Southampton) which are then resold to students (Kent), employee bicycle purchase salary sacrifice (Northampton), tax free cycle purchase schemes (Coventry), mileage allowances for business trips made by bike (Bath), a cycle buddies scheme to link novices and more experienced cyclists who live in the same area (Brighton), local cycle maps showing safe routes to campus (Hull), institution-wide bicycle user groups (Cardiff), cycle training courses (Dundee), discounts on cycle purchases and maintenance at local shops (Reading), on-campus bike shop offering bike health check service (East Anglia), cycle lock loan for students (Bath), cycle security coding (Leicester), and promotional events, such as the bike to work week (Lancaster).

The use of public transport is seen as being a more sustainable alternative to private car and university plans contain measures to address some of the financial implications of providing public transport services and/or offer economic incentives to encourage public transport use amongst staff and students including: income from parking charges providing a subsidy towards bus operating costs (Derby), on-campus parking charges harmonised with the price of public transport (Southampton), discounts provided on public transport ticket purchases (Warwick), salary sacrifice scheme for season ticket purchase (Reading), students residing in halls given free bus tickets to introduce the bus as a viable mode and to encourage behaviour change (Derby), a university-wide smartcard used to provide building access and the library also includes a purse for public transport fares (Plymouth), and promotional events like a ‘try the bus for free week’ (UCLAN).

Depending upon their local context institutions adopt different strategies in relation to the provision of bus services. Some limit involvement to lobbying operators for service improvements (Reading), whilst others attempt partnership working with PTEs and bus companies (Leeds Metropolitan). Some work with operators in a franchise arrangement to create a dedicated high quality bus network along popular commuting routes (Oxford Brookes) or to provide a free city-link bus service with subsidised onward fares (Manchester) whilst one university owns and operates its own bus network (Hertfordshire). Other measures include the development of walking routes to public transport interchanges (Brighton), upgraded bus stops with real-time information (Lancaster), a redesign of campus road layouts to allow more efficient bus operations (Northampton), or information provision in the form of public transport options leaflets for staff, students and visitors (Brighton) and on-campus information stands providing bus/rail maps and timetables (Highlands and Islands).

Some university campuses are sited close to railway stations and in these cases the institutions also promote rail use through similar measures to those suggested for developing bus mode share.

4.3.2 Review of Non Mode Specific Travel Plan Measures

As stated in section 2.5 the primary aim of the travel plan is to reduce the number of SOV users, and this explains the apparent emphasis of mode change identified in 4.3.1. However, whilst travel mode is an important element in determining the impact of any trip, the simple equation below (after Banister and Stead, 1997) demonstrates that other factors also influence this.

Trip Impact = Trip Mode x Trip Frequency x Trip Length x Trip Timing

A reduction in the frequency with which a particular trip is taken will decrease impact through an absolute reduction in the number of trips made, whilst the origin and destination for a trip will determine its length, and the departure and arrival times for the trip will determine whether the trip takes place during the peak or off-peak period (trip timing). University travel plans may contain measures that address some of the elements in this impact equation. Many plans describe trip mitigation measures for staff in the form of flexible working and flexi-time schemes, whilst a reduction in staff trip frequency is addressed through teleworking arrangements and the offer of a compressed working week where the job allows it. Flexible working arrangements potentially retime commuting trips away from the peak period (trip timing), whilst teleworking and a compressed working week reduce the absolute number of commuting trips (trip frequency), although some of these may be offset by additional home-based non commuting trips (Vilhelmson and Thulin, 2008).

Evidence of student travel reduction measures is more limited although a remote working approach is suggested, and travel plans highlight the provision of a virtual learning environment, or a blended learning approach, to deliver or support some part of the curriculum online (Anglia Ruskin, Cardiff, Exeter, Glasgow, Gloucestershire, Hertfordshire, Huddersfield, Kent, Swansea Metropolitan). Other

ICT related measures include the provision of Skype pods (Huddersfield), and document sharing/instant message services for students (Cardiff).

Organisational users of workplace travel plans are usually unable to influence the length of the commuting trips made by their workers, as they are unable to specify where they should live, but universities are unique in this sense in that they exert some degree of control over the estate land-use policy and the location of student residential accommodation. Consequently measures to reduce student trip length and raise the share of the active modes by increasing the provision of student residential accommodation on or close to campus is a common theme (Bath, Durham, Greenwich, Hull, Portsmouth, Sussex, UCL, Warwick). Other plans suggest a similar approach for staff (Manchester, Cambridge) whilst Swansea Metropolitan suggests offering incentives to staff who relocate closer to campus.

Middlesex's travel plan cites their long term strategy of consolidating all of their operations onto a single campus as a means of reducing inter-site travel and achieving agglomeration benefits, whilst Bath and Kent both highlight the provision of on-campus services (nursery, doctor) and shops as a measure to reduce day-time trips away from campus.

4.3.3 Evidence of Timetable and Timetable Related Measures

Evidence of the effect of the timetable on student travel behaviour is limited although some examples were found in the reviewed travel plans.

The academic timetable is cited as a barrier to the uptake of certain travel plan measures. Low levels of car sharing by students is blamed on mismatches in session start and end times (Aberystwyth, Bath Spa, Swansea Metropolitan), whilst the scheduling constraints imposed by the timetable represent a barrier to students who might want to move peak-time commuting trips into the off-peak period (Derby). Northumbria explains the differences between student morning arrival time profiles in two annual surveys as being possibly caused by changes in lecture schedules.

Guidance on the preparation of a travel plan for higher education institutions suggests that consolidation of timetables (reducing the number of TTDs per week) is a measure to be considered for implementation within a university travel plan (Forum for the Future, 2003, p. 41) and two institutions suggest that attention to the design of the timetable could constitute a main measure for influencing student travel behaviour (Southampton, Hertfordshire), although both recognise problems associated with this approach. Southampton's travel plan suggests that changes to timetabling are outside the scope of the travel plan to deliver, whilst Hertfordshire's plan limits commitment to a review of timetabling policy. Two travel plans cite the example of timetable consolidation (Hull, Swansea Metropolitan) but neither makes this a specific measure in their plan.

Other travel plans suggest more limited timetable related measures. Alterations to the timing of the first and last sessions of the day is suggested as a possible measure for influencing the timing of student commuting trips (Warwick) whilst extending the academic day to twelve hours (from 8:00 to 20:00) to achieve some degree of peak spreading is proposed in Southampton's plan. Harper Adams and Huddersfield both suggest limiting the need for inter-campus travel between sites by scheduling all sessions on one site to run consecutively.

4.3.4 Analysis of Travel Plan Survey Methodology and Data Collected

All travel plans should include a set of SMART targets or objectives (Department for Transport, 2008, p. 10). A target or objective is SMART if it is Specific, Measurable, Attainable, Realistic and Time-bound. In a university travel plan a SMART target will refer to the level of travel behaviour change expected to be seen by a particular type of user (staff, student, visitor, supplier) for a certain type of trip (commuting, business, delivery) over a specific time period.

When setting the targets for behaviour change the national guidance suggests that they should be expressed as, for example: "*the number of commuter cars arriving per 100 employees*" (Department for Transport, 2008, p. 19) since "*this allows you to judge progress over time"*.

This guidance focuses targets for workplace trips towards changes in the relative percentages of trips taken by each mode. So a reduction in car trips of 5% will be traded with an increase in trips by other modes that sum to a total of 5%.

Measurement of progress towards the plan's targets should be performed by conducting travel surveys which examine travel behaviour characteristics of the organisational population at the start and the end of the time period (Forum for the Future, 2003, p. 35). The travel survey will aim to capture sufficient information about individual travel behaviour to make measurement/calculation of total trip levels possible. A sample travel survey included in the national guidance suggests that the following data items are obtained for employee commuting trips (Department for Transport, 2008, p. 62): home post code, normal place of work, normal travel to work distance, normal arrival and departure time, working days/week, travel mode for each trip taken over last 7 days, alternative travel mode(s) used if main mode not available. The sample survey then continues with further questions related to the willingness to use more sustainable modes, the barriers preventing the uptake of these modes and a set of questions related to business travel behaviour.

The main items collected through this survey pro-forma define all the attributes of a typical commuting trip: origin, destination, length, frequency, mode and timing. Using this data the overall modal trip percentages required for assessing progress towards the targets specified in the travel plan can be calculated relatively easily.

The university travel plans which included data on travel behaviour expressed this as the percentage of trips by each mode, matching the national guidance. Most travel plans recognised the need to stratify trips by user type, and displayed a different set of modal split percentages for staff and student trips. Similarly when targets were specified for travel behaviour change these were generally specified as decreases (or increases) in the percentages of trips being undertaken by specific mode, and again these were stratified by user type.

The modal split percentage for the least sustainable trip mode, single occupancy vehicle (SOV) trips, for both staff and students was found in 46 of the travel plans[3]. Analysis shows that the staff SOV mode share varies widely by institution from a low of 18% (Bristol) to a high of 74% (East Anglia) and similarly for students from a low of 4% (York) to a high of 44% (Derby). This confirms the analysis of Enoch (Enoch, 2012, p. 2 and chapter 3) who proposes that each organisation will have a unique demand profile that depends on spatial conditions, local land use policy and transport system supply combined with organisational, locational and user travel behaviour characteristics.

The range of values in this data-set also suggests that mode share percentage comparisons across universities are meaningless since the figures represent responses to the unique conditions existing at each institution, and that mode share percentages only have validity for measuring travel behaviour change over time within an institution.

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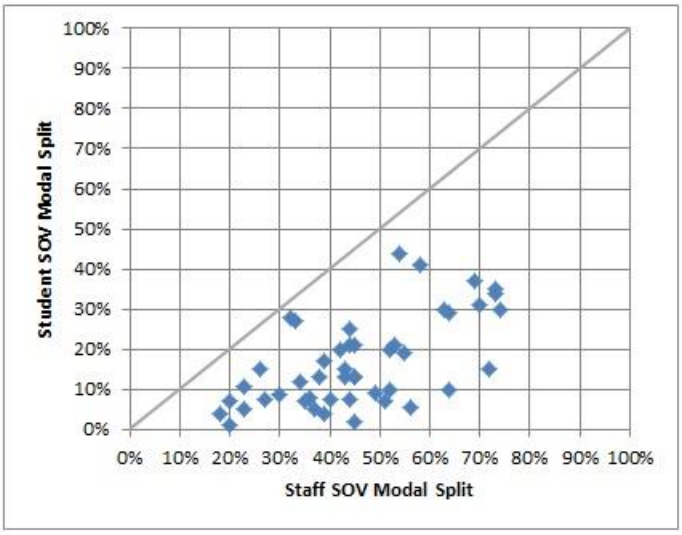
[3] The HESA environmental dataset contains figures for institutional staff and student SOV mode share. However, these appears to be of a poor quality with many obviously incorrect data points which differ from the figures given in the travel plans. Therefore the SOV mode share figures contained in the travel plans were felt to be more accurate.

What the figures do show, however, is that within the plans reviewed SOV use by staff always exceeds the equivalent SOV mode share figure for students attending the same institution, Graph 1. This is not surprising as students are less likely to have access to a vehicle, whilst the measures identified in the plans typically discriminate against students and in favour of staff car users, discourage student car use through parking restrictions and the denial of student parking permits for campus and halls of residence.



Graph 1 – UTR: Staff/Student SOV Modal Splits By Institution

Of the 75 university travel plans that were analysed, 58 (77%) were found to include results from a travel survey. Three of these institutions based their analysis on the hosting local authority's workplace travel survey data (Huddersfield, Leeds Metropolitan, and Cambridge), whilst another three conducted a parking survey (Surrey, East Anglia and UCL). Three institutions only surveyed staff (City University, Roehampton, Southampton Solent), although all three indicated that a student survey would be conducted in the future. In 11 cases (15%) no evidence of a survey was found even though a travel plan or transport policy measures were defined (Anglia Ruskin, Birmingham, Essex, Greenwich, Hull, Lincoln, Liverpool, LSE, Manchester Metropolitan, Oxford, West of Scotland). Of the remaining travel plans, 22 of them either included a pro-forma of their survey, or contained a sufficiently detailed analysis of the survey responses to allow the content of the survey to be inferred. Table 2 lists the institutions which specified their travel survey instrument together with the data items relevant to commuting trips to campus that were collected in each surveys.

The data collected through these surveys matches that specified in the DfT guidance, and whilst all surveys capture the main trip mode, most also ask about either the most frequently used alternative mode, the split of modes used across each day of the week, or request details of all legs in a multi-modal commuting trip chain. All but one of the surveys requested details of the commuting trip origin and trip distance, whilst 14 (66%) also included a question about trip duration. Trip frequency information was captured by 18 (81%) of the surveys in one of two ways. Participants are asked either to specify the number of days on which the commuting trip is made, or to specify which days of the week the trip is made. 12 (54%) of the surveys ask the respondent to provide information on arrival and departure times. In 13 (60%) of the surveys the same set of questions related to the commuting trip are asked of both students and staff, whilst only 3 surveys asked students about their academic timetable and its relationship to the trips they made. None of the travel surveys analysed attempted to capture information on the level of student leave-and-return trips although two travel plans suggested that this behaviour might exist (Manchester, Warwick).

Institution	Date	Mode Details				Trip Length			Trip Frequency		Trip Timing	Student Survey Different from Staff Survey	Lists Time Table Info.
		Main Mode	Alt. Mode	Week Modes	Trip Chain	O/D	Distance	Duration	No. of Days	Days of Week	Arrival and Departure		
Bath Spa University	2004	1	1			1	1	1	1		1		
Coventry University	2008	1	1			1	1						
De Montfort University	2011	1				1	1		1				
The University of Bath	2011	1			1	1	1	1		1	1	1	
The University of Southampton	2010	1				1	1	1	1	1	1		
The University of Plymouth	2007	1			1	1	1	1		1	1	1	1
The University of Newcastle	2009	1	1			1	1	1		1	1	1	
University of Cumbria	2009	1	1			1	1	1	1		1		
The University of Northampton	2007	1		1		1	1			1			
The University of Manchester	2006	1				1	1		1			1	
The University of Aberdeen	2010	1				1	1	1	1				
Loughborough University	2010	1				1	1	1	1			1	
University of Durham	2010	1	1			1	1			1			
Aberystwyth University	2009	1				1	1	1	1				
The University of Glasgow	2010	1	1			1	1	1	1	1	1	1	
The University of Northumbria	2011	1				1	1	1	1		1		
Kingston University	2008	1	1			1	1	1	1		1	1	1
The University of St Andrews	2009	1				1	1						
The University of Sunderland	2009	1	1			1	1	1	1		1	1	
Queen Margaret University	2011	1				1	1				1		
Harper Adams University	2007	1											
The University of York	2011	1		1		1	1	1	1	1	1	1	1
Total	**22**	**22**	**8**	**2**	**2**	**21**	**21**	**14**	**13**	**8**	**12**	**9**	**3**

Table 2 – UTR: Student Travel Surveys, Data Items Captured

4.4 Discussion

This section identifies a number of themes that arise out of the analysis of the travel plan data described in section 4.3.

4.4.1 Mode Share and the Changing Role of the Travel Plan

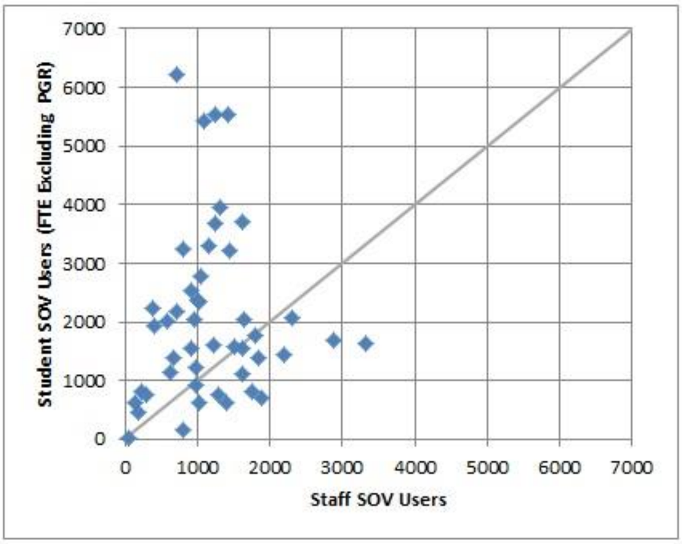
The implicit focus of the measures contained in any travel plan is the reduction of SOV trips. This is made apparent in both the national guidance for workplace travel plans and in the specific guidance for the implementation on travel plans within universities. Similarly the targets for the plan are expressed as percentage changes in the mode share distribution across all trips, with plans typically including targets to increase the share of active and public transport trips matched by a reduction in SOV trips.

The travel plans show that SOV mode share for staff is higher than the equivalent figure for students, and that in most cases the plan's measures are aimed at further reducing staff SOV mode share, whilst restricting student SOV mode share through tight control of student car use on-campus and at halls of residence.

An early motivation for the development of (workplace) travel plans was to meet the conditions placed on organisations to indicate how they would manage and/or mitigate the traffic impacts of any new development (Enoch, 2012, p. 38, Roby, 2010). This is particularly true for the university sector which has undergone a period of rapid expansion over the last 20 years and consequently 23 (31%) of the travel plans surveyed indicated that they had (partially) been developed to support a planning application. Recently universities have begun to consider their wider sustainability profile and in particular to demonstrate a year-on-year reductions in carbon emissions. Staff and student commuting trips have been shown to be an important contributor to total emissions meaning that the method for controlling and monitoring commuting trips, the travel plan, is now assuming a more central and strategic role within university policy (Higher Education Funding Council England, 2012). As noted by Selby (Selby et al., 2009) university travel plans are increasingly being used to identify and address sustainability issues and in particular institutional carbon reduction targets, and 46 (61%) of the plans identified the need to meet sustainability targets as a plan aim. This chimes with the analysis of Roby who suggests that motivation for the development of the travel plan is entering a second phase, in which rather than being seen as a reactive document that is produced in response to specific (traffic or planning) issues, the plan is now evolving into a proactive mechanism addressing the wider objectives of the organisation (Roby, 2010).

Across the university sector, the focus of the travel plan is shifting and it is no longer primarily limited to the management of traffic on campus and instead must consider the impact of all trips. Under this revised view it is trip intensity, or the absolute effect of commuting trips, which is now important rather than the proportion of SOV trips relative to other modes.

Although staff SOV modal share may always be higher than the equivalent figure for students, the staff/student ratio means that in absolute terms there are more student than staff SOV users at many institutions, Graph 2. Across the UK there are 1.75 as many student SOV trips compared to staff, and the highest number of student SOV trips occurs at The University of Northumbria, where 28% of the 22,000 FTE students use the SOV mode.



Graph 2 – UTR: Staff/Student FTE SOV Users By Institution

A consideration of mode share allows one dimension of each trip's total impact to be calibrated but when assessing the impact of all trips this becomes inadequate since the sustainability of any individual's travel behaviour depends upon more factors than just their chosen mode. This suggests that the measures adopted in the travel plan that simultaneously influence commuting behaviour and increase institutional sustainability cannot now be limited to mitigating the effect of vehicle movements on campus, but instead must have a broader focus and aim.

The higher numbers of student SOV trips, when compared to staff, suggest that students trips should be the main target of future travel plan measures. However, existing measures have reduced student vehicles on campus to (very) low levels meaning that a further reduction using existing strategies may be difficult to achieve.

4.4.2 The Workplace Model and Student Travel Behaviour

The travel plans examined in this survey show a bias towards influencing and measuring staff commuting trips. This is evidenced through travel plans that deal solely with staff trips (City University), base their measures on generic employee workplace travel data (Huddersfield, Leeds Metropolitan, Cambridge), or conduct surveys that are distributed solely to staff (Anglia Ruskin, Roehampton, Southampton Solent).

The analysis shows that university travel plans have been developed using guidance written for workplace environments even though for the majority of university commuters, the campus is their study-place not their workplace. Guidance on the development of travel plans for the HE sector highlights the importance of considering student movements in the plan (Forum for the Future, 2003, p. 35). However, when students are considered in the travel plan they are often subsumed within the workplace commuting behaviour of staff. Thirteen out of the twenty two travel plan surveys examined used the same methodology to elicit commuting behaviour for staff and students. Even the HEFCE’s own guidance on the collection of staff and student commuting data for the purposes of reporting emissions levels includes an indicative pro-forma workplace survey with a note that it can be adapted for use as a student travel survey (Higher Education Funding Council England, 2012, Annex B).

Is it reasonable to consider that student study-place commuting is synonymous with staff workplace commuting? If it is then the adoption of the workplace travel planning methodology for student trips is a sensible choice. However, what if the characteristics of student trips differ from those of staff? This then suggests that university transport planners do not fully understand student study-place commuting behaviour or that the workplace metaphor is being used as a second-best alternative in the absence of anything more appropriate.

Institution	Survey Date	Arrival Before 9:00 (%)	Variable Arrival Time (%)	Depart between 17:00-18:00 (%)	Variable Departure Time (%)	Notes
Newcastle	2006	77		51		08:30-10:00 and 16:00-18:00
	2008	82		62		
Northumbria	2009	32		57		16:00-18:00
	2011	21		39		
Sunderland	2007	89		52		
	2009	23		22		
Queen Margaret	2011	42		33		16:30-17:30
Southampton	2010	53		39		
Glasgow	2010	38	21	22	25	

Table 3 – UTR: Reported student on-campus arrival and departure times

The workplace travel model, when applied to students, assumes that the trip-making behaviour of the student population is independent of the academic timetable, and that their choice of arrival times, departure times, trips per week and trip distribution across the week are no more constrained than those of the staff at the same institution. This leads to a confusion in both survey methodology and interpretation. For example, six travel plans include a presentation of student on-campus arrival and departure times, and a summary of these figures are shown in Table 3.

The percentage of students arriving before 9:00 and to a lesser extent departing between 17:00 and 18:00 shows little consistency across institutions and whilst this might be expected due to the differing context of each campus, a similar disparity exists between survey years at the same institution. The figures for Sunderland show a 66% decrease in the number of students arriving before 9:00 over a two year period. It is unlikely that such a large reduction is attributable to travel behaviour change alone when some other external factor, such as changes to the timetable, might explain some of the variation.

The data for Glasgow shows that 21% (25%) of students have variable arrival (departure) times. These relatively high percentages could be partially as a result of variation in the start and end time of the academic day in individual student timetables and as such a variable arrival and departure time might be an expected student behavioural response. However, none of the other surveys allow respondents to indicate variable arrival or departure times. Indeed Sunderland includes an ‘it varies’ category in the staff questionnaire (presumably to capture information related to flexi-time) but not in the equivalent student version.

Other data appears to be similarly misinterpreted with distributions of the percentage of students on-campus each day accompanied by comments about ‘students least popular’ days (Southampton) or ‘students travelling to university slightly less often than in previous years’ (Sunderland). If timetable influences trip-making behaviour then the proportion of students with timetabled sessions on a given day will largely determine the percentage of students attending on that day and changes to the timetable will produce knock-on changes to trip-rates which may then incorrectly be attributed as a change in behaviour.

If student study-place commuting is different from workplace commuting, then the data collected in most of the university travel surveys can only provide a partial understanding of student travel behaviour, and student timetables need to be considered in parallel with the trip data in order obtain a fuller insight into student travel behaviour.

The survey approaches of Kingston, Plymouth and York obtain data about each student's academic timetable. Kingston and Plymouth use the same instrument, and importantly use the same question wording, asking first for information on attendance at timetabled sessions together with a statement of the number of visits made by the student to each campus site, Figure 2.

Q3 At what times during a typical week do you attend educational sessions?

	Early Morning	Late Morning	Early Afternoon	Late Afternoon	Evening	No sessions this day
Monday						
Tuesday						
Wednesday						
Thursday						
Friday						
Saturday						
Sunday						

Q4 On how many days in a typical week would you travel to each of the following university sites for educational purposes?

Penrhyn Road	
Kingston Hill	
Knights Park	
Roehampton Vale	
St George's University	

Figure 2 – UTR: Timetable Specific Questions (Kingston University)

The question Q3 seems to be both ambiguous and based on assumption. If a student has no sessions on a Wednesday but they attend campus on that day how do they respond? What does ticking 'no sessions this day' mean? Are students assumed to never attend on-campus when they don't have timetabled sessions? Similarly if a student has timetabled sessions in the late morning on a Tuesday but they arrive on campus before 9:00 and depart after 17:00 what boxes do they tick? and what does this reveal about travel behaviour? If a student habitually misses a timetabled session do they leave the appropriate box blank? Is this question capturing information about the student's timetable, their attendance on campus or their travel behaviour? The second question, Q4, is also ambiguous since it does not differentiate between home to campus trips and inter-site trips once the student is already on campus.

The University of York travel survey provides evidence of best practice and includes separate questions for travel behaviour and then timetable, Figure 3. This approach potentially allows the full relationship between a student, their trips and their timetable to be observed. It can reveal any difference in the likelihood of attendance on-campus on TTDs (mandatory trips) and NTDs (discretionary trips), and can demonstrate the relationship between on-campus arrival and departure time and session start and finish times. However the survey method will be unable to capture any instances of student leave-and-return trips, or behaviour that evolves over the term, semester or academic year.

THE UNIVERSITY of York

5. On what days / times do you usually attend University? (please complete for all days you attend University. If there are days you don't go to University, please leave row blank)

	Before 0800	0800–0900	0900-1000	1000-1500	1500-1600	1600-1700	1700-1800	After 1800
On Mondays I arrive at University								
On Mondays I depart University								
On Tuesdays I arrive at University								
On Tuesdays I depart University								
On Wednesdays I arrive at University								
On Wednesdays I depart University								
On Thursdays I arrive at University								
On Thursdays I depart University								
On Fridays I arrive at University								
On Fridays I depart University								
On Saturdays I arrive at University								
On Saturdays I depart University								
On Sundays I arrive at University								
On Sundays I depart University								

6. Please specify the times and days of your lectures (tick all that apply for the current term)

	Before 0800	0800-0900	0900-1000	1000-1100	1100-1200	1200-1300	1300-1400	1400-1500	1500-1600	1600-1700	1700-1800	After 180
Monday												
Tuesday												
Wednesday												
Thursday												
Friday												
Saturday												
Sunday												

Figure 3 – UTR: Timetable Specific Questions (University of York)

This review of university travel survey methodologies indicates that there is little consensus amongst university travel planners and between institutions in terms of the data to be collected from students in order to understand their travel behaviour in relation to their academic timetable.

If the contemporary view of the timetable applies then a revised trip model is required to represent study-place commuting behaviour as distinct from workplace commuting behaviour.

4.4.3 Timetable and Student Soft Measures

If student trip-making behaviour conforms to a contemporary view of their timetable, then this suggests that a travel-aware timetable design could be deployed as a soft measure within a university travel plan.

Many of the university travel plans contain soft measures to reduce the impact and intensity of staff commuting behaviour, section 4.3.1, and as demonstrated in Table 4 potentially all of these soft measures have parallels for student study-place trips achieved through manipulation of the academic timetable.

Staff Workplace Measure	Equivalent Student Study-place measure
Flexi-time	Retime the start time of the first session and end time of the last session away from the commuting peak periods. For example, in the UoL sample timetable 25% of all TTDs start with a session at 9:00, whilst 20% of TTDs end at 17:00
Remote working and home working	Encourage students to use VLE's and blended learning approaches to reduce the need for a trip to campus on NTDs
Compressed working week	Consolidate timetabled sessions into fewer days, by delivering more hours per day, and then by taking advantage of remote/home working techniques minimise the trips to campus taken on the newly released NTDs

Table 4 – UTR: Student study-place soft measures

However, the potential uptake of such soft measures for students is hindered by a number of factors. Firstly, as has been suggested travel planners may not properly understand the relationship between the academic timetable and student travel behaviour. Secondly, the use of relative mode share as the main method for specifying targets can potentially discourage the use of this type of policy measure since its effectiveness is likely to be hidden within the mode share figures. For example, if the soft measures identified above were equally attractive to users of all modes then they will have no apparent effect on the mode share figures; if all commuters work at home one day per week relative mode share must remain the same. Similarly if the measures were more appealing to one modal sub-group then a distorting effect could occur; if public transport users will more readily switch to home-working in comparison to car drivers, then SOV mode share might rise as a result. In both cases the absolute number of trips will have been reduced, but this will not be apparent in the headline figures used to demonstrate progress and viewed by policy makers when judging the success of their travel plan. The uptake of soft measures should be thought of as a mode switch from a travel to a non-travel mode. This almost suggests that a further mode is required, the trip-not-taken mode, to make this switch explicit in the figures. Finally, the organisational structure within a university may prohibit the consideration of the use of timetable as a travel measure. Southampton's plan identifies that changing the timetable is out of the scope of the travel plan to deliver and perhaps the group responsible for devising the travel plan (typically within the Estates department) and those responsible for developing the academic timetable (typically within student services) are organisationally distinct.

However, the shift in focus of travel plans towards sustainability goals orientates them away from being a pure transport planning problem and suggests that other disciplines might also have a role to play in their formation. Enoch cites an example of tax consultants providing advice and guidance on the development and implementation of a salary sacrifice scheme for the purchase of discounted public transport tickets (Enoch, 2012, p. 139).

4.4.4 Consideration of Factors Influencing Relative Mode Share

Relative mode share presents travel behaviour data in a manner that is insensitive to the absolute number of trips and trip frequency, and it represents a pragmatic compromise for balancing travel reduction measures within the context of economic growth. This is spelt out in the DfT guidance which states that measuring mode share "*allows you to judge progress over time even if staff numbers go up" (*Department for Transport, 2008, p. 19).

The overall mode share figures shown in a travel plan are averages created through the aggregation of data from many individual trips. This can lead to the false view that the users of a specific mode are homogenous, and are evenly spatially distributed.

The relative mode share levels for trips from a specific location will be unique to that location and will depend upon factors such as: availability, convenience, attractiveness, travel times and travel distance. Ignoring the relative suitability of different modes for trips of varying lengths or durations can lead to false inferences being made, such as in the study of Whalen et al which incorrectly attributes a student preference for bike trips which increases with travel time as an example of the positive utility of travel time (Whalen et al., 2013). Figure 4 shows an interpolation of student relative mode share for active (walking and cycling), public transport and car trip by distance from campus extracted from data contained in the travel plans for Newcastle, Northumbria and Glasgow universities. The overall share for each of the three modes is also shown.

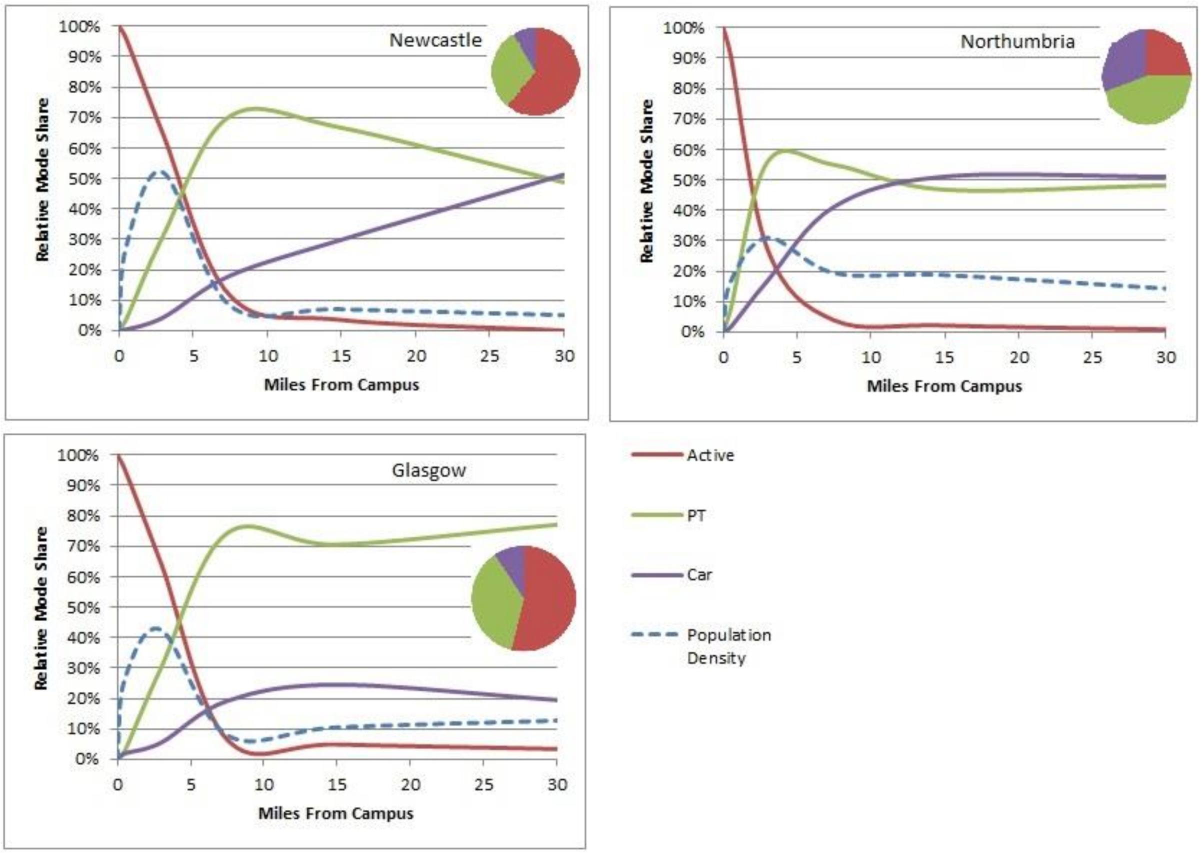


Figure 4 – UTR: Relative and Overall Mode Share By Distance

Overall mode share is a product of the population density at different spatial locations and the relative mode share distributions. In the example shown car mode share for students living at distances of more than 10 miles from campus is higher at Newcastle compared to Glasgow, but the overall car mode share at Newcastle is lower (7% compared to 8.8% at Glasgow) due to a higher proportion of students living closer to campus. The relative mode share by distance represents the product of the inherent attractiveness of each mode at a given distance combined with the effectiveness of existing travel plan measures to influence the travel behaviour of those living at that distance. Travel plan measures can modify modal attractiveness but only from the (unknown) base level which would have existed if no travel plan measures had been applied. Mode specific travel plan measures will have limited effect on the uptake of certain modes at given distances from campus, and this suggests that travel plan measures should be targeted and identify both the mode switch desired (car to PT, PT to active) and the segment of the population for whom this switch is most likely.

The data demonstrates that in absolute terms measures to influence travel mode behaviour change amongst students may have a limited effect since most of the population reside at distances from campus where the active modes already predominate and where car use is low. This suggests that for a given population distance distribution there will be an upper limit for the share travelling by sustainable modes.

The overall mode share figures are sensitive to changes in the student population distance distribution and trends towards students living at home may result in a reduction in the overall sustainable mode share (active and PT) percentages even though there has been no change in student travel behaviour at any given distance.

This analysis demonstrates that whilst the use of overall mode share is a reasonable metric for measuring the success of ‘on the ground’ TDM measures it becomes inadequate when the focus shifts towards institutional sustainability. This is particularly the case for student study-place behaviour where trip frequency may be more variable than it is for workplace trips and in an institutional context where land-use policies can be used to influence the population distance distribution.

An alternative trip representation method is required which is sensitive to changes in size of the population, recognises the progress towards smarter non-travel choices, reflects trip frequency and takes account of trip length (residential distance).

The method would need to be able to be used to represent targets and describe progress in travel plans, to provide an accurate description of travel related emissions and to give an easily accessible means for comparing institutional performance.

One possible approach might be to use car equivalent study-miles. This metric would be similar in scope to food-miles, which give an indication of the environmental impact of foods and their ingredients incorporating the distance to get food items from field to consumer and the waste away to landfill (Food Miles, 2014). However, a car equivalent study-mile would represent one mile travelled by car by one student as a result of their studies. If a mode other than car was used then the study-mile distance would be scaled according the emissions of the chosen mode relative to a baseline emissions value for a car. When a student used an active mode their car equivalent study miles would always be zero, since the walking and bike modes are assumed to produce no emissions at source. The same approach could also be adopted to measure home to university trips.

4.4.5 The Possible Effect Of Timetable on Student Trip-Making

This review has shown that the main focus of university travel plans is around mode choice, with less attention being paid to both trip generation rates and trip length, and almost no attention at all being given to the possible effect of the academic timetable on student trips.

Although no evidence has so far been presented to suggest that timetable does affect student trip-making behaviour, and that the traditional view of regular student attendance on campus introduced in Chapter 1 may hold true, it would seem that one area where students might behave differently is in regard to their trip-making behaviour on timetabled and NTDs.

Based on the contemporary view of the timetable, student trips to campus on TTDs should be considered to be mandatory, whilst those on NTDs might be thought of as discretionary. It could also be reasonable to assume that any individual student might value the utility gained from a mandatory trip differently from that obtained through a discretionary one, and in this case a student could be thought of as making mandatory and discretionary trips according to two separate trip-making probabilities.

An academic semester will include a defined number of teaching days, and any individual student will have timetabled sessions scheduled on a proportion of these teaching days and no sessions scheduled on the rest of them. The likely trip frequency for the student over the whole time period can be represented by the sum of two products: the proportion of teaching and non-teaching days and the trip probabilities for TTDs and NTDs, equation 4-1.

$$\begin{aligned} Total\ Trips = \quad & Timetabled\ Days\ \times Mandatory\ Trip\ Probability + \\ & Non\ Timetabled\ Days\ \times Discretionary\ Trip\ Probability \end{aligned} \tag{4-1}$$

Two students may have the same timetables but adopt different trip probabilities or they may have differing timetables but the same trip probabilities. In all cases the resulting number of trips will differ.

If the contemporary view of the timetable is correct then this suggests that ignoring the timetable when considering student trip rates could potentially lead to false assumptions being made about student behaviour and result in discrepancies between the number of estimated and actual trips taken by students.

To demonstrate this effect consider the 2010 UoL student travel survey (University of Leeds, 2010b). This included a question asking how many days per week on average the respondent made a trip to campus. Considering just weekday trips (Monday to Friday), and based on the responses of undergraduate students only, the average figure across all students was 4.2 trips per week, meaning that 84% of all student days included a trip to campus. On the face of it this suggests that most students attend on campus on an almost full-time basis and appears to confirm the traditional view of student trip-making behaviour.

Analysis of the UoL's academic timetable for 2010 (University of Leeds, 2010a) indicates that around 75% of student days are timetabled. If it is assumed that students have perfect attendance on TTDs then the mean trip probability for NTDs must be 0.36 if 84% of student days are to include a visit to campus. This now suggests that student behaviour is more akin to the contemporary view of the timetable.

Excluding the effect of timetable when considering student trip rates means that university travel plans are both vulnerable to unforeseen changes to university timetabling policy and are also potentially missing opportunities for reducing the total number of student trips by influencing timetabling policy.

4.5 Summary And Conclusions

A desktop review of UK university travel plans was conducted. The review suggested that university travel plans tend to adopt the workplace commuting model as the method for surveying, measuring and understanding student study-place trips (answering RQ5 and supporting H2). This mirrors the focus of most of the academic research discussed in section 2.6. The explanation of student travel behaviour is centred around their mode choice whilst the measures adopted by universities appear to be mainly directed towards achieving travel behaviour change through the promotion of sustainable modes.

Whilst the influence of the academic timetable on student travel behaviour is informally implied, the travel plans contain little evidence to demonstrate that this relationship is fully understood. Similarly, minimal evidence has been found to suggest that universities recognise that students may exhibit leave-and-return behaviour.

If the academic timetable does affect student travel behaviour then the methodologies employed within university travel plans are inadequate (except for York), and focus on the workplace commuting model and the traditional view of the timetable this implies. An alternative survey methodology might be needed, perhaps which establishes the respondent's trip-making behaviour relative to their timetable. Once this relationship is established it can be used to describe both current trip-making patterns and the likely behavioural responses to possible future timetables.

Travel plans that were originally developed to address specific traffic management issues are now being refocused with the aim of delivering some of the emissions savings required by institutions as they become more sustainable organisations. This requires that travel plans place a greater emphasis on mitigating student study-place trip-making since students, and not staff, make the bigger contribution to overall commuting emissions levels.

The mode change centric focus of current travel plans inadequately addresses the need for large absolute reductions in emissions from commuting and does not fully exploit the unique position of universities to exert influence over both trip length and trip frequency.

Within this new travel plan landscape, targets defined through mode change percentages will fail to encompass the effect of the full range of possible policy measures. When sustainability aims are considered in parallel to traffic management objectives then an alternative measurement metric is required. Car-equivalent study-miles (Car-EQ) is one possible proposed alternative.

Chapter 5 – University of Leeds Travel Plan Pilot

5.1 Introduction

The aim of this chapter is to perform an assessment into the effectiveness of different travel plan measures on improving the environmental sustainability of the UK university, with a particular emphasis on the potential effect of timetable design on carbon emissions levels and on the scope for using intelligent timetable design as a travel plan measure to deliver an absolute reduction in these levels.

The work reported in this chapter completes the delivery of research objective O2 (conduct a review of university travel plans) and partially addresses RQ8 (what are the impacts of timetable design on university sustainability?).

As was demonstrated in Chapter 4 university travel plans primarily focus on measures related to mode change and in some cases land-use policy but generally ignore the potential effect of timetable on travel behaviour. This mode-centric focus means that current student travel planning measures do not consider the full range of potential options available within the unique environment of the university campus.

It was proposed in Chapter 4 that the focus on mode change becomes less relevant when institutional priorities move towards sustainability issues and this chapter examines the scope of four types of travel plan policy measure to deliver the reductions in emissions required to meet sustainability objectives as opposed to traffic management targets.

A similar modelling based approach was conducted by Mathez et al, who used the travel behaviour patterns of staff and students attending McGill University, Montreal, Canada to build a trip model that could be used to estimate GHG emissions for the whole university population (Mathez et al., 2013). However, their approach assumes that student and staff travel behaviour is largely synonymous by adopting a work-place commuting model, whilst simultaneously making simplifying assumptions about commuting trip frequencies.

5.2 Methodology

A suitable analysis methodology for this element of the study was selected based on an idea originally developed for assessing the impact of population changes (Ehrlich and Ehrlich, 1991). This was subsequently adopted for use within the sustainability arena (Ekins, 1993), and then used for assessing the impact of transportation on long-term sustainability targets (Potter, 2007).

The method involves identifying the major parameters associated with the impact being measured, CO_2 emissions in this case. By defining the current situation as the base case, with an impact factor of one, all alternative or future scenarios can then be represented through proportional changes to one or more of the parameters and compared against the base case.

In order to assess the impact of student trips to/from campus on emissions levels the equation 5-1 is used. This incorporates the main elements from trip impact equation introduced in section 4.3.2 combined with dual student trip probabilities for TTDs and NTDs as suggested in section 4.4.5.

$$Impact = Population \times Mode \times Emissions \times Distance \times Trips \qquad \text{5-1}$$

$$Trips = Timetabled\ Days \times Mandatory\ Trip\ Probability + Non\ Timetabled\ Days \times Discretionary\ Trip\ Probability$$

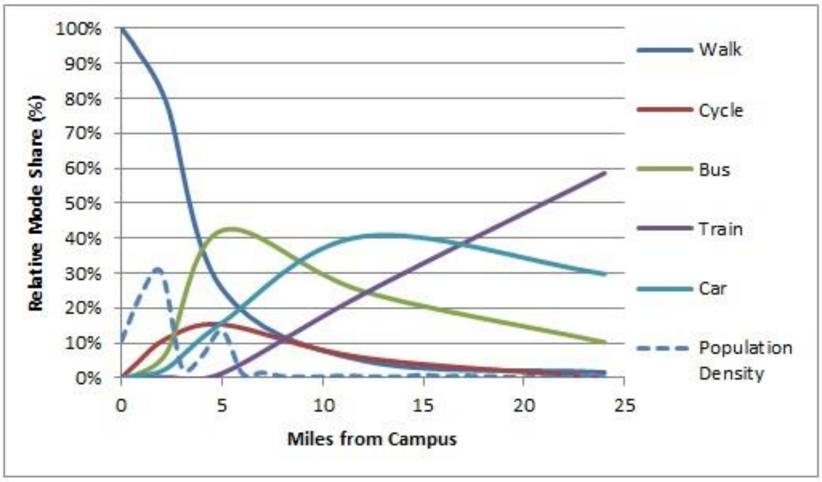
The impact equation implies that students adopt a contemporary view of their timetable (RQ1, H1). This research question has not been answered and will be addressed in the later chapters of this thesis. However, this assumption is justified at this stage as it allows the motivation for and potential of the whole study to be reinforced.

If it is assumed that the student population remains constant, and that there will be no changes in the emissions efficiency of cars, buses and trains then the reductions required in greenhouse gas emissions will need to come from changes to either trip distance, trip mode share, or trip generation rates.

The following sections describe the data on which the model is based.

5.2.1 Mode Share and Residential Distribution

The model is developed using demographic, travel behaviour data and timetable data obtained from the UoL.



Graph 3 – UTR: UoL Relative Mode Split By Distance

Data was obtained from the 2010 UoL student travel survey, and the 2010 academic timetable (University of Leeds, 2010a, University of Leeds, 2010b). This was used to estimate distance-based relative mode choice functions for the five major modes used by students: walking, cycling, bus, train and private car, Graph 3. The modal distribution for UoL was shown to be similar to that for other UK universities (see Figure 4, section 4.4.4).

A distribution for student residential distance in 2010 was also obtained from the University's registry team. This shows that 10% of students live on or very close to campus, that another 30% live between two to three miles away and that overall 96% of students live within 20 miles. The population density distribution is bi-modal due to a previous university policy of housing students in halls away from the city centre.

Representative figures for CO_2 emissions per passenger kilometre by each of the five modes considered were derived using national guidelines (UK Department for Environment Food and Rural Affairs, 2011). For private cars, it was assumed students would drive older but smaller cars, and that each car would hold 1.2 students per trip, (UK Department for Transport, 2010).

5.2.2 Student Academic Timetable

In order to understand the ways in which the timetable may affect student travel behaviour it is necessary to analyse an existing university timetable.

The UoL timetable for all non-medical undergraduate students enrolled onto years 1 to 3 of a degree programme during ten teaching weeks of the second semester of the 2011-2012 academic year (from Monday 23rd January 2012 to Friday 27th April 2012) was examined. This period consists of 50 teaching days, and all activity scheduled through the timetable between 9:00 AM in the morning and 18:00 PM in the evening was examined. Summary figures are shown in Table 5.

Timetable Attribute	Count	Hours
Students	15,986	
Scheduled Sessions	1, 420,834	1,810,534
Inter Session Breaks	309,144	696,507
Student Days (Days * Students)	799,300	
Timetabled Student Days	677,298	
Timetabled Days/Student/Week		4.236
Contact Hours/Student/Week		11.32
Scheduled Sessions/Student/Week		8.9
Break Hours/Student/Week		4.36

Table 5 – UoL Timetable Summary Figures

The average duration of each scheduled session is 75 minutes indicating that most sessions will be one hour long, whilst the average inter-session break length is 135 minutes.

A student’s course and their subject will determine both the number of sessions they must attend and the number of contact hours that will be scheduled for them. This varies widely with around 33% of students receiving fewer than 75 hours over the 10 weeks, whilst 10% receive more than 165 hours in the same period. Overall 86% of the population receive between 55 and 205 contact hours within the 10 week time period.

Students will typically have sessions scheduled on at least four out of every five days across the week (4 TTDs/week). The most popular timetable arrangement includes at least one session on every day of the teaching period (50 days in total) with over 20% of the population having a timetable conforming to this arrangement, whilst timetables with sessions on 4, 3 and 2 days each week are used by 13%, 8% and 3% of the population respectively. All other arrangements, between these modal values represent timetables which include some degree of between-week variability and the distribution suggests that 56% of students have such a timetable.

Monday, Tuesday and Thursday are the busiest days of the week within the timetable, with 71% of sessions and 70% of contact hours scheduled across these three days, and with around 90% of students having at least one session on each of them. Activity levels on Wednesday are lower, reflecting the tradition of keeping the afternoon free for sports activities, as they are on Friday with less than 75% of students having any sessions scheduled at all on this day. Monday’s, Tuesday’s and Thursday’s can be classified as timetable high days (TTH) whilst Wednesday’s and Friday’s are timetable low days (TTL).

Peak timetabled activity levels occur in the morning between 10:00 and 11:00 when over 35% of the cohort are engaged in a scheduled session on four out of the five days. Activity participation falls over the lunch period and then rises again to slightly lower peak during the afternoon between 14:00 and 15:00. Timetabled activities on Wednesday and Friday afternoons are generally lower, but still 10% of Wednesday afternoons contain a session, whilst 8% of Friday afternoons include sessions scheduled up to 17:00.

Any timetabled day will consist of a series of scheduled sessions with zero or more breaks between each pair of sessions. There is a clear relationship between sessions and breaks in that as the number of scheduled sessions in the day increases, the availability of time for breaks reduces. An analysis of this relationship across all TTDs within the period is shown in Table 6.

	Total Daily Contact Hours		Total Daily Break Length		Maximum Daily Break Length
Hours	%	Average Break (minutes)	%	Average Contact (minutes)	%
0			54%	121	54%
1	25%	0	16%	214	19.5%
2	29%	63	13%	210	13%
3	21%	100	9%	199	9%
4	14%	104	5%	190	3%
5	6%	103	2%	175	1%
6	2%	78	1%	159	<0.5%
7	2%	46			
8	1%	8			

Table 6 – UoL Daily Contact Hours and Break Length

About a quarter of all TTDs consist of a single session and 54% of TTDs include no breaks, whilst 75% have less than four hours of contact time. However, 17% of TTDs include total breaks of ≥3 hours and 14% include a single break of ≥3 hours. The provision of these longer breaks within the timetable potentially provide students with the opportunity to exhibit leave-and-return behaviour.

5.3 The Effect of Travel Plan Measures on Institutional Sustainability

The impact equation outlined in section 5.2 was used to establish a base case for the overall emissions levels attributable to student commuting at the UoL and then to examine the effect of four travel plan scenarios on these levels.

5.3.1 Student Travel Behaviour – Base Case

Given the distribution for student residential distance, and modal split by residential distance, a total undergraduate population of 24,000 students, a stated student trip rate of 0.84 trips to university per day and an assumption of a 34 week academic year (two 17 week semesters), then the impact equation suggests that the current total emissions attributable to student commuting are 3,793 tonnes of CO_2 per year, Table 7.

Mode		g/CO_2/ Student/ Mile	Mean Distance (miles)	Timetable		Trip Rate		Sum
				TT Days	Non TT Days	TT Day	Non TT Day	
Cycle	8.4%	0	3.7	0.75	0.25	1	0.36	0
Walk	61.0%	0	1.9	0.75	0.25	1	0.36	0
Bus	14.2%	237	5.9	0.75	0.25	1	0.36	168.0
Private	9.8%	272	10.1	0.75	0.25	1	0.36	226.6
Train	6.6%	86	14.8	0.75	0.25	1	0.36	70.2
x 24,000 students, 5 days, 2 trips/day, 34 weeks								**3,793 tonnes**

Table 7 – UTR: UoL Commuting Emissions, Base Case

This is lower than the figure of 4,900 tonnes quoted in the current UoL travel plan (University of Leeds, 2013) since it excludes the emissions attributable to 8,100 Masters and PhD students whose commuting patterns are likely to be more regular. However as this represents the base case against which all alternative scenarios will be assessed it is the relative values, rather than the absolute ones that are important in this context.

5.3.2 Scenario 1 – Mode Change

The first scenario explores the scope for environmental savings from mode change. This involves identifying students who would be willing to substitute their current mode for a more sustainable alternative. Given that individuals are generally reluctant to change their mode, and that the use of the car mode is a societal addiction (Banister, 2005, p. 7), it would seem reasonable to assume that even in the best case mode change will only occur at a given residential distance if there is a less polluting alternative mode that is already more popular at that distance. This means that walking or cycling might be a good substitute for the bus and car modes at short distances, whilst bus might replace car for intermediate distances and train might replace car for longer distances.

Mode		g/CO_2/ Student/ Mile	Mean Distance (miles)	Timetable		Trip Rate		Sum
				TT Days	Non TT Days	TT Day	Non TT Day	
Cycle	*9.0%*	0	3.6	0.75	0.25	1	0.36	0
Walk	*62.0%*	0	1.9	0.75	0.25	1	0.36	0
Bus	*16.7%*	237	5.9	0.75	0.25	1	0.36	196.3
Private	*5.8%*	272	13.2	0.75	0.25	1	0.36	176.6
Train	*6.8%*	86	15.0	0.75	0.25	1	0.36	73.5
x 24,000 students, 5 days, 2 trips/day, 34 weeks								**3,643 tonnes (96%)**

Table 8 – UTR: UoL Commuting Emissions, Mode Change Scenario

These constraints limit the total scope for savings through mode change, since mode split is dependent on distance and the less polluting modes are not equally as attractive at all distances, and so that even in the best case mode change can deliver only a 4% saving on current emissions levels. This is despite overall car mode being reduced from 9.8% to 5.8% (40%).

5.3.3 Scenario 2 – Land Use Policy

The second scenario explores the scope for environmental savings through changes to institutional land use policy in order to encourage to students to live closer to campus. Students who live closer to campus are more likely to use active travel modes, even if they adopt the travel behaviour prevalent at that distance, i.e. no change in relative mode share by distance.

To demonstrate scope for savings in this area, the scenario assesses the effect of closing the students halls of residence that are remote from campus (they actually closed at the end of 2012) and relocating the students displaced by this closure within 3 miles of campus, so that 25% of students live within 0.5 miles of campus, and almost 85% within 3.5 miles Table 9.

This scenario sees almost a halving of the total emissions levels. Due to increased proximity of students to campus, walking mode share increases from 61% to 75%, although the percentage cycling falls by 2%, as there are now less students living at the residential distances at which cycling is attractive.

Mode		g/CO_2/ Student/ Mile	Mean Distance (miles)	Timetable		Trip Rate		Sum
				TT Days	Non TT Days	TT Day	Non TT Day	
Cycle	6.1%	0	*3.0*	0.75	0.25	1	0.36	0
Walk	74.6%	0	*1.6*	0.75	0.25	1	0.36	0
Bus	7.7%	237	*6.1*	0.75	0.25	1	0.36	92.4
Private	6.8%	272	*8.6*	0.75	0.25	1	0.36	133.2
Train	4.9%	86	*9.4*	0.75	0.25	1	0.36	33.1
x 24,000 students, 5 days, 2 trips/day, 34 weeks								**2,111 tonnes (56%)**

Table 9 – UTR: UoL Commuting Emissions, Land Use Change Scenario

This finding confirms that suggested by Boussauw (Boussauw and Witlox, 2009) who investigated commuter trip energy consumption and found that trip distance rather than mode is the main determinant of energy use.

These savings can be achieved through changes in university land use policy, something over which the university has at least some influence and which may be implemented given sufficient reserves of capital and suitable land availability. However, these potential gains are not secure and may be offset by emerging trends in student residential choice, with more students opting to live at home to offset the higher costs associated with a university education (Smith, 2009, p. 1798, University of Central Lancashire, 2011, p. 2), coupled with the longer term trend that sees the increased availability of virtual facilities through ICT, encouraging a reduction in the number of trips but an increase in their distance (Banister, 2005, p. 186). For example, in this scenario, 96% of students will live within 20 miles of campus. However if 5% of these students relocated to their home address, (assumed to be at least 20 miles from campus) then emissions saved reduces from 44% to 13%, with total emissions now being 87% of the original baseline.

5.3.4 Scenario 3 – Timetabling Policy

The third scenario explores the scope for environmental savings through changes in timetabling policy, and the introduction of soft measures to encourage students to study remotely on NTDs.

Students have 3.86 TTDs per week in the 2010 UoL academic timetable and receive an average of 2.66 contact hours per timetabled day. If the average mandatory attendance requirement was reduced to 3 days per week, average contact hours per day would increase to 3.4 hours/day giving students a slightly fuller day in return for fewer TTDs per week. The trip frequency figure from the 2010 UoL travel survey suggests student attendance probability on NTDs is around 0.36.

If the university invested further in online teaching resources, allowing students to study more effectively remotely from campus, then this might further reduce the number of discretionary trips taken by students and this scenario assumes that the probability for trips on NTDs is reduced to 0.2.

Mode		g/CO_2/ Student/ Mile	Mean Distance (miles)	Timetable		Trip Rate		Sum
				TT Days	Non TT Days	TT Day	Non TT Day	
Cycle	8.4%	0	3.7	*0.60*	*0.40*	1	*0.2*	0
Walk	61.0%	0	1.9	*0.60*	*0.40*	1	*0.2*	0
Bus	14.2%	237	5.9	*0.60*	*0.40*	1	*0.2*	136.0
Private	9.8%	272	10.1	*0.60*	*0.40*	1	*0.2*	183.4
Train	6.6%	86	14.8	*0.60*	*0.40*	1	*0.2*	56.8
x 24,000 students, 5 days, 2 trips/day, 34 weeks								**3,070 tonnes (81%)**

Table 10 – UTR: UoL Commuting Emissions, Timetable Change Scenario

Taking these two changes together reduces emissions by 19% compared to the baseline scenario, whilst the change in timetabling policy alone results in a saving of over 11%. This scenario confirms that influencing student trip generation rates through changes to timetabling policy has the potential to deliver emissions savings which are almost three times, and potentially up to five times greater than those achievable through encouraging student mode change. Implementation of the changes required to make these savings are entirely within the University's control and need a low level of capital investment, when compared to land use policy. They would also be more certain in their outcome as they are less dependent on student travel behaviour change (RQ8).

5.3.5 Scenario 4 – Inclusion of Leave-and-return Trips

The analysis described in this chapter and the consequent discussion has included sporadic references to student leave-and-return trips. None of the travel plans analysed mention this behaviour and although there are two passing references to its existence there is little evidence that this behaviour exists. However, should students really take this type of trip then it further invalidates the workplace trip assumption and means that these hidden leave-and-return trips have the potential to increase student trip rates and emissions levels above the assumed baseline conditions. This scenario explores the potential effect of leave-and-return behaviour.

Opportunities for leave-and-return trips are supplied by the timetable in the form of inter-session gaps and the reference timetable shows that 13%, 9%, 3% and 1% of

TTDs include gaps of 2, 3, 4 and 5 hours respectively. A proportion of students may consider leaving campus if their travel time back to their place of residence is not excessive relative to the total break time available. In the absence of any data on real student behaviour a set of assumptions were used to quantify this effect, Table 11. For each length of break, a proportion of the population might consider making a leave-and-return trip, and within this group the trip would only then be taken if their time spent at home exceeds their return travel.

Break Length (minutes)	Timetable Days including a break of this length (%)	Subset of population that would consider a leave and return trip (%)	Total return travel time for trip to be worthwhile (minutes)
120	13%	50%	≤60
180	9%	60%	≤90
240	3%	70%	≤120
300	1%	80%	≤150

Table 11 – UTR: Leave and Return Behaviour Assumptions

As the UoL 2010 travel survey did not include reliable journey time information, mode specific mean travel speeds were obtained from WebTag. Using these speeds, the journey time information, relative mode share by distance and population distributions figures, the number of leave-and-return trips can be determined and potential additional emissions levels calculated, Table 12.

Break Length	Leave and Return Trips by Travel Mode					Total Trips		Available days
	Cycle	Walk	Bus	Private	Train			
120	9,907	21,233	10,992	11,809	5,213	59,154	1.9%	14.9%
180	13,236	55,373	21,242	11,787	6,563	108,201	3.5%	39.3%
240	5,303	36,562	8,655	5,459	3,170	59,149	1.9%	64.4%
300	2,026	13,928	3,413	2,168	1,208	22,743	0.7%	74.3%
Total Trips	30,472	127,096	44,302	31,223	16,154	249,247	8.1%	
	11.9%	6.8%	10.3%	11.5%	10.7%			
Additional Emissions (tonnes)	0	0	97.6	102.3	18.1	**+218 (5.7%)**		

Table 12 – UTR: UoL Potential leave-and-return trip opportunities

The results show that over the academic year almost 250,000 leave-and-return trips will be taken, and that just over 8% of all student days on-campus will include such a trip. The additional emissions created by these trips increase overall levels by almost 6%. Although these results are based on behavioural assumptions they demonstrate that invisible student leave-and-return trips have the potential to raise overall trip rates and baseline emissions levels. The additional emissions generated by these hypothetical but invisible trips can potentially wipe out any emissions savings achieved through the student travel behaviour change in described in scenario one. Timetabling policy can facilitate a reduction in the impact of these invisible trips, by reducing the supply of longer inter-session gaps within the timetable. Leave-and-return behaviour (if it exists) is solely a function of the timetable, and as such elimination of these trips is within the control of the university itself.

5.3.6 Comparison of Scenarios

Four hypothetical scenarios have been used to demonstrate the relative effectiveness of different types of travel planning measures on institutional sustainability, Table 13.

Policies which concentrate on travel behaviour mode change may cause a marginal reduction, whilst those related to land-use policy can potentially deliver big savings but may be affected by emerging trends in student accommodation choice. Attention to timetabling policy has the potential to deliver reasonably large savings whilst a lack of attention to the presence of inter-session gaps in the timetable could generate additional emissions that are currently invisible to travel plan survey methodologies.

Scenario	Overall Travel Mode Share					Emissions (tonnes)	Study Miles/ Student Day	
	Cycle	Walk	Bus	Car	Train		Raw	Car-EQ
Baseline	8.4%	61.0%	14.2%	9.8%	6.6%	3793 (100%)	7.19	3.41
Mode Change	9.0%	61.7%	16.7%	5.8%	6.8%	3643 (96%)	7.19	3.28
Land-use	6.1%	74.6%	7.7%	6.8%	4.9%	2112 (56%)	4.78	1.90
Timetable	8.4%	61.0%	14.2%	9.8%	6.6%	3071 (81%)	5.82	2.76
Leave and Return						4011 (106%)	7.43	3.60

Table 13 – UTR: UoL Travel Scenarios, Comparison of Results

The work presented in Chapter 4 introduced a new measure for representing the impact of student commuting trips, the car equivalent study mile (Car-EQ) and the results table includes a representation of the study miles per student day that are generated in each scenario. These are shown as the real mileage for an average return trip to the university campus , and a corresponding Car-EQ figure. The Car-EQ figure is sensitive to all types of travel planning measure whether it modifies mode share, trip frequency or trip length. It is directly proportional to the total emissions figures in each scenario whilst representing a quantity that is simultaneously relevant to the individual and the institution, is directly comparable between institutions and is intuitive and easy to understand.

5.4 Summary And Conclusions

This chapter used a simple comparative modelling method to explore the potential effect of academic timetable design on student trip making behaviour at UoL whilst assuming that students hold a contemporary view of their timetable.

The results demonstrate that employing intelligent timetable design as a travel plan measure could have a large impact on the environmental sustainability of campus-based universities. However, the analysis also shows that leave-and-return behaviour, induced through the presence of breaks in the timetable, could potentially be generating additional invisible emissions on top of those currently recorded.

The model demonstrates that whilst encourage mode-switching through individual behaviour change will produce small emissions savings, policies around land-use and timetable design have the potential to deliver much greater and more certain reductions.

The results presented in this chapter partially answers RQ8 (what are the impacts of timetable design on university sustainability?) in that they demonstrate that timetable design can deliver an improvement in environmental sustainability. However, the model is unable to show the effect of such a policy on the economic and social sustainability of the institution and consequently this question will be further explored in Chapter 10.

The results produced by model developed in this chapter are underpinned by the joint assumptions that students hold a contemporary view of their timetable (RQ1) and that under certain conditions they will consider and make leave-and-return trips (RQ4). Therefore, for the results from the model to have any validity these assumptions must be tested further, and both the TQS (Chapter 6 and Chapter 7) and the OSS (Chapter 8, Chapter 9 and Chapter 10) address these questions.

Chapter 6 – The Timetable Quality Survey

6.1 Introduction

The aim of this chapter is to explore student preferences towards their timetable in order to determine the features that are to be found in a high quality student-centred timetable.

The material contained in this chapter is based around the findings of a timetable quality survey (TQS) that was conducted to measure student attitudes towards their timetable. This partially delivers research objective O3 (conduct a survey of student timetable preferences) whilst addressing RQ1 (do students hold a traditional or contemporary view of their timetable?) and RQ3 (what constitutes a high quality timetable?)

As has been shown in Chapter 4 UK institutions generally assume a workplace model for student trip-making behaviour, suggesting that students take a traditional view of their timetable. However, the evidence tentatively suggests that timetable may influence student trip-making and an examination of student timetable preferences may provide more of an insight into the links between trip-making and timetable.

It is important to understand the degree to which timetable preferences are influenced by individual student characteristics such as their gender, their position within the academic process and their home to campus travel time. If certain timetable preferences are only applicable to particular student subpopulations then given that the allocation of timetable to student is the result of a semi-random process, designing timetables which favour certain attributes may be self-defeating and disadvantage as many students as it helps.

6.2 Methodology

The broad aim of the timetable quality survey was to obtain data from students about the attributes within their timetable which they value, and identify those attributes that are regarded by students as being indicative of a poor timetable.

As has already been shown in chapter 2 there has been little discussion in academic literature in terms of what constitutes a high quality student timetable, and whilst some attributes have been identified as being problematic for students there is no overall consensus of what constitutes a good timetable.

Given this uncertainty it was felt that a student timetable survey which asked about specific timetable characteristics would be too prescriptive and could run the risk of not having the representational power to capture the full set of student timetable preferences and dislikes.

For this reason it was decided to adopt an unstructured approach towards survey data collection using a metaphor of the standard weekly timetable grid, Figure 5. Respondents would be asked to complete three grids, by putting crosses in the appropriate cells, to reveal their current, their ideal and their worst possible timetables.

	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19
Mon										
Tue										
Wed										
Thu										
Fri										

Figure 5 – TQS: Example Timetable Grid

Analysis would allow timetable preferences to be obtained by examining the differences between the current and ideal grids, whilst the features which students disliked could be inferred in a similar way by comparing the current and worst grids. At the same time a set of supplemental questions would be used to obtain information about the relationship between the timetable and the respondent trip-making behaviour.

6.2.1 Pilot survey

A paper-based pilot survey was distributed to 150 students in the UoL refectory over a Tuesday and Wednesday lunchtime late into the teaching period of semester 2 of the 2011-2012 academic year.

Although the survey produced some interesting findings, analysis of the results also identified problems with the methodology. Firstly, the current timetables for the respondent group were biased towards those students who had taught sessions on a Tuesday or Wednesday and had a break at around the time the survey was administered. This was not surprising but highlighted the fact that the audience which could be reached through a paper-based survey would always be biased towards those students with particular temporal and spatial preferences. It would under-represent those students whose timetable prevents them from being in the survey area when the survey was being administered and be likely to overlook those students who spent less time on campus overall.

Secondly, some respondents took the guidance to specify their worst possible timetable too literally and chose almost impossible combinations of all early morning and late afternoon sessions with a long breaks across most of the day. Whilst such a timetable would be impractical, it was also felt that it would be very unlikely to occur in any real timetable, and that what respondents really needed to specify was their worst realistic timetable.

Thirdly, whilst the three grid approach allowed respondents to specify their timetable preferences, it did not allow the reasoning behind the preferences to be made explicit. Consequently analysis of the data captured through the pilot survey appeared to involve making assumptions about why certain arrangements of sessions had been chosen, for example with regards to preferences around Wednesday afternoon. The data generated through the survey was purely quantitative, and this highlighted the need for some qualitative data to make student timetable preferences clearer.

Finally, administering the survey in a paper-based form was time consuming, taking six researcher hours spread over two days to collect the 150 responses (1 response for every 2.5 minutes of researcher time). Although a full paper-based survey, with a target of at least 1,000 responses, would have been achievable given 40-50 researcher hours, a less labour intensive delivery method was felt to preferable, thereby reducing survey variable costs and allowing the survey to be repeated if necessary.

To address these issues it was decided that the full survey would need to be administered electronically and distributed through email or the student VLE. This approach simultaneously addressed concerns around the spatial and temporal bias that could occur in a physical survey and reduced the researcher time overhead associated with administering it. It was also decided to replace the third timetable grid (listing the worst timetable) with a more general question about the days and times of day that respondents thought were least preferable, and to add an unstructured descriptive question to allow respondents to list any specific concerns that they might have about their timetable.

6.2.2 Survey Instrument

The survey instrument consisted of an online questionnaire containing twenty questions divided into three sections. The first section requested information about the student’s current timetable and elicited preferences regarding their best and worst timetables. The second section contained a series of questions related to the student’s relationship with campus, and their trip-making behaviour to/from campus, whilst the third section elicited demographic information about the respondent.

The questionnaire was encoded electronically using the Bristol Online Survey Tool (BOS) to which the UoL has a subscription (Bristol Online Survey, 2014). This package offers a more sophisticated set of question types when compared with other tools, such as Survey Monkey (Survey Monkey, 2014). Most importantly the BOS allowed the creation of a grid structure that could be made to look similar to a real timetable.

The online version of the survey was tested by a small group of volunteers both within UoL and externally who identified a few minor errors that were corrected prior to the survey week. Screenshots showing the layout and format of the questionnaire are listed in Appendix B.

The content of the questions in each section of the survey will now be described.

6.2.2.1 Survey Section 1: Timetable Quality

The students were presented with two blank timetable-like grids, similar to that shown in Figure 5, with slots for fifty 1 hour sessions spread over five days, Monday to Friday, with the first session starting at 9:00 AM and the last finishing at 19:00.

Students were asked to transcribe their existing timetable for the survey week onto the first grid by placing a check mark in the grid cells in which they had a session. Only information about the presence or absence of a session in each slot was obtained, the type of each session was not recorded.

Students were then asked to think about their ideal timetable and to reorganise the placement of their sessions in the second grid so that it represented their ideal as opposed to their real timetable. In order to reduce respondent effort options were provided to allow students to indicate if their current timetable for a specific day matched their ideal one.

A third question asked students to think about what they regarded were the worst possible days and times of day for timetabled sessions, whilst a fourth question allowed respondents to write any comments they wished to make about their timetable and it’s layout/design.

6.2.2.2 Survey Section 2: Trip-Making Behaviour

The second section on the survey obtained attitudinal data about the respondent’s relationship to campus, and behavioural data regarding the time they had spent on campus.

One set of questions asked about the number of days they had missed coming to campus on TTDs and to estimate the approximate proportion of NTDs that had included a trip to campus. They were then asked to specify the reasons why they might prefer to spend time off-campus on NTDs.

The students were then asked to consider three hypothetical scenarios; a timetabled day starting at 11:00 AM, a timetabled day finishing at 15:00 and a day containing a three hour gap between sessions. They were then asked about their likely arrival time on the first day, their likely departure time on the second day, and about the activities they might consider undertaking during the long break.

6.2.2.3 Survey Section 3: Demographic Information

In the third section of the questionnaire students were asked to specify some basic demographic information about themselves and their course including: their gender, age and nationality, their academic level, faculty and year of study, whether they were full-time or part-time, their travel time to campus and normal travel mode.

The survey concluded with two invitations; the first for a prize draw and the second to indicate if they would be willing to take part in further timetable related research. Both of these invitations required the student to leave a contact email address.

6.2.3 Survey Delivery

It was decided that the online survey would be open for one week, and the 8th teaching week in the first semester of the 2012-2013 academic year (19th – 25th November 2012) was chosen. This week was chosen because it was felt that students would have largely settled into their studies, that they would still be using the regular timetable associated with the taught part of their course, and that the disruptive influence of the end of term on behaviour would be minimal.

The aim was to target all taught students enrolled at UoL during the survey week and for the survey to be successful, all of this population had to be made aware of it. Two possible notification strategies considered included: posting an online advertisement on the front page of the student VLE, and distributing flyers outside the Union building. However, it was felt that both of these strategies would generate insufficient responses and that for the survey to be truly representative a bulk email was required. UoL policy restricts the distribution of unsolicited emails, including those associated with PhD research projects. However, the good relationships built up with both the timetable and information systems groups, meant that a joint approach enabled authorisation for a bulk email to be obtained.

To further encourage participation all respondents were offered the opportunity of being entered into a prize draw, with three first prizes of £50 together with five smaller prizes of £20. It was felt that these prize amounts were large enough to attract students who would normally not be motivated to complete an online survey.

The prizes were funded for out the money saved through not having to pay researchers to administer a physical survey.

6.2.4 Survey Response

A total of 1,804 surveys were completed and after excluding 60 responses received from research postgraduates this left 1,744 valid responses of which 1,553 (89%) were from undergraduates and 191 (11%) from taught Masters students. Monitoring tools provided within BOS showed that the initial response rate was very high with 75% of all surveys being completed in the first 24 hours, and with 90% completed by the end of day two. The response profile illustrates the power and immediacy of using email to advertise a survey, and suggests that sending a second ‘chaser’ email half-way through the survey week would have further boosted the response total.

6.2.5 Supplemental Data

The data captured through the TQS was supplemented with two additional data-sets obtained from UoL. The first, timetable data, contained details of the 229,447 sessions, scheduled for 22,000 students, that took place over the survey week. This excluded details for some medical students who work to a locally administered timetable. Furthermore start/end times were missing from 15% of the scheduled sessions. These typically represent activities like tutorials that the student and their tutor schedule for a mutually convenient time, and as it was not possible to calculate a duration for these sessions they were excluded from the dataset. Around 4.7% of the sessions started or ended on the half-hour, rather than the hour, and these times were adjusted by plus/minus thirty minutes so that this data-set matched the form of the surveyed current and ideal timetables. The second additional data-set, obtained from UoL’s student information system (BANNER) contained aggregate demographic data listing the gender, age category, study mode, degree programme, year of study and faculty of study for all 27,714 undergraduate and taught postgraduate students enrolled at UoL during the survey week.

The discrepancy in numbers between the demographic and timetable datasets, of over 5,000 students represents those students who had no timetabled sessions during the survey week, those who were away on placement and those medical students whose timetable is administered locally.

6.3 Survey Validity and Bias

This section discusses the validity of the data captured by the TQS and any bias present within the data. This is split into two sections, examining bias evident through the demographic characteristics of the survey respondents, and then through their timetables.

6.3.1 By Demographic Category

The overall the response rate for the survey was 6.3%. Female students, who make up 59% of the undergraduate population, comprise 69% of the survey sample. A single proportion z-test statistic (null hypothesis: the response rate for males and females is equivalent) shows that female are overrepresented in the sample, significant at the 1% level. Consequently data was grouped by gender before testing for bias in all other demographic categories, Table 14.

	Male Students		Female Students	
	Population	Survey	Population	Survey
Age Group				
<22	65.0%	77.0%$^{++}$	66.2%	78.6%$^{++}$
22-30	25.6%	19.5%$^{--}$	23.7%	18.3%$^{--}$
>30	9.4%	3.5%$^{--}$	10.1%	3.2%$^{--}$
Nationality (not broken down by gender)				
UK+EU	87.0%	88.5%$^{++}$		
Overseas	13.0%	11.5%$^{--}$		
Year of Study				
1	35.5%	38.6%	38.8%	36.3%
2	28.9%	30.8%	28.5%	36.3%$^{++}$
3	26.0%	19.9%$^{--}$	24.6%	17.2%$^{--}$
4	9.7%	10.8%	8.1%	10.1%$^{+}$
Mode of Study				
Full-time	91.1%	98.7%$^{++}$	89.3%	97.3%$^{++}$
Part-time	8.9%	1.3%$^{--}$	10.7%	2.7%$^{--}$
Degree Programme				
Undergraduate	83.5%	87.4%$^{+}$	83.0%	89.8%$^{++}$
Taught Postgraduate	16.5%	12.6%$^{-}$	17.0%	10.2%$^{--}$
Faculty of Study				
Arts	15.1%	18.0%	19.3%	28.0%$^{++}$
Biological Sciences	8.3%	10.6%	6.9%	10.0%$^{++}$
Business	9.6%	8.7%	8.6%	8.5%
Education	10.0%	8.3%	13.5%	13.6%
Engineering	18.4%	20.6%	2.9%	3.5%
Environment	7.4%	8.3%	4.4%	6.0%$^{++}$
Maths And Physics	9.9%	13.9%$^{++}$	5.4%	8.8%$^{++}$
Medicine	12.7%	7.2%**	24.3%	12.4%$^{--}$
Visual Communications	6.3%	2.8%$^{--}$	12.2%	7.1%$^{--}$
Cross-Faculty	2.3%	1.5%	2.6%	1.7%

Table 14 – TQS: Responses by Demographic Category

[++ (+)/--(-) Over/under represented at the 1% (5%) level using single proportion z-test statistic with null hypothesis: no difference between the population and sample]

The analysis suggests that the sample is also biased towards young (18-22) full-time undergraduate students who are in their first two years of study. This group forms a majority of students at UoL and consequently the survey responses may under-represent any specific concerns of the university's minority groups: older students, part-time students, final year students and Masters students. It also demonstrates that responses from certain faculties are over-represented and that these differences cannot explained solely by differences in the gender makeup of each faculty.

6.3.2 By Timetable Attributes

In a survey assessing timetable quality it makes sense to check for bias in the timetables submitted by each respondent, as specific attributes might be particularly unpopular, resulting in a bias towards those students with timetables containing these attributes.

To check for bias by timetable, the mean contact hours, contact days/week and break length in the population and sample grouped by faculty and gender were compared. The analysis was restricted to undergraduate students in the first three years of their studies, this being both the largest group and that of most interest in terms of timetable preferences. The results are given in Table 15. No timetable data was available for medical students as their timetables are administered locally.

The results show some significant differences by both contact hours and contact days/week, and that with the exception of Visual Communications the sample reports higher values than those found in the underlying population. However, as previously stated, the population timetable includes some sessions (tutorials) which not allocated to timetabled slots, and these are excluded from the calculations, whilst the sample timetables will include these sessions, as they are part of the timetabled week, and this explains why all these measures are significantly higher.

A further comparison was made between the distribution of contact hours across the whole population and within the sample and this showed that timetables with under 10 contact hours/week are significantly under-represented in the survey whilst those within the 10-14 contact hours range are significantly over-represented. One possible explanation could be that very low contact hours timetables will have a minimal impact on the students who use them and hence the survey would be of less interest to these students compared to those students with more contact hours who may find that the timetable constrains their ability to undertake other activities.

Overall the timetables of the survey respondents appear to be generally representative of the timetables in the population.

			Contact Hours/Week				Contact Days/Week				Break Hours/Week			
			Population		Sample		Population		Sample		Population		Sample	
	Faculty	*n*	μ	σ	$\bar{x}$	*s*	μ	σ	$\bar{x}$	*s*	μ	σ	$\bar{x}$	*s*
Male Students	Arts	85	8.2	3.2	**9.3****	4.0	3.9	0.9	**4.1****	0.9	4.7	3.4	5.0	3.3
	Biological Sciences	54	11.8	3.7	11.4	3.8	4.3	0.7	4.4	0.7	5.3	2.9	5.8	4.2
	Business	33	12.1	3.2	11.8	2.8	4.5	0.5	4.5	0.6	7.5	3.6	**6.2***	2.9
	Education	36	7.9	2.6	**9.3****	3.1	3.8	0.8	**4.1***	0.9	3.7	2.8	4.5	3.2
	Engineering	78	15.9	3.1	17.0	3.8	4.6	0.6	4.7	0.7	4.3	2.2	**5.3****	2.7
	Environment	36	11.7	4.8	**13.7***	4.9	3.9	0.9	**4.3***	1.0	4.8	3.0	4.2	3.0
	Maths And Physics	57	17.3	3.4	17.6	3.8	4.8	0.4	4.8	0.4	7.6	2.8	7.0	2.7
	Medicine	26			23.5	8.3			4.6	0.9			4.5	2.7
	Visual Communication	12	9.0	3.2	**6.8****	3.5	3.5	0.9	3.2	1.3	2.4	2.2	2.8	2.8
Female Students	Arts	273	8.1	2.8	**9.4****	3.3	3.8	0.8	**4.0****	0.8	4.2	2.8	4.1	3.0
	Biological Sciences	107	12.4	3.7	12.2	4.0	4.5	0.7	**4.6****	0.7	5.6	2.9	6.0	4.0
	Business	67	11.8	3.1	**13.1****	3.0	4.5	0.5	**4.7***	0.5	7.2	3.5	7.3	3.8
	Education	133	7.6	2.3	**8.7****	3.3	3.6	0.9	**3.8****	1.0	3.2	2.4	3.6	2.9
	Engineering	30	15.5	3.0	15.4	3.8	4.6	0.6	4.6	0.7	4.3	2.6	**5.5***	2.6
	Environment	56	10.8	4.7	**12.4***	5.7	3.8	0.9	4.0	1.3	4.2	3.1	3.4	3.0
	Maths And Physics	84	17.3	3.6	17.7	3.4	4.8	0.4	4.9	0.4	7.1	2.7	7.0	2.9
	Medicine	117			15.3	8.0			3.8	1.0			3.0	2.4
	Visual Communication	70	9.3	3.5	8.7	3.4	3.4	0.9	3.4	1.0	2.2	2.0	2.2	2.0
All Students (excluding. medical)		1211	11.4	5.9	11.7	4.8	3.9	1.1	**4.2****	0.9	4.2	3.5	**4.8****	3.4

Table 15 – TQS: Responses By Timetable Attribute

[**(*): Difference significant at the 1% (5%) level using one sample z-test with null hypothesis: no difference between the population and sample]

6.4 Identification of Survey Themes and Issues

This section introduces the timetable quality themes and issues identified by the comments made by 970 (56%) of respondents to the unstructured question included in the survey.

In order to decode the responses to this question, a thematic analysis approach was taken, breaking down the comments into broad themes, followed by a second pass to identify the issues raised within a single theme. Where a respondent commented about more than one issue, their statement was broken down into discrete sentences or phrases which were then associated with the appropriate issue.

The main themes identified through this analysis are listed in Table 16. They are shown in descending order, based on frequency of occurrence, and for each theme the number of responses that mentioned it is given as both a count and as a percentage of the total sample. The table also shows the difference between the mean values for contact hours, contact days/week and break hours in the timetables of those respondents identifying each theme those within the sample group as a whole. Significant differences between the two are identified. These statistics demonstrate a degree of consistency between the comments made by the students and their individual timetables. For example, students commenting about the need for fewer breaks in their timetables have significantly more breaks than the survey mean, whilst the students desiring a more convenient timetable, with fewer TTDs, have significantly fewer contact hours but a similar number of TTDs when compared to the survey mean. The issues are categorised as either being related to a within-day timetable attribute (W) or a between-day attribute (B).

Those issues and themes identified through the qualitative data that are directly relevant to timetable design quality and trip-making behaviour will now be briefly discussed. Where respondent comments are included, codes in the following form will identify characteristics of the student making the comment: GYFFFAA where: G=M or F (gender), Y=1,2 or 3 (year of study), FFF=ART: Arts, BIO: Biological Sciences, BUS: Business, EDU: Education, Social Sciences and Law, ENG: Engineering and Computer, ENV: Environment, MAT: Mathematics and Physical Sciences, MED: Medicine and Health, VIS: Performance, Visual Arts and Communications, XFC: Cross Faculty (Faculty of study), AA=22: <22 years,30: 22-30 years,40: >30 years (age at enrolment).

Comment Category	Number of comments		Difference between mean in comment group and sample			Group	Summary of Comments
	N	%	Contact (Hours)	Days (Trips)	Breaks (Hours)		
Inter-session breaks	267	15%	1.02**	0.37**	1.59**	W	Students dislike inter-session breaks of all lengths
Session Timing within the day	189	10%	0.43	0.11	0.32	W	The 09:00-10:00 and 17:00-18:00 slots are unpopular
Study duration and back-to-back sessions	147	8%	1.07*	0.11	-0.10	W	A long run of back-to-back sessions reduces concentration levels and causes difficulty in terms of taking comfort breaks
Timetable Convenience/The need for a free day(s)	123	7%	-1.10*	-0.10	-0.90**	B	Sessions should be compacted into fewer days to give a free day without timetabled sessions
Commuting related issues	78	4%	-0.59	0.19	1.01**	W	Fear of walking home in the dark, problems with arrival/departure at peak times, time/cost of extra trips
Timetable Balance	67	4%	0.45	-0.01	-0.39	B	Sessions distributed unevenly across the week
Course design issues	57	3%	1.18	0.09	-0.53		Non timetable specific issues
Session placement in week	56	3%	-0.44	-0.10	-0.48	B	Preference for sessions earlier in the week
Session location on campus	51	3%	-1.11	0.09	0.75	W	Back-to-back sessions at different locations means late arrival
Single Sessions on one day	50	3%	-2.32**	0.14	-0.52	W	Days with one one-hour session are problematic
Satisfied with the timetable	47	3%	1.82*	-0.19	-1.13*		Generally happy with the timetable
Sports related issues	45	2%	1.06	0.09	0.71		Difficulty fitting timetable around competitive sports (Wednesday PM)
The presence of lunch breaks	35	2%	2.91**	0.23	-0.68	W	Important to include time for a proper lunch break
Lack of contact hours	33	2%	-5.05**	-1.05**	-1.82**		Would appreciate more contact hours and feel course is poor value for money
Timetable Clashes	21	1%	-1.20	-0.32	-0.57		Two timetabled sessions clash, or timetabled sessions clash with other non-academic activities
Timetable variability	17	1%	-2.62	-0.85**	-1.36	B	Timetables that vary across the weeks of the semester are harder to manage
Timetable Equity	14	1%	1.30	-0.01	1.15		An appreciation that the timetable is the result of a semi-random process, meaning some timetables are better than others
Appreciate opportunity to give feedback	10	1%	2.20	0.22	2.28*		Pleased that the university is researching this area as changes could improve the overall student experience

Table 16 – TQS: Timetable Themes And Issues

[**(*): difference significant at the 1% (5%) using one sample z-test with null hypothesis: no difference between the population and the sample]

6.4.1 The Frequency and Duration of Breaks

The theme most frequently commented on by respondents was around the frequency and duration of breaks. Students indicated that in general they would prefer to have all daily sessions compacted into one block after taking into account a break for lunch and giving sufficient time to move between sessions. Students appear not to value the time they spend on campus between sessions and would prefer to return to home during breaks. When they do use breaks to spend time on campus this is often regarded as a second-best alternative,

> *"I really don't like the 3-4 hours gaps between the sessions. I 'd rather have a couple of sessions straight after another (maybe with one 1h break between for lunch) , than waiting around on pointless frees"* (F2EDU22).
>
> *"On Thursdays I am in uni from 9 until 5 yet only have three sessions … it isn't ideal because the gaps are not long enough for me to go home (where I work most effectively) and so I have to stay in uni all day (where I find it much harder to focus and concentrate on work!), and I feel it is not a good use of my time"*, (F2ENV22).
>
> *"If I then want to be productive I then have to bring my laptop into university to get work done (I have an old and very heavy laptop), or email it back and forth to myself using the university computers. I also normally end up paying extra to have lunch in university instead of being able to have it at home … I find it quite difficult to get any productive work done in a two hour break that involves heading to the library, searching for a plug, just getting into your work and then realising it's time to stop and go to your next lecture. Whilst yes, it breaks up the day, for me it also breaks up productive work sessions. I work much better if I am in the library for an entire day at a time than if I am there just for a couple of hours here and there",* (F2BUS22).

The one hour break (apart from a lunch break) is particularly unpopular, and some students mentioned the frustration felt at having a series of timetabled sessions all separated by one hour breaks. Similarly, students dislike very long breaks,

> *"Gaps of one hour are too long between sessions. They are also too short, and do not allow for any decent work to be done and thus waste ~30 minutes of a day"* (M2ART30).
>
> *"… 1 hour breaks between each lecture or seminar. a lot of time is wasted on campus and there isn't enough time to do anything productive in breaks"* (M1ENG30).
>
> *"I hate having splits with a lecture at 9 and then nothing until another lecture at 5"* (M1BUS22).

Students who live close to campus often go home over these longer breaks (RQ4, supporting H1b), whilst other comments indicated that this type of arrangement disadvantages those with longer travel times, *"My accommodation choice for years 2 and 3 were based on the fact that if I lived further away I probably would have to hang around at university during lecture gaps"* (F3BUS30).

"On my current timetable I have a gap of 3 hours, where I live this is unpractical to come home, and seems to result in a wasted 3 hours" (F1ENV22).

Others reported that long breaks reduce motivation to attend later timetabled sessions, particularly if they have left campus in the interim,

"The times of the modules are so spread some days and that leads to the wasting of the whole day, being completely tired when you finally finish and without appetite for study" (M2BUS30).

"Having such a large gap in between means you lose concentration and sometimes it is difficult to find the motivation to return for your afternoon session" (F1MED22).

Long breaks are a cause of particular frustration for those students who have external time constraints, whilst other comments indicated that shorter gaps between sessions would be useful. A few respondents (<10) indicated that breaks helped them to organise their day,

"I find it hard to spend three or four hours on a break just for a one hour lecture at four o'clock. I also need to stay at home as much as possible as I am a carer for my father, and this timetable is just ignorant of responsibilities people may have outside of university. I am very disappointed in it." (F1MAT22)

"Instead of timetabling lectures back to back, there should a small break in between them, just to stretch your legs or get a drink. This could be done if a 10 minute gap could be timetabled between lectures" (M1MED22).

"The few hours in between [sessions] encourage me to use the library rather than go home in between and results in me getting more work done!", (F2EDU22).

6.4.2 Session Timing Within The Day

There was a general feeling that sessions should not be scheduled from 9:00 to 10:00 because: it is difficult for some to get up for this time, there is no chance to eat beforehand and these sessions suffer from poor attendance and low levels of engagement,

"I feel that early starts, and this isn't even from a lazy student perspective, do not really have any positive impact on the day. Getting up early can be difficult for anyone, meaning often one will have to rush into uni, I myself often don't get the opportunity to have any breakfast and once I am sat in a lecture I feel tired and distracted by my constantly rumbling stomach. And I know I am not alone in this experience!", (F2ART22).

"9 and even 10 o'clock sessions will mean worse performance. It should not be that way, however it is. Having to do be in a seminar for 9 or even 10 decreases how effectively the session works because students will be both less switched on and less likely to attend. Sad truth", (M3EDU22).

Students felt that the first timetabled session of the day should begin in the morning (earlier in the day) and not in the afternoon (later in the day), (M1BIO22

"Having later morning starts (11am) and lectures more compact within the day would allow students to study before the lectures in the morning and be less tired by having to get to a lecture for 9am every morning. I feel by having the lectures 11am and … between 13:00 - 14:00 most days allows students to be fresh and for their lectures for a great learning environment", (M1BIO22)

"I work more after lectures than before, making morning lectures beneficial. However, I struggle with early mornings, so I prefer a 10 o'clock start to a 9 o'clock start", (M2BIO22).

Students with childcare commitments mentioned that it would be more convenient if sessions were clustered around the middle part of the day whilst other comments suggested that late finishes meant sessions clashed with extra curricula activities organised by societies. Comments suggested that when a day contains few hours they should not be scheduled at the most unpopular times, whilst others indicated that students should not have an early start and a late finish on the same day,

"If days only have one lecture, don't make it 09:00, students need their rest, especially when bombarded with coursework", (M2ENG22).

"Lectures should not start at 5 or 6 in the evening, especially on days which begin with a 9am lecture - by the time you reach 5 or 6pm most students are exhausted and just want to go home. Starting at 9am can be required at times, but when possible it's better to start at 10", (M1MAT30).

However, a few respondents (<10) commented that a 9:00 AM start was preferred as it motivates them to work for longer across the whole day,

"Although 9 o'clock sessions have a painful impact on my social life, I find having something concrete to get up for in the morning facilitates my completion of work for the rest of the day. If my day doesn't start until four o'clock, getting up early to get my work done requires much more discipline", (M1ART22).

6.4.3 Study Duration and Back-To-Back Sessions

Students commented on the problems caused by a long run of back-to-back sessions, or by an extended single session. A run of back-to-back sessions results in reduced concentration levels in the later sessions, difficulties in preparing properly for all sessions, student restlessness and problems with taking comfort breaks, whilst lecturers do not necessarily appreciate the potential difficulties back-to-back sessions cause, *"Our lectures are blocked together for 2 or 3 hours at a time which can also cause problems. I would say after a hour and a half the majority of students have lost concentration and it becomes a difficult environment to learn in"*, (F2EDU22).

"Two thirds of my contact hours are placed in one day, and by the last hour of the second lecture, as a group we all struggle to concentrate and as a result do not reap the benefits of that session", (F2EDU22).

"I have a part time job & and when I work a 4 hour shift I have a 15 minute break and I think students who have a 4 hour block should be allowed to decide whether they do any longer than that without a break. Being told wanting a break is apparently a 'convenience' reason, but students know how they work best & automatically being allocated 5-hour blocks is problematic", (F2ART22).

Others described how they would miss one session within a series of back-to-back lectures to take a break and get some food, whilst others linked falling concentration levels to feelings of hunger and resentment. Staying in the same room for an extended period was also seen as problematic,

"On Tuesdays I have a consecutive run of 6 sessions and on Thursday a consecutive run of 8 hours. This is ridiculous as there is no time to eat, meaning I miss at least one session from each of these days every week.", (M2ENG22)

"On a Thursday I have a completely full timetable from 10am - 5pm with just an hour break from 2pm - 3pm. This means that by the time it is my lunch time I am very hungry, tired & fed up as late lunch effects [sic] my mood. I then continue until 5pm with no more breaks, meaning that in my later lectures, I am much less focused & mostly just don't want to be there. This is effecting my learning ability", (F1ART22).

"6 hours a day for one module in one room is too much!", (F2MED22)

"It can be difficult to concentrate when there are more than three lectures in a row, especially if they are in the same room or building as it gives you no chance to get fresh air", (F1MAT22).

Whilst there was general agreement that an extended run of back-to-back sessions was detrimental to the learning experience, there was little consensus in terms of a maximum session length, although comments might indicate that academic maturity improves concentration levels,

*"Too long in one room without break is not good, **max of one hour** sat on one subject before concentration declines",* (M1MED30)

*"3 hour lectures are tough, by the end of the first 90 minutes you're losing focus. **2 hour lectures maximum**"*, (F2ART22)

*"it's better if the maximum you have without a break is **3 hours**"*, (F2VIS22)

*"Clumped together sessions (for example 6/7 hours) can be a pain especially if in different locations and with no time for food. 3-**4 hours is probably the most acceptable**"*, (M3BIO22).

6.4.4 Timetable Convenience and The Need for Free Days

Respondents indicated that they value NTDs as they allow them to catch up on their work,

> *"I would prefer my lectures to be condensed into days rather than spread out throughout the week, it makes it hard in third year to be trying to do work yet always having to leave halfway through each day for lectures"*, (F3BIO22)
>
> *"There is a strong reasoning for having at least 1 day off per week, or at least 1 half day from 12pm as it provides time to catch up on work or to assess work done so far in the week",* (M2ENG30)
>
> *"I have a very spread out timetable this year with numerous days where there is just one thing in the middle of the day which makes it difficult when I have serious assignments due I can't just have a day to get on with work and the middle of the days are taken out with having to get to uni for lectures. I would rather a day a week off as a study day to get work done and to have things less spread out"*, (F2ART22).

Students suggested that free-days or free half-days provide space for other important activities. For students enrolled on courses with a heavy reading element, a free-day provides time to concentrate on this activity,

> *"Yes, I'd really like my hours to all be bunched up over 1/2 days, and then have the remaining days free so we can do extra-curricular things which will enhance our CV and set us up to be in a good position for when we leave university, for example part time work, volunteering etc"*, (F2ART22).
>
> *"By cramming [sessions] into one or two days, it would make commuting into university more worthwhile for more than just a one hour session. Having a day or two un-timetabled I would find incredibly helpful in terms of extra work, as I would be able to focus full days to essays/preparatory reading"*, (F2ART22).

Fewer TTDs also reduces the need to commute thereby saving time and money, and provides some flexibility for those who work.

> *"It would be great to have at least one day in a week (or ideally two) free. Especially when I sometimes have to come just for one hour (which makes almost 3 hours of my time including transport). Putting this one hour into another day, when I have to come to school anyway, would be so much better. This would help me to save a lot of time"*, (F1BUS22)
>
> *"It is preferable for me, as a mature student who has to travel in to university, to have sessions scheduled fairly close together and concentrated into a couple of days rather than dotted through the week. I know that other mature students who do not live on or near campus prefer this too"*, (F3EDU30)
>
> *"In my third year my contact hours week-to-week vary from 5-8 hours. It would be ideal for this to be over 2 days rather than spread over 4 as it has been, due to my personal circumstances meaning I commute from Derby by train"*, (F3ART22).

Compacting sessions into fewer days would place more onus on the students to manage their time effectively, whilst grouping sessions into fewer days might help boost attendance as the amount of material lost through not attending on campus would be higher, compared to days with fewer sessions.

6.4.5 Commuting Related Issues

Many students commented that sessions timetabled later in the day meant that they had to walk home in the dark, resulting in concerns around personal safety,

> *"Walking back after this lecture means walking back in the dark and don't feel very safe, particularly since it is the semester heading towards winter"*, (F3ART22).
>
> *"When travelling to Uni at 5-6 it is scary walking home at night past hyde park, especially in the darker nights. It also doesn't allow me to do anything throughout the day and often un-motivates me from attending the session"*, (F2BUS22).

Those who live far from campus commented that days with only one or two timetabled sessions meant that their travel time was often greater than the duration of the sessions attended. Some students identified that TTDs starting at 9:00 AM and finishing at 17:00 mean that student commuting trips clash with the city-wide rush hour, resulting in extended and less reliable journey times, and that users of public transport faced having to pay higher ticket prices to travel as these times,

> *"It costs me £9 per day to travel into uni and that isn't including parking (up to £9 per day) and the commute takes 1 hour each way in the summer and 1 and a half hours each way in the winter. … Therefore any days with either 1 or 2 hours sessions I spend more of the day traveling then teaching.",* (M3MED30).
>
> *" I had one seminar scheduled for the whole day, which could mean i'd have to go all the way to Leeds (about an hour travel each way) just for one seminar - if the bus didn't come and/or there would be traffic, I'd be late and there would be no point in coming in at all",* (F2EDU22).
>
> *"As a student that commutes daily, I find travelling in rush hour traffic to be unpredictable. Sometimes I have missed whole lectures from being late even after setting off early"*, (M3MAT22).

Other respondents mentioned that later finishes (after 18:00) meant lower frequency public transport services and potentially longer travel times.

6.4.6 Timetable Balance

This theme refers to the balance between the number of contact hours scheduled on each day over the academic week or semester. Respondents reported that some days were very full, with back-to-back sessions whilst other days had one or no sessions, and that some balance is required so that all days have approximately the same number of sessions, *"I have an overly filled Monday and a rather empty Wednesday. It's a bit ridiculous that I'm in 6 hours straight on a Monday and only an hour on Wednesdays. I'd much rather split the hours evenly"*, (F2ART22)

"I feel my timetable is very much weighted to a Thursday …I had lectures all day due to an extra session put in at 1-2. This lead to me having to be very late for a lecture as I had to eat. As my day also goes on until 6 … I find myself losing concentration and not listening", (F1BUS22).

Some low contact hours students reported that more than half of their hours were on a single day each week, resulting in lower concentration levels by the end of the day, whilst others highlighted feelings of isolation,

"2/3's of my hours are on Tuesday … This makes the week very uneven in terms of workload with nothing to do during the later parts of the week", (M2ART22).

"My timetable is very bitty and extremely inconsistent .. Only having an hour seminar on a Tuesday at 11am is very awkward … Equally having back to back lectures and seminars on a Thursday from 11am till 4pm is extremely bad timetabling, I do not even have time to eat lunch and my concentration by the end seminar of the day is zero", (F2EDU30).

"Having the majority of contact time clumped on one day means the others get very lonely - probably not great for your mental health to be shut up with books all day", (F3ART22).

Some suggested that having some contact time each day (especially in the morning) gives some structure to the day, encourages good discipline and motivates students to work on their studies and generally be more productive,

"I don't like how on usually 4 out of 5 days I have 1 hour in the morning and then on one day … I have a full day. I would rather have a couple of hours each day starting at 10", (F2BIO22).

"If I had to go into campus every day for a lecture or seminar I would be more likely to spend time in the library", (F2ART22).

6.4.7 Session Placement Within The Week

Students commented on the positioning of their sessions across the days of the week. Many indicated that they would like some or all of Friday free so that they could travel home at the weekend, and similarly Monday mornings,

"Also 5-6 on a Friday for a lecture is not nice too for people who might want to go home on a weekend and do live quite far away. Although university does come first it is sometimes nice to go home when you are feeling homesick so having a lecture Friday 5-6 is really awkward. I think this is especially important in first year when you are more likely to go home at the weekend", (F1ART22)

"If students were to return home for the weekend, Friday afternoons and Monday mornings off would be useful for cheaper train tickets and to spend more time at home with family/friends etc", (M2BIO22).

A few students highlighted that lectures on a Friday afternoon meant that they had difficulties attending religious services. Some students suggested that clustering the sessions into the first part of the week would be preferable as they were fresher and more motivated during this time,

> *"I would prefer the bulk of my lectures earlier in the week, giving me the latter half to do my own admin/work"*, (F2BUS22)
>
> *"I would personally prefer to have busier days as the start of the week"*, (F2BUS22).

Many students commented on the need to keep Wednesday afternoon free for sports related activities (see sports specific comments).

6.4.8 Session Location on Campus

Students commented on the difficulties they experienced moving between back-to-back sessions when they are held at different locations on campus. University policy is for sessions to finish five minutes before the hour and start five minutes after, but comments suggest that lecturers don't necessarily observe this rule,

> *"you are sat for four hours straight in lectures without a break because teachers do not end at 5 to and do not start 5 past, it all ends and starts at the same time and it makes it impossible to walk from one site to another that usually takes 10-15 min"*, (F2BUS30)
>
> *"Lectures and seminars which are timetabled to follow each other are problematic when the locations are on opposite sides of campus. It is unavoidable to leave at the end and arrive before the next session has started. This creates a poor impression. It is exacerbated when sessions overrun, or when important questions need asking (especially for seminars)."*, (F1ART30).

Some reported excessive walking distances, having a series of back-to-back sessions which alternate between opposites ends of the campus, whilst difficulties with moving around campus are exacerbated since many students change classes simultaneously, congesting walking routes and causing delay,

> *"On Tuesday, I have a lecture in Roger Stevens at 2pm, followed by a lecture in the Engineering building at 3pm(opposite library pub), then a seminar at 4pm in the Social Sciences building. I have to constantly choose between missing 10 minutes at the start or end of each, which is not great when I'm miss info about essays or exams. I often have to run, so I arrive to my sessions tired and sweaty",* (F2EDU22).
>
> *"Next semester I am supposed to have 6 straight hours of lectures and seminars, on different sides of campus. I will not have time to eat and I will probably be late to all but the first"*, (F2ART22).
>
> *"Feels very backwards / forwards with little time to walk between, Roger Stevens can get very crowded and can take over 5 minutes alone making your way through the building"*, (F1ENV22).

Lecturers can be unsympathetic when students arrive late, even when the late arrival is no fault of the student,

"I am frequently timetabled in the conference auditorium immediately before either the business school or engineering, it is impossible to make it on time and results in disapproving looks from your next lecturer or a rant about being late", (F2BUS22).

6.4.9 Single Sessions on One Day

Students comments indicated that scheduling a single session on a timetabled day was not an effective use of time, whilst a single hour from 09:00-10:00 means an early start for many students, and a rush to get to campus. Similarly single sessions during the middle of the day are very disruptive since it causes the non-timetabled time to be split into two blocks,

"I appreciate that lecturers have other classes to teach, but if they could do a two hour session … then it would save time. I waste more time walking to and from uni for one lecture, when I could be doing work/revision", (F2BIO22).

"A lot of days we are made to get up for 9 o'clock to just do 1 hour and then thats it for the day", (M1BIO22).

"My only lecture on a Wednesday is 9-10. This makes it a lot of effort to come into uni (bearing in mind I live 40 minutes from campus)simply for an hour.", (F2MED22).

"Having one session at midday on Thursday and Friday … wastes a large portion of my day just on travelling in for just one hour or lecture/seminar. Literally have no time for work this year as I am just wasting my day travelling!", (F2EDU22).

When most of the students in a session only have that session during the day then attendance is noticeably lower, especially when the session is early in the day, and that this disadvantages the students who do attend, whilst some reported not attending on-campus at all on single-session days,

"I have a one hour lecture each week at 9 am, many people do not turn up as it is 'not worth it'", (F2MED22)

"*Having a one hour session at 9a.m and nothing else does make me feel I have little incentive to go (silly I know)and If I do the quality of my responses is lesser than if it had been later in the day*", (M3EDU22).

"I don't go to lectures if there is less than 2 lectures in that day", (F2BIO22)

"One seminar, for one hour, on one day, from 4-5pm is very off putting, and I have consequently missed it 2/3 times", (F1VIS22).

6.4.10 Sports Related Issues

Some respondents were vociferous in their comments about clashes between the academic timetable and their desire to partake in sports related activities, and although comments primarily highlighted the importance of keeping Wednesday PM free, other suggested that this provision alone was insufficient,

“no lectures or labs should ever be put on a Wednesday. If you want to represent your university at sport, why should your university make it impossible for you to do so?”, (M2ENG22).

“This lack of contact time needs to be for the entire day as some teams travel to away games, which can take several hours and they have to depart Leeds early in the morning”, (M3XFC22).

“I can never train on Thursday with LUUWAFC due to having my only lecture finishes at 17.00 which is when training starts which means I have not got time to get to training”, (F1MAT22)

“Being a member of a University sports team … Thursday mornings are very difficult after Wednesday night socials”, (M2ENV22).

Other commented on the compromises that sports players have to make when sessions are scheduled on Wednesday’s and of the impact it can have on their education,

“I was told when I started I would have Wednesday afternoon of for sport because sport is very important to me, yet I have a lecture timetabled when I have sports fixtures. I then have to choose between 2 things I live doing which it's truly unfair!!!”, (F1BIO22)

“I personally have chosen modules that were perhaps my second choice so I didn't have to drop sporting commitments”, (F3ART22).

Some mentioned that planners use the free time available on Wednesday afternoons to schedule optional sessions (careers) which sports players miss out on.

6.4.11 The Presence of Lunch Breaks

Some students specifically commented about the need to include sufficient time for a lunch break in the timetable. Students justified the need for a lunch break to maintain concentration levels, or to reduce the risk from migraines, and to compensate for a missed breakfast due to an early timetabled session,

“an hour at least for lunch is needed every day, for concentration”, (M1VIS22)

“It is very difficult on days where there are lesson timetabled through lunch time. It can be difficult to concentrate on the lecture and is also quite unhealthy. As a person who suffers from migraines and has been told to eat approximately every three hours, a five hour session through lunch time is sometimes a worry”, (F1BUS22).

Students living in halls on-campus highlighted a specific problem that indicates a lack of joined up thinking within the University, *"All of my lunch breaks fall between 11 and 2 … the refectory just happens to deny catered students the use of their meal plan cards during this time period. Frankly, this means I have to spend money I don't have to buy lunch. I would prefer to have a full timetable until 2, rather than have my break at a time I have to purchase food on top of my extortionate accommodation rates"*, (F1EDU22).

Others suggested that a one hour lunch break is too long and that 30 minutes would be more appropriate, particularly for students who work, or who want to get their day on campus finished sooner.

6.4.12 Lack of Contact Hours

Although the number of contact hours in a timetable is dependent upon the curriculum being studied rather than being a function of the design of the timetable itself, some students used the survey as a means to comment on the perceived lack of contact hours within their timetable. Comments focused around a desire for more contact hours to allow for more in depth coverage of the material being taught or to consolidate their knowledge,

"I don't feel I have that many timetabled sessions for my subject and would actually prefer more", (F2VIS22)

"I would prefer more contact hours", (F3XFC22).

"I have 6.5 hours a week!! I want more teaching time and less independent learning time, otherwise I am paying for almost three free days a week. I am at university to learn, yet at the moment I am spending days with no structure of group work, only solo research and writing with no guidance of aid from any tutor", (F1ART22)

"For a third year student … the fact that I am only in 5 hours a week is ridiculous … it is disheartening when there are so few classes to share ideas with students and profs", (M3ART22).

Others commented that fewer hours left them lacking motivation or feeling isolated from their peers and the University,

"I have a huge issue with the minimal amount of hours I am prescribed … I find it incredibly difficult to find motivation to do anything at all when my actual university hours are only currently 5 hours a week", (F2ART22)

"I would like more contact hours, even if it's just in the form of group-work with peers .. otherwise you don't get to meet people on your course and its lonely and difficult. It is because I don't know anyone on my course … I really dislike Leeds and my course… I would have really appreciated it especially in this first semester!", (F1ART22).

Another common theme was the perception that lower contact hours courses represent poor value for money, especially when all costs are considered and compared to those enrolled on higher contact hours courses who pay the same fees, *"Considering how much degrees cost now, I would have expected the timetables it provides to be a little more logical- especially as third year humanities students only have three hours in a week! ... Paying for a house in Leeds is completely illogical",* (F3ART22)

"There are a ridiculously low amount of contact hours for the humanity subjects. We are paying £9,000 for 6 contact hours a week which is frankly a bit of a joke", (F1ART22)

"I am annoyed that my fees cost the same as a student doing geology, sciences etc. but I have 7 contact hours a week. I realise my degree has a lot of reading involved but some more sessions would make coming into uni a little bit more worth while", (F2EDU22).

6.4.13 Timetable Equity

Comments showed that students recognise that the assignment of session times to an individual is a random process resulting in more (or less) convenient timetables. Some students have a greater need for convenient timetables and feel it would be useful if there was a mechanism through which students could indicate their need for this,

"Despite the fact that I'm in 5 days a week so I'm not able to find part time job I can live with it. On the other hand, it's unfair how some people have almost perfect timetable (day off during the week, no gaps between lectures etc.) and some (including me) have a timetable which looks like job done by toddler", (M3ENG30).

"There are groups in my year that have a free day a week. I would like some way for the system to prioritise people who this is a important requirement, rather than a nicety and allocate them to this timetable", (M3MED30).

Others highlighted feelings of inequality between students in terms of the number of 9:00AM starts experienced. Those with more are potentially disadvantaged due to fatigue and because these sessions are badly attended and therefore the educational experience may be poorer as a result. Similarly others recognised that those students who get a free day in their timetable have an advantage over those who don't,

"I am in at 9am four days in a row, which is considerably more early starts than the average BA student and is bad even compared to others on my course who selected different modules", (F2ENV22)

"I think that it is generally unfair that I have 4 9 ams each week.I think this should be avoided as I am constantly tired", (F2BUS22).

"I am quite annoyed with the fact that my peers have at least one or two days completely free every week, and I understand that this is due to the difference in modules chosen in the second year, however I would need and appreciate at least having one weekday completely free to catch up on studying or reading, rather than going through the effort of having to get ready to go to university. The people who get at least one day free have an unfair advantage over others who don't get this opportunity and need this opportunity to remain up to date", (F2BUS22).

6.4.14 Student Appreciation for the TQS

Students commented that the design of the timetable was a serious issue for them, and that the survey provided a platform to air their views,

> *"I feel that this survey is really important to establish the issues students face week to week with their timetables. I hope that issues raised are seriously considered and hopefully improvements are made upon the outcomes of this survey."*, (F1ENV22).
>
> *"I am glad that we have been given the opportunity to give feedback on our timetables as it is something which really bothers me this year."*, (F2ART22).

6.4.15 Discussion

The TQS qualitative data uncovers a student narrative that is focused around conversations on waste and conflict. Wasted time spent on-campus during breaks, wasted time spent travelling to campus for a single session, wasted money spent on excessive commuting, wasted effort spent making leave-and-return trips, wasted money spent buying food on-campus, wasted opportunities from courses with minimal contact hours. Conflict between the desire to sleep or attend early sessions, conflict between participation in sports activities or Wednesday afternoon sessions, conflict between the desire to go home for the weekend or attend sessions scheduled on a Friday afternoon, conflict between the need to work/care or attend piecemeal sessions on-campus, conflict between the desire to remain on-campus or to walk home before dark.

The narrative around waste implies that students hold a contemporary view of their timetable (answering RQ1, and supporting H1). Students appear to have an aversion to the campus, they clearly wish to minimise the time they spend on it, and don't seem to appreciate that non-timetabled time spent on-campus adds value. The view of on-campus study presented by the students is one of specialisation and compartmentalisation. The campus is seen as a unique destination at which knowledge transfer takes place but only within the mediated confines of pre-scheduled sessions and that it seems to be an inappropriate venue for other elements of the learning process. The campus has become semi-toxic and the student collective behaves like some kind of animated fairground sideshow; during timetabled sessions the lights come on and the music plays but for the rest of the time it lies dormant.

The comments suggest a direct connection between the academic timetable and commute trip-making behaviour whilst if the student's residential distance allows, then leave-and-return behaviour is also seen as an integral part of the day. The comments suggest that if students are not currently attending a session, they will invariably be either travelling to or from one.

When student behaviour normalises a view of the timetable seen as a series of on-campus appointments, then conflict will be arise around the timing of those appointments. For some students engagement with the university experience is similar to engaging in a battle (Krause, 2005, p. 9). The view presented in the TQS of student interaction with their timetable and the campus matches this description. The culture of the institution is seen as alienating, foreign and uninviting (ibid, p. 9). A timetable that seemingly forces the student to attend briefly, to shuttle between spatially separated sessions, to endure extended hours of back-to-back teaching, and then to wait for hours for their next session for no apparent reason can only reinforce this view.

6.5 Quantitative Analysis Techniques

The analysis of the TQS quantitative data that follows in section 6.6 uses some standard parametric statistical analysis techniques and background material and an explanation of the techniques used is contained in the following sections.

6.5.1 Independent and Paired Samples t-tests

Independent and paired sample t-tests are statistical methods for determining if two samples were drawn from the same underlying population. The independent t-test is used when participants in the two samples are distinct, whilst when participants are sampled under two conditions (so called before and after tests) the paired samples t-test is used.

These methods examine the difference between the two sample means relative to their associated standard errors assuming the null-hypothesis that the two samples are equivalent.

The formula for the independent t-test is shown in equation 6-1, (Field, 2013, p. 367-368)

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}}$$

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} \qquad \text{6-1}$$

Where

$\bar{X}_1, s_1, n_1$ Sample mean, sample standard deviation and sample size for sample 1 (sample 2 defined similarly)

The calculated t value is used to index the table of t-statistics at $n_1 + n_2 - 2$ degrees of freedom to obtain a p value, which if significant indicates that the two samples are independent (null-hypothesis rejected).

The independent t-test assumes that the two samples are normally distributed or large (>30) and that their variances are equal. Levine's test for equality of variances can be used to check the second assumption and if this test is significant an alternate form of the t-test can be used (not shown).

For the paired sample t-test the mean and standard deviation of the differences between each pair of observations is calculated, and the t-statistic obtained using equation 6-2 (Field, 2013, p. 368).

$$t = \frac{\bar{D} - \mu_d}{\left(\frac{s_d}{\sqrt{N}}\right)} \qquad \text{6-2}$$

Where

$\bar{D}, s_d, N$	Mean and standard deviation of differences between paired samples and number of pairs
μ_d	Hypothesised population mean (0 if the null hypothesis is that there is no difference between the before and after conditions)

The paired sample t-test assumes that the paired sample differences are normally distributed or that the sample size is large (>30).

The t-tests don't assume that the population standard deviation is known and consequently for small samples the tails in the t-distribution are longer than those for a normal distribution and the difference between the means must be larger to be statistically significant than it would need to be for a z-test. As the number of samples being tested increases the tails become smaller and the t distribution begins to approximate a normal distribution.

6.5.2 Chi Squared Tests

A categorical variable has a measurement scale consisting of a set of categories (Agresti, 2007, p. 1). Ordinal categorical variables describe a natural ordering across the categories, for example a car's emissions tax band, whilst nominal categorical variables describe situations where no order exists; travel mode for example.

In any population a set of underlying probabilities define the expected likelihood that a member of the population will choose each of the categories (the probabilities for all categories summing to one) whilst a series of independent and identical trials can reveal the observed likelihood of their selections.

When I distinct samples are taken and there are J levels within a categorical variable then an IxJ contingency table T can be used to classify all possible outcomes from a series of trials in which all instances of category j identified within observations taken in sample i are summed in cell T_{ij} within the table.

When J is 2, the observed count in each cell will approximate the underlying population category likelihood with a standard error defined by equation 6-3, (Agresti, 2007, p. 9).

$$SE_{ij} = \sqrt{\frac{p_{ij}(1-p_{ij})}{n}} \qquad \text{6-3}$$

$$p_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}$$

A Chi squared test can be used to determine if the category distributions observed in each sample are drawn from the same underlying population (the null hypothesis), using the test statistic calculated according to equation 6-4 comparing the observed cell frequencies with the values that would be expected if the samples were related, (Field, 2013, p. 723) .

$$\chi^2 = \sum_i \sum_j \frac{(T_{ij} - E_{ij})^2}{E_{ij}} \qquad \text{6-4}$$

$$E_{ij} = \frac{\sum_i T_{ij} \cdot \sum_j T_{ij}}{\sum_i \sum_j T_{ij}} \qquad \text{6-5}$$

The Chi squared distribution for (I-1)(J-1) degrees of freedom provides a critical value at the required level of significance and if the test statistic is larger than this value then the null hypothesis can be rejected and the samples assumed to be drawn from different populations. The Chi squared test treats the data as being nominal with no ordering between the categories (Agresti, 2007, p. 41).

The Chi squared test assumes that in a 2x2 contingency table none of the expected frequencies, Eij, are below 5, and that in larger contingency tables all expected frequencies are greater than 1 and no more than 20% are less than 5 (Field, 2013, p. 735).

6.5.3 Linear Regression

Linear regression models (LRM) are used within this chapter, and this section provides an introduction to this technique. A multiple LRM allows a mathematical relationship to be defined between a dependant response variable, Y, and one or more independent predictor variables, X, (Pardoe, 2006, p. 73) through equation 6-6.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots \beta_k X_k \qquad 6\text{-}6$$

The dependant variable should be continuous and unbounded whilst the independent variables must be quantitative or categorical (with two levels) (Field, 2013, p. 312).

For a sample containing n observations of X and Y the model is fit and values found for parameters $\beta_0 .. \beta_k$ by minimising the sum of the squared errors (SSE) between the expected value of Y calculated through equation 6-6 and the observed value of Y from the sample, equation 6-7, (Pardoe, 2006, p. 77), whilst equation 6-8 determines the total sum of squares (TSS) which describes the fit of the data to the model in the absence of any predictor variables.

$$SSE = \sum_i (Y_i - \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} \ldots \beta_k X_{ki})^2 \qquad 6\text{-}7$$

$$TSS = \sum_i \left[Y_i - \frac{\sum_i Y_i}{n} \right]^2 \qquad 6\text{-}8$$

The difference between the expected value and the observed value is known as the residual. The standard error of the regression, the mean absolute difference between the expected and observed values is defined by equation 6-9, (Pardoe, 2006, p. 81).

$$s = \sqrt{\frac{SSE}{n - k - 1}} \qquad 6\text{-}9$$

The goodness of fit of the overall model is determined through the coefficient of determination, R^2, equation 6-10, and describes the proportion of the variation in the model explained by the parameters. An adjusted R^2 measure, equation 6-11, (Wherry’s equation) compensates for indicator inflation that occurs when parameters are added, and describes the fit that would occur if the model was built against the population as a whole and not a sample of it, (Pardoe, 2006, p. 83-85) and (Field, 2013, p. 312).

$$R^2 = 1 - \frac{SSE}{TSS} \qquad 6\text{-}10$$

$$Adjusted\ R^2 = 1 - \left(\frac{n - 1}{n - k - 1}\right)(1 - R^2) \qquad 6\text{-}11$$

The significance of the individual k^{th} coefficient is determined by calculating a t statistic at n-k-1 degrees of freedom using equation 6-12, where SE_{bk} is the standard error of the predictor. The null hypothesis for the test statistic is that a coefficient of zero will be as adequate a predictor as the fitted value.

$$t_k = \frac{\beta_k}{SE_{b_k}} \qquad 6\text{-}12$$

The assumptions of the LRM are as follows. Firstly, that the dependant variable should be linearly related to the predictors and that their combined effect can be described through addition. Secondly that the residual values should be independent (uncorrelated) and exhibiting a lack of auto-correlation. Thirdly, that at each level of the predictor variable the variance of the residuals are homoscedastic (uniform). Fourthly, that the residual terms are normally distributed around a mean of zero. Finally that the predictors should be uncorrelated with any external variables not included in the model, and that no two pairs of predictors exhibit multi-colinearity (Field, 2013, p. 311-312).

When auto-correlation is present in a model the significance of the coefficients for each parameter to be under or overestimated. The Durbin Watson statistic can be used to test for the presence of auto-correlation. This compares the difference in the residuals between pairs of observations relative to the magnitude of each residual value when taken in isolation, equation 6-13, (Field, 2013, p. 874).

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \qquad 6\text{-}13$$

The statistic will lie between 0 and 4 with a value of 2 indicating no auto-correlation, and with values below (above) this suggesting the presence of positive (negative) correlation. The critical values for detecting the presence of correlation depend both on the number of observations and the number of parameters (Durbin and Watson, 1951) and positive correlation is indicated in the models used in this study if the test statistic is below around 1.6.

When heteroscedasticity is present in a model the significance tests and confidence intervals associated with each predictor are invalidated, however the coefficients themselves remain valid (though non optimal). Heteroscedasticity can be detected by examining a scatter plot of the standardised residuals against standardised predicted values. This points should be randomly distributed with no discernable pattern.

Non-normally distributed residuals is only a problem for small samples and causes the significance test and confidence intervals to be invalidated, but in large samples this is not an issue. A histogram showing the distribution of the residuals or a Q-Q plot provides a check for this assumption.

6.5.4 Binary Logistic Regression

The quantitative analysis uses two instances of both binary logistic (BLR) and ordered logistic (OLR) regression models. To maintain the flow of this chapter these techniques are not described here, but are instead introduced in section 7.2.4, as logistic regression is used more extensively in this subsequent chapter.

6.6 Quantitative Analysis of Student Timetable Preferences

The themes and issues outlined in section 6.4 highlighted general areas of concern, but did not quantify the overall level of dissatisfaction nor the magnitude of change desired by the student population. At the same time whilst the qualitative narrative around waste and conflict was clear, student suggestions of possible solutions seem contradictory. Students simultaneously want less breaks and also more, later starts but also earlier finishes, a more balanced timetabled but also a more compact one.

The TQS's main instrument involved asking respondents to specify their current timetable, and to then rearrange the sessions to demonstrate their ideal timetable. Comparison of the current and ideal timetables then allows student preferences for specific timetable characteristics or design attributes to be identified. Using the results of the qualitative analysis as a guide, the quantitative data collected through the survey will be analysed to identify how representative the themes are.

6.6.1 Data and Variable Selection and Inspection

The TQS was open to all taught students and responses were received from both full-time and part-time students on undergraduate and Master's programmes. However, as stated in section 6.3.2, to eliminate some of the heterogeneity between respondents the quantitative analysis was limited to full-time undergraduate students enrolled on years one to three of their course

The study relies on inferring timetable preferences from the choices made by respondents when rearranging the sessions in their current timetable to create their ideal timetable. Since the survey was not asking students to redesign their curriculum, just the timing of its delivery, the current and ideal timetables would be expected to encompass the same number of contact hours. Unfortunately the BOS tool did not allow for an inline check to enforce this condition, and 333 respondents specified differing contact hours totals in their two timetable grids. Although in most cases the difference was just one hour, to reduce the risk from unexpected bias these responses were excluded.

The contact hours in the timetables for the remaining responses ranged from between 1- to 36 hours per week. There were very few responses at the low and high ends of this range and in order to reduce the effect of unrepresentative extremes all responses outside of the range 4-21 contact hours per week were excluded. This reduced the samples by a further 5% of samples, but meant that there were a representative number of responses (>=30) at each level of contact, apart from at 5, 18, 20, 21 contact hours which included 25, 28, 29 and 17 responses respectively. This filtering process produced a final set of 1,004 responses for analysis representing a population of around just over 18,000 full-time undergraduates within years one to three enrolled on courses with between four and twenty one contact hours per week. Demographic characteristics representing each respondents gender, age, nationality, year of study, faculty of study, travel time from home to campus in minutes were captured as part of the survey. To aid analysis the number of levels in the categorical variables for faculty of study, age and nationality were collapsed to give representative counts at each remaining level, whilst new categorical data variables were created for both timetable contact hours and travel time by dividing the range of responses into best-fit quartiles, Table 17.

		n	%
Gender	Male	291	29.0
	Female	713	71.0
Age	18-21 years	888	88.4
	>=22 years	116	11.6
Nationality	British	861	85.8
	EU and Overseas	143	14.2
Year of Study	1st Year	359	35.8
	2nd Year	419	41.7
	3rd Year	226	22.5
Faculty of Study	Arts: Arts, Business, Education and Social Sciences, Visual Communications	575	57.3
	Science: Biological Sciences, Engineering, Environment, Mathematics and Physical Sciences	357	35.6
	Health: Medicine and Health	72	7.2
Timetable Contact Hours	4-7 hours	235	23.4
	8-10 hours	268	26.7
	11-14 hours	264	26.3
	15-21 hours	237	23.6
Home to Campus Travel Time	0-7.5 minutes	123	12.3
	7.6 - 15 minutes	342	34.1
	16-30 minutes	394	39.2
	>30 minutes	144	14.3

Table 17 – TQS: Respondent Summary Statistics

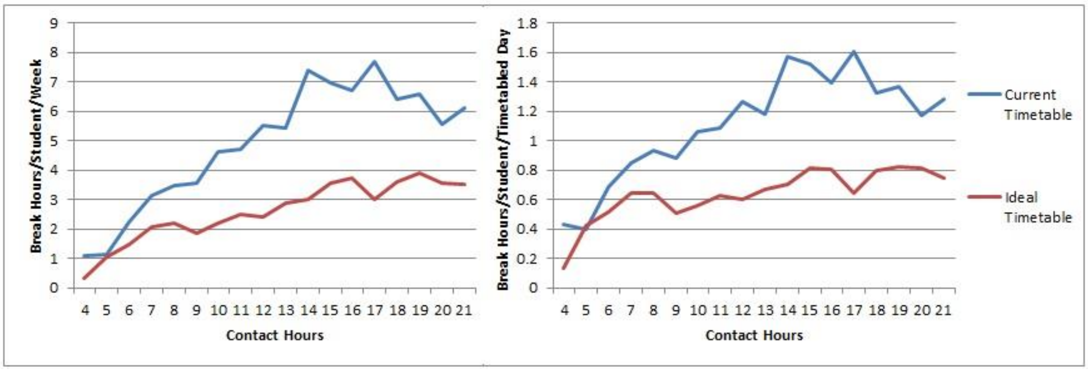
The following sections examine the quantitative evidence of timetable preference. Within-Day timetable preferences are examined first: break length, back-to-back session length, session timing, moving between sessions on-campus, walking trips in darkness, and single session days. The discussion then continues with an analysis of Between-day preferences: timetable balance, the distribution of sessions into full and half days, and the overall convenience of each timetable.

6.6.2 Within-Day: Frequency and Duration of Breaks

The most frequent comment made in the qualitative data was related to the presence of breaks (or gaps) between timetabled sessions, with respondents indicating that they would prefer many fewer breaks overall. This preference is hinted at in previous work which identified that breaks of 2 or more hours before or after a session reduced attendance at that session (Fjortoft, 2005).

Analysis of the TQS survey respondents' current and ideal timetables reveals a similar message to that described in the qualitative data. Across all levels of contact, the mean break hours per week and per timetabled day is lower in the ideal timetable, Graph 4.

Overall, mean break hours per week fall from 4.67 in the current timetables to 2.48 in the ideal timetables, a 48% reduction, whilst similarly break hours per timetabled day fall from 1.09 hours/timetabled day to 0.65 hours/timetabled day a 41% reduction.



Graph 4 – TQS: Break Hours/Week and per TTD by Contact Hours

In addition to a reduction in the absolute number of break hours respondents also specified marked preferences in terms of how the break hours remaining in their ideal timetable should be split into contiguous break periods within each timetabled day.

TTDs can be categorised as either containing no breaks (all sessions back-to-back), a single one hour break, or two hours or more of breaks either split or taken as a longer single break. Respondents show a clear preference for more TTDs containing either no breaks or a single one hour break and for many fewer TTDs containing two or more break hours (down from 31% to 14% of TTDs).

Two continuous measures and two discrete measures can be derived from the quantitative data to represent respondent attitude towards breaks: break hours/week, mean break hours/day, the number of TTDs containing no breaks (0-4), and the number containing two or more break hours (0-5).

The two survey questions asking participants to list their current and their ideal timetables can be regarded as being analogous to an experiment in which the participant condition is recorded before and after a treatment is administered, the treatment in this case being the chance for the participant to design their own timetable. Therefore a paired samples t-test can be used to determine if the differences between the two measures are significant, see section 6.5.1.

The distribution of the differences for each measure is approximately normal although all exhibit a degree of kurtosis in that they are leptokurtic around the value in the distribution representing no change in the measure between the current and ideal timetables. The t-tests show a statistically significant preference for timetables with both fewer break hours overall ($p<0.001$), and less break hours per timetabled day ($p<0.001$). The respondents also have a significant preference for fewer TTDs containing breaks of two hours or more ($p<0.001$), although there does not appear to be any desire to increase the number of TTDs with no breaks ($p=0.776$).

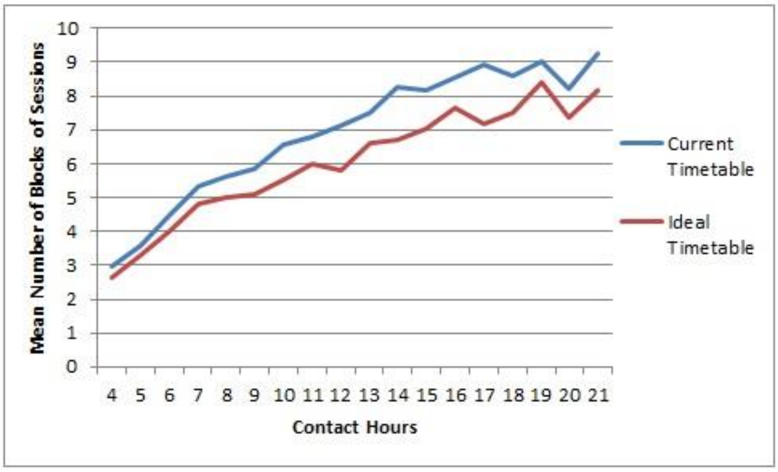
Whilst the quantitative data indicates a clear dislike of TTDs with excessive break hours, there is less evidence to suggest that shorter breaks are similarly disliked. This appears to contradict the qualitative data which indicated that all breaks were unpopular. However, the qualitative data also suggested that shorter breaks between back-to-back sessions would be useful. This length of break could not be represented within the TQS's timetable grids, and it could be that some of the indicated preference for one hour breaks represents a latent desire for a still shorter length of break.

The qualitative data suggests that gaps between sessions are disliked because students regard them as wasted time, or as time which cannot be used productively whilst on-campus, with students who live close enough to campus going home during breaks. These comments suggest that travel time may influence student preference for timetabled breaks.

To test this hypothesis an OLR model was built using total break hours in each ideal timetable to create a three level categorical dependant variable representing timetables with 0-1, 2-3 and >3 total break hours. The model included independent categorical variables for contact hours, gender, year of study and travel time. The model passed the goodness of fit and parallel lines tests, giving a Nagelkerke pseudo R^2 value of 0.138. However, only the coefficients for contact hours were identified as being significant, and total break hours naturally increase with contact hours, Graph 4. To correct for this, the categorical dependant variable was recalculated after adjusting each individual's total break hours by the group mean for all timetables with the same number of contact hours. The revised model gave a very poor fit (Nagelkerke pseudo R^2<0.01) and no significant coefficients. Therefore, it can be concluded that travel time does not influence preference for breaks or rather that a universal over-arching desire for timetables with significantly fewer break hours might be hiding any relationship which does exist.

6.6.3 Within-Day: Study Duration and Back-To-Back Sessions

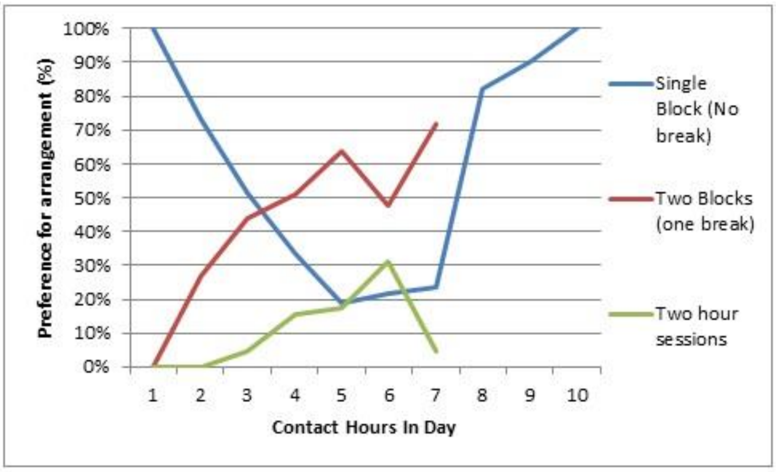
The qualitative data indicated that many students found a series of back-to-back sessions difficult in terms of concentration, suggesting that these be broken up into shorter blocks, although little consensus was apparent of the maximum acceptable number of hours of consecutive contact.



Graph 5 – TQS: Preferences for Session Blocks by contact hours

Contiguous sessions can be regarded as forming a block of sessions within the timetable, and the number of such blocks within a timetable can be counted, Graph 5. Students appear to desire fewer blocks of sessions, and a higher mean number of consecutive hours in each block. Overall the number of session blocks falls 14% in the ideal timetables, compared to the current ones.

In order to test if this change is significant a paired sample t-test was performed on the difference between the number of session blocks in each pair of respondent timetables. The differences are normally distributed and the t-test is significant at the 1% level confirming that students desire fewer session blocks in their timetables.



Graph 6 – TQS: Session Arrangement Preferences

The quantitative data suggests that preference for an acceptable maximum number of consecutive contact hours within a session block is dependent upon the total number of contact hours being delivered on that day, and the respondent ideal timetables show preference for sessions organised into one of three patterns: all sessions back-to-back with no breaks, sessions grouped into two blocks with a single break between them, sessions grouped into two hour blocks, with a break between each pair of blocks. Student preference for each of these three arrangements with respect to timetabled hours/day is shown in Graph 6. Preference for TTDs with all the sessions arranged into a single block will be universal when there is either a single session in the day, or when sessions are scheduled in every slot. Between these two extremes preference for a single block of back-to-back sessions drops as contact hours rise, with a corresponding increase in preferences for sessions grouped into two blocks and into a number of two hour blocks. The survey included a question asking participants about the importance of a lunch break in their timetable. Just over 60% stated that a lunch break was important or very important, whilst 22% indicated that it was either not or only slightly important. Whilst the need for a lunch break depends upon the number of contact hours in the day, the fact that 20% don't value a lunch break at all appears to coincide with the lower limit on the number of students who would always prefer all of their sessions back-to-back.

The preference for blocks of two hour sessions falls (and is almost completely compensated for by a corresponding increase in the two block preference) when daily contact hours reach seven. A similar step change occurs in the preference for a single block of back-to-back sessions between seven and eight daily contact hours. Both of these changes might be explained by an overarching student preference to limit daily time on campus to eight hours (the length of a normal work day) presumably so that it can be fitted in between 09:00 and 17:00 hours.

Students exhibit a degree of consistency in their preference for session arrangement. The second and third columns in Table 18 show the percentage of respondents who have the same session arrangement across all TTDs in their current and ideal timetables. There is an increase in preference for consistent session arrangements in the ideal timetable, such that even when the student's timetable contains five contact days, almost 30% of students desire the same session arrangement across all five days.

TTDs Per Week	Consistency in session arrangement across all TTDs		Consistency in maximum back-to-back session hours across all TTDs	
	Current Timetable	Ideal Timetable	Current Timetable	Ideal Timetable
2	61.5%	60.7%	46.7%	63.0%
3	33.9%	52.6%	22.4%	37.6%
4	13.1%	31.9%	8.9%	21.7%
5	9.2%	28.3%	6.5%	19.4%

Table 18 – TQS: Consistency for Session Pattern Across Timetable

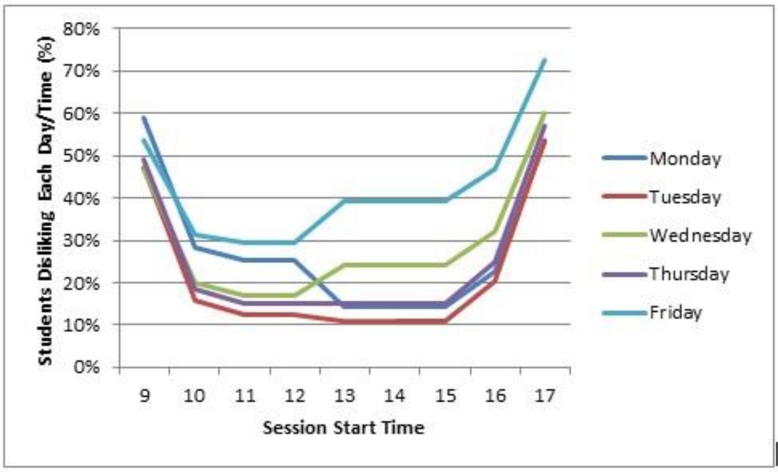
A similar increase in the desire for consistency is apparent when examining the number of back-to-back hours in the largest session block in the current and ideal timetables. Again almost 20% of all students with five contact days demonstrate a preference for a timetable which has the same maximum session length on each day.

This analysis suggests that there is no absolute maximum number of back-to-back hours or sessions that students are prepared to endure, but rather that students appear to desire a pragmatic approach to scheduling their sessions which simultaneously limits the duration of a block of back-to-back sessions whilst at the same time minimising the number of break hours in their timetables.

6.6.4 Within-Day: Session Position in Day and Day of Week

Qualitative comments made by students suggest that they dislike timetabled sessions at the extreme ends of the day, and this is supported by findings of other studies into the links between timetable and session attendance (Kelly, 2011, Kottasz, 2005, Persky et al., 2013, Devadoss and Foltz, 1996, Davis et al., 2012).

Students were asked to list their least preferable times and days of the week for timetabled sessions, Graph 7.



Graph 7 – TQS: Least Popular Session Times

The most unpopular session time is from 17:00-18:00, closely followed by those sessions scheduled between 9:00-10:00. Tuesday is the least unpopular day, followed by Thursday. Monday mornings and Wednesday afternoons appear to be equally unpopular, but neither is as unpopular as Fridays (morning and afternoon). Around 20% of survey respondents indicated that on any given day they had no preferences regarding session position, and that all slots were equally preferable. Combining the session preference data with the respondent current timetables allows the potential inconvenience caused by sessions scheduled at the unpopular times can be estimated. The most inconvenient time for timetabled sessions is between 9:00-10:00 with 12-15% of all students potentially finding these sessions inconvenient. Inconvenience levels decline across the day reflecting the fact that fewer sessions are scheduled later in the afternoon and as a consequence only 2%-4% of students might be inconvenienced by sessions scheduled from 17:00-18:00 even though this appears to be the most unpopular session time overall.

The qualitative data also includes comments which suggest a general preference for a later start, an earlier finish but also with more sessions earlier in the day.

To analyse the individual timetable preferences, three continuous measures were derived representing the: mean timetabled day start, day end and session start time across the week for each respondent for both the current and ideal timetables.

The value of each of these measures was found to vary systematically by contact hour, with successively earlier mean start times and later mean end times with increasing contact hours. Therefore the measures were adjusted by the group mean for all the current timetables with an equivalent number of contact hours. This adjustment allows the measures taken from the current timetables to have distributions centred around a mean value of zero, whilst for the measures taken from the ideal timetables the distributions will be centred around a non-zero mean, with the difference from zero reflecting the degree of preference demonstrated by the respondents.

Paired sample t-tests were used to test for significant differences between the value for each measure in the respondent current and ideal timetables. The distributions of the differences for each measure were normal, although slightly leptokurtic, with a higher than statistically expected frequencies of students indicating no change. The t-tests report highly significant preferences ($p<0.001$) for both earlier finishes, and for sessions scheduled earlier in the day, but no general support is shown for a change in start times with a mean difference close to zero and a non-significant p value ($p=0.441$).

This is surprising given that a discrete measure for the number of days including an early start before 10:00AM is consistently lower at all levels of contact hours, and that the percentage of days with an early start falls from 29% in the current timetables, to 17% in the ideal timetables.

This disparity suggests that although current mean day start times are acceptable for some students, others would prefer either a later, or an earlier start time, and that the effect of these complementary preferences may be cancelling each other out in the paired t-test. One possible explanation is that start time preference varies systematically and is influenced by student commute time.

To test this hypothesis each respondent was classified into one of four categories by comparing the mean day start time in their current and ideal timetables with the respective group mean start time for their given number of contact hours, classifying each as falling either before or after the group mean, Table 19.

Category	Current Timetable Classification	Ideal Timetable Classification	n	Travel Time (minutes)	
				μ	σ
1	Earlier Start	Earlier Start	347	24.06	20.31
2	Earlier Start	Later Start	178	19.83	13.1
3	Later Start	Earlier Start	178	25.79	23.61
4	Later Start	Later Start	299	20.6	18.96

Table 19 – TQS: Travel Time by Session Start Time Preference

The mean travel times for the two categories that specify a preference for an earlier session start time are longer than those for the two categories which demonstrate a preference for a later start. This suggests that respondents with longer travel times have a preference for earlier starts, and those with shorter travel times for later starts.

To test if the differences between the travel times in each category were significant independent t-tests were performed between pairs of similar and opposite categories. The results of the t-tests are consistent with the hypothesis. There is no significant difference between the travel times between the pairs of categories which demonstrate similarity in preference for start time, whilst there are significant differences when the preferences expressed by the categories are opposite.

Survey respondents with the longer travel times to campus prefer earlier starts, whilst those whose travel time is short prefer later starts. Similar tests were performed to investigate any relationship between preferences for day finish time/mean session time and home to campus travel time but no significant relationship could be found in either case.

6.6.5 Within-Day: Getting around the Campus

The qualitative data suggested that some students felt they had insufficient time to get their next session when it was located elsewhere on campus, and that the notional ten minute gap between sessions was insufficient.

To investigate this further, a GIS was used to map all possible walking routes between buildings on-campus, thereby allowing the shortest route, and fastest walking time, between each pair of buildings to be calculated. Whilst the TQS survey data did not capture session location information, this was available through the full timetable allowing the walking distance between every pair of adjacent sessions to the determined.

The data shows that distance walked increases with contact hours and reaches a peak for students with around 12-15 contact hours who will walk an average of 1.4 km/week between all timetabled locations and around 1km/week between back-to-back sessions. Distance walked is lower for the higher contact hours courses, and this may be due to these courses being more homogenous and specialised (maths/physics and engineering) meaning that less use can be made of centralised teaching resources, with a greater proportion of sessions taking place locally with the host school's buildings. To determine the optimal inter-session gap length, the walking time between each pair of adjacent sessions was calculated based on an average walking speed of 1.2 metres/second (Web Tag) and a building entry/egress times of 2.5 minutes. Varying gap lengths were assumed between 0 and 15 minutes, and the number of potential late arrivals at each following session for each gap length was noted, Table 20.

Break length between back-to-back sessions	Late Arrivals (%)	Average Minutes Late (minutes)	Student days containing one or more late arrival (%)
0 minutes	69.2%	8.3	37.0%
5 minutes	33.2%	7.5	17.7%
10 minutes	17.9%	3.4	9.6%
15 minutes	2.7%	2.3	1.4%

Table 20 – TQS: Late Arrivals as a function of session break length

The analysis shows that when there is no inter-session gap, 70% of students are over 8 minutes late, lending support to the need for a 10 minute gap. However, even if the 10 minute gap was observed in all cases, almost 20% of back-to-back sessions still incur a late arrival, and it is only when this gap is extended to 15 minutes that late arrivals falls to a negligible level (2.7%).

6.6.6 Within-Day: Walking Home in the Dark

The TQS qualitative data revealed that some students have concerns about walking home in the dark during the winter.

To investigate this issue, the daily sunrise and sunset times in Leeds over the winter months were obtained (www.timeanddate.com, 2012). This data, combined with timetabled day finish time distributions from the full UoL timetable, and TQS data for student travel mode and travel time allowed the proportion of the population who make return trips from campus in the dark to be calculated. Only students who stated they walk, have a travel time of ≥5 minutes and have sessions finishing on or after 16:00 were considered, and it was assumed that they left campus immediately their last session was over. Their journey was said to have been affected by darkness if their home arrival time was ≥30 minutes after the sunset time for that day.

Excluding the minority of students with evening lectures, student days are only affected by darkness during the period between the day light saving changes from the end of October onwards, weeks 6-11 of semester 1 and weeks 1-5 of semester 2. During this period all trips by students who finish on or after 17:00 will be affected, whilst the proportion of those affected who finish at 16:00 increases as sunset times get successively earlier. In the first semester, on TTH days, the proportion of walking trips taken in darkness increases from 30% in week 6 to almost 40% by the last week of term. However, since the second semester begins in the last week of January only 25% of walking trips are taken in darkness at this and this proportion reduces as the sunset time recedes again.

It would be expected that students with concerns about their personal safety would wish to minimise or eliminate dark walking trips from their timetable.

To test this hypothesis each walking student’s current and ideal timetable was classified according to whether it contained one or more finishes after 16:00 on the assumption that students with concerns about dark-walking would be more likely to eliminate these days from their timetable. Overall the current timetables show that 63% of walking students have at least one day with a finish after 16:00, whilst this figure falls to 32% in the ideal timetables. However, some of this reduction may be due to the general preference for earlier finishes identified in section 6.6.3.

If concerns about dark-walking is a factor in this preference, a significant difference in preference should be detectable between those students who live on-campus, and those who don't. A binary logistic model was constructed to examine the factors affecting this preference using timetables containing no dark finishes after 16:00 as the dependant variable (0=no after dark finishes, 1=some after dark finishes) and with independent categorical variables for timetable contact hours, year of study, travel time and gender. Travel time is classified into four categories (section 6.6.1), with the first (0-7.5 minutes) taken to indicate those students who live on-campus.

The results and output for the model are shown in Table 21. Analysis of the standardised residuals shows that 5% are more than 1.96 standard deviations from the expected value whilst 2% are more than 2.58 standard deviations. The coefficients associated with the contact hours and year of study categories are all significant and these describe the variation in the model attributable to the timetable and the curriculum. The likelihood of at least one dark finish increases with contact hours, whilst decreasing with year of study since contact hours are lower for later years students.

Factors Affecting Preference for Later Finishes							
Diagnostic Tests	Nagelkerke Pseudo R2		0.224				
	Hosmer and Lemeshow Test		Chi-square: 9.376, df=8, significance=0.312				
	Classification Table,		Cells Correct, 0: 84.6%, 1: 39.8, Overall: 70.2%				
			b	Std. Error	Wald	df	Sig.
COEFFICIENTS	Constant		-0.788	0.352	5.011	1	0.025
	Contact Hours	4-7				3	<0.001
		8-10	0.154	0.305	0.254	1	0.614
		11-14	1.205	0.287	17.620	1	<0.001
		15-21	1.952	0.288	48.865	1	<0.001
	Year of Study	1^{st} Year			8.897	2	0.012
		2^{nd} Year	-0.403	0.203	3.953	1	0.047
		3^{rd} Year	-0.774	0.270	8.239	1	0.004
	Travel Time (minutes)	0-7.5 (On-campus)			9.258	3	0.026
		7.5-15	-0.566	0.254	4.972	1	0.026
		16-30	-0.123	0.254	0.234	1	0.629
		>30	-1.008	0.534	3.559	1	0.059
	Gender	Male					
		Female	-0.367	0.189	3.756	1	0.053

Table 21 – TQS: Dark Finishes Binary Logistic Regression Model

The coefficients for travel time and gender describe the degree to which individual preferences for dark finishes vary systematically and independently from timetable and curriculum related factors. The coefficients for travel time are negative and decrease indicating that preference for dark finishes declines when walking students live off campus, and a negative coefficient for females suggest that they prefer fewer dark finishes to male students.

The model indicates that 76% of first year male students living on-campus with a timetable of between 15-21 contact hours would be satisfied with a timetable containing at least one finish after 16:00. However, for equivalent students who must walk more than 30 minutes to campus, this figure falls to 53% suggesting that when a student who lives at this distance they are 2.8 times as likely to desire a timetable that allows them to get home before dark. The equivalent figures for first year females are 68% and 44% with an odds ratio of 2.7, whilst those for a male student living within a walking distance of 8-14 minutes are 76%, and 64% giving an odds ratio of 1.7.

These odds ratios, which are consistent for all categories of contact hour and year of study, suggest that walking time to campus does affect preference for timetables which allow students to get home in daylight and that perhaps around a quarter to one third of the students who walk are concerned about this.

6.6.7 Within-Day: Single Sessions on a Timetable Day

The TQS qualitative responses suggest that single session days are disliked by students in general and by commuting students in particular, whilst previous studies examining links between timetable design and attendance have identified this timetable attribute as having a negative effect on attendance (Persky et al., 2013, Kelly, 2011). A comparison of the proportion of TTDs containing a single session in the TQS current and ideal timetables is shown in Graph 8.

Graph 8 – TQS: Comparison of Single Session Timetabled Days

Single session days are a regular feature of the student experience with almost a quarter of all TTDs comprising a single one hour session (24%), whilst the student's ideal timetables express a preference to halve this frequency, to one in every eight TTDs (12%) overall. Single session days decline as contact hours increase, simply because the free time available in a single session timetabled day represents a greater proportion of the total free time available in which to schedule a further session. The survey data suggests that students demonstrate dislike of single session days at all levels of contact.

A paired samples t-test was used to test for a difference in the number of single session days in each pair of respondent timetables. The distribution of the differences in single session days between each pair of timetables shows a clear preference for fewer single session days, being negatively skewed (-0.757) with few values above zero, and as such it almost represents one half of a full normal distribution. However, 95% of the values appear to be within the full normal curve suggesting that the t-test is appropriate. The t-test itself is highly significant ($p<0.001$) suggesting that students demonstrate a significant preference for fewer days containing a single session.

The qualitative responses indicated that one reason for disliking this timetable feature was due to the time/money wasted through commuting to campus for days containing a single session. To test if travel time has an effect on preference for single session days, an OLR model was built, with the number of single session days in each respondent ideal timetable being treated as the categorical dependant variable for the model.

OLR models require that, if possible, samples for each combination of the independent variable categories are represented in the data. This means creating a parsimonious model that avoids the inclusion of insignificant parameters, since each additional categorical variable has a multiplicative effect on the number of category combinations. Therefore the independent variables were restricted to timetable contact hours, travel time and gender. For the same reason the dependant variable was restricted to three levels: no single session days, one single session day and 2 or more single session days. The OLR model also operates within the assumption of proportional odds. The distribution of single sessions days within the sample timetables violates this assumption since the frequency will vary with contact hours, and timetables in the highest contact hours category (15-21 contact hours) are likely to have very few single session days. To control for this effect samples from this highest contact category were excluded from the model, The results for the model are shown in Figure 6.

Test Statistics		Total Samples	767				
		% Cells With Zero Expected Value	5 cells (6.9%)				
		Model Fit p Value	<0.001 (Chi square: 41.906, df=6)				
		Pearson Goodness of Fit, p Value	0.789 (Chi square: 32.658, df=40)				
		Nagelkerke Pseudo R^2	0.063				
		Test of Parallel Lines, p Value	0.043 (Chi square: 13.009, df=6)				
COEFFICIENTS			Estimate	Std. Err.	Wald	df	Sig.
	Threshold	No Single Session Days	1.785	0.260	47.244	1	<0.001
		1 Single Session Day	3.074	0.275	124.848	1	<0.001
	Timetabled Contact Hours	4-7 contact hours	0.873	0.188	21.465	1	<0.001
		8-10 contact hours	0.699	0.184	14.497	1	<0.001
		11-14 contact hours	0				
	Travel Time	0-7.5 minutes	0.885	0.310	8.151	1	0.004
		7.5-15 minutes	0.766	0.263	8.492	1	0.004
		15-30 minutes	0.827	0.258	10.286	1	0.001
		>30 minutes	0				
	Gender	Male	0.306	0.166	3.390	1	0.066
		Female	0				

Figure 6 – TQS: Preference for Single Session Days

The results show that the model is a reasonable fit for the data and passes the goodness of fit test (result not significant). However, the test for parallel lines is just significant at the 5% level due to the underlying reduction in single session days as contact hours increase. The coefficients in the model are all significant, apart from for gender which just misses being significant at the 5% level (p=0.066). The signs and magnitudes of the coefficients reflect the natural reduction in the frequency in single session days as contact hours increase, and show that preference for single session days decreases when travel time is higher than 30 minutes, but that shorter travel times appear to have little effect on this preference. Using the model the predicted preference for single session days in timetables of varying degrees of contact, and for students residing on campus and remotely can be calculated and compared with the actual frequency of occurrence of single session days in the current timetables, Table 22.

		Current Timetable, Single Sessions	Ideal timetable Single Sessions			
			Travel time = 0-7.5 minutes		Travel time >= 30 minutes	
		Days/week	Days/week	% original	Days/week	%original
Female students	4-7 hours	1.3	0.71	55%	0.39	30%
	8-10 hours	1.26	0.63	50%	0.34	27%
	11-14 hours	0.84	0.39	46%	0.19	23%
Male students	4-7 hours	1.73	0.84	49%	0.48	28%
	8-10 hours	1.38	0.76	55%	0.43	31%
	11-14 hours	1.03	0.49	48%	0.24	23%

Table 22 – TQS: Preference for Single Session Day by Travel Time

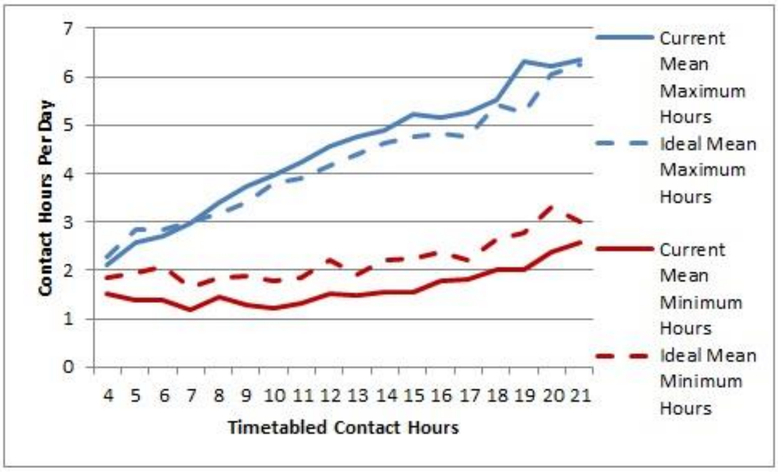
The analysis suggests that whilst students exhibit a general preference for a reduction of single session days by just under 50% those living remotely desire a further reduction of 20% on top of this, and that these preferences are relatively consistent at all levels of contact hour. It also shows that students on lower contact hours courses are prepared to tolerate some single session days in their timetables.

In the TQS sample, 14% of the respondents live at more than 30 minutes travel time away from campus, meaning that overall only 5% of the preference for a reduction in single session days is attributable to travel time and that the 95% of the total preference expressed by survey respondents represents a more general desire to remove this feature from the timetable.

6.6.8 Between-Day: Timetable Balance

The qualitative feedback indicated that students prefer their sessions to be spread evenly across all TTDs with minimal variation between the number of contact hours delivered over each day. This mirrors the finding of an earlier study which suggested that timetable balance was the attribute most valued by students (Algonquin College of Applied Arts and Technology Ottawa, 2004).

The quantitative data shows some evidence of these preferences, Graph 9, with an increase in the mean minimum and a decrease in the mean maximum contact hours delivered on each timetabled day, between each respondent's current and ideal timetables. The number of contact hours delivered on the student's busiest day appears to grow linearly with total contact hours, whilst the hours delivered on the easiest day remain relatively constant (at 2 hours) for low contact hours courses and then also begins to rise linearly.



Graph 9 – TQS: Timetable Balance

The preferences expressed through the ideal timetables suggest that students desire a more balanced timetable with fewer hours delivered on the busiest day and more on the quietest day.

The significance of the difference between two measures of timetable balance: the number of contact hours delivered on the busiest and lightest TTDs in each respondents current and ideal timetables can be tested using paired sample t-tests. The distribution of the differences for maximum contact hours is normal, although leptokurtic, whilst that for minimum contact hours is both leptokurtic and positively skewed. However, this distribution is not widely dispersed and the extremes fall within the bounds expected for a normal distribution meaning that the assumptions for a t-test are met in both cases. The t-tests show that the means of the differences for both measures are highly significant ($p<0.001$ in both cases) with an average reduction of 0.2191 session hours in the length of the longest day, and an increase of 0.564 session hours in the duration of shortest.

Can this preference for greater balance in timetables be explained further, and do those students with longer travel times to campus express different preferences to those who live closer? To test this hypothesis two linear models were built using the maximum and minimum daily contact hours measures as the dependant variables. A linear model requires that the dependent variables are quantitative, continuous and unbounded (Field, 2013, p. 312) whilst these two measures are discrete cardinal values and both have fixed lower and upper bounds. However, it could be argued that if these measures do vary systematically then the discrete values that they hold are approximations of a continuous underlying variable and similarly though both measures are bounded, respondent preferences might be restricted to a small range within the extremes defined by the bounds and so they can be regarded as being unbounded.

Two models were built using the 4 blocks of independent variables, introduced step-wise: block 1: timetable contact hours (continuous, 4-21), TTDs (continuous, 1-5), block 2: year of study (categorical), block 3: travel time (categorical), block 4: gender (categorical). The stepwise approach allows the effect of the introduction of each successive block of variables to be measured in a manner which is independent of the significance of each predictor. For these two models it was found that the variables in the first block contributed most in terms of explaining the variation in the model, with blocks 2, 3 and 4 only increasing the overall adjusted R^2 value by 0.03 in the minimum contact hours model and by 0.02 in the maximum contact hours model. None of the predictors for travel time were shown as being significant with the exception of travel time category 4 (≥30 minutes) in the model for minimum contact hours only. However, this predictor contributed little to the overall result of the model (standardised coefficient value = 0.05) and it was thought that the coefficient was describing the differential preference for fewer single session days discussed in section 6.6.7. Given the limited power of coefficients in all but the first blocks a decision was taken to create more parsimonious models by including only contact hours and TTDs as independent variables, Table 23.

Given the limited number of explanatory variables the models fits the data reasonably well with adjusted R^2 values of 0.59 (0.68) in the minimum (maximum) hours model. The sum of squares of the residual error in each model will be inflated because the expected values are cardinal, so the continuous predicted value will always differ by between 0 and 0.99, meaning that the R^2 values will be below their true values. The residual values in each model are normally distributed. A correlation exists between contact hours and TTDs (Pearson correlation coefficient of 0.596) but this does not appear to introduce any co-linearity into the models since the variance inflation factor (VIF) is below 2, and the variance is proportionately distributed across dimensions in the co-linearity diagnostics (not shown).

The coefficients associated with the models suggest that the number of hours expected to be delivered on the busiest and lightest days increases with contact hours in the timetable, but decreases with the number of TTDs. This suggests that students with fewer TTDs expect their contact hours to be distributed more evenly across those days, whilst students with more TTDs are prepared to accept a more unbalanced timetable.

		Minimum Daily Hours			Maximum Daily Hours		
Test Statistics	N	1004			1004		
	Adjusted R2	0.594			0.681		
	Standard Error	0.653			0.723		
	Durbin-Watson	1.880			2.071		
	Predicted Value	0.0061-4.6973 (2.07)			1.605-7.425 (3.93)		
		B	Std. Err.	Sig.	B	Std. Err	Sig.
Coefficients	Constant	3.408	0.081	<0.001	3.071	0.090	<0.001
	Contact Hours	0.191	0.006	<0.001	0.301	0.007	<0.001
	Timetabled Days	-0.910	0.026	<0.001	-0.654	0.028	<0.001

Table 23 – TQS: Timetable Balance Models

The balance between the heaviest and lightest days predicted by the model for timetables with 10 and 16 contact hours, spread over 3 to 5 TTDs are shown in Table 24. In each case the model predicts a balanced distribution of hours across the TTDs.

	3 timetabled days		4 timetabled days		5 timetabled days	
	Lightest Day Hours	Heaviest Day Hours	Lightest Day Hours	Heaviest Day Hours	Lightest Day Hours	Heaviest Day Hours
10 contact hours	2.61	4.11	1.71	3.46	0.81	2.81
	Hours/Day = 3,3,4		Hours/Day = 2,2,3,3		Hours/Day = 1,2,2,2,3	
16 contact hours	3.76	5.92	2.86	5.27	1.95	4.61
	Hours/Day = 4,6,6		Hours/Day = 3,4,4,5		Hours/Day = 2,3,3,3,5	

Table 24 – TQS: Timetable Balance Model Examples

The lack of any other significant independent variables in these models suggest that this desire for timetable balance is universally shared across all respondents and is driven simply by the number of contact hours and TTDs in the timetable.

Two further models were built to examine the equivalent relationships in the current timetables. In both models the adjusted R^2 values were lower (0.44 in the minimum hours model and 0.66 in the maximum hours model) indicating that the models for the ideal timetables capture genuine student preferences and aren't simply a result of some function of the timetable itself.

6.6.9 Between-Day: Distribution of Timetabled Sessions across the Week

The qualitative data suggested that respondents prefer sessions in the earlier part of the week with fewer sessions scheduled later in the week, particularly on Friday, whilst at the same time desiring more sessions scheduled earlier in the day.

To test if these preferences could be detected in the quantitative data the TTDs in the current and ideal timetables were classified into one of four session categories: days completely free from sessions, days with sessions just the morning (last session completed by 13:00), days with sessions just in the afternoon (first session begins on or after 13:00), days with sessions in both the morning and afternoon. An analysis of change in the categorical proportions between the current and ideal timetables was performed, Table 25.

Day Category		Current Timetable (%)	Ideal Timetable (%)	Change (%)
Free Day		17.0	23.3	6.3**
Sessions in AM Only	Mon, Tue, Thu, Fri	17.3	18.1	0.7
	Wed	12.2	8.4	-3.9**
Sessions in PM Only		12.7	8.3	-4.5**
Sessions in AM and PM		40.7	42.0	1.3
		100%	100%	0%

Table 25 – TQS: Day Session Category

[**(*): Difference significant at the 1% (5%) level, tested using two proportion z-test, with null hypothesis: no difference between current and ideal timetables]

A preference is indicated for more completely free days (+6.3%) although the number of completely full days also increases (+1.3%, not significant). This increase is achieved through a reduction in the number of half days, and afternoon only days are particularly unpopular (-4.5%) as are sessions confined to Wednesday mornings (-3.9%). Given that there is a small non-significant increase in the proportion of morning based half-days over the rest of the week, this suggests that student preferences for Wednesday's mornings are somehow different.

The changes between session categories on Wednesday show that students wish to convert morning only sessions (-19%) into full TTDs (+15%), a free day (+3%) or afternoon only sessions (+1%). This suggests that although the qualitative feedback identifies a group of sports playing students within the population this group is a minority compared to those students don't appreciate the value of a free Wednesday afternoon, over any other free weekday afternoon.

Overall the respondents indicate a slight preference for more sessions earlier in the week, with 66% of all TTDs scheduled to take place between Monday and Wednesday in the ideal timetables, compared to 62% in the current timetables (not significant), and for preferences for more free days later in the week with 34% of all student days being free from sessions on Thursday and Friday in the ideal timetables, compared to 21% in the current timetables (significant at the 1% level). The number of TTDs containing sessions in the morning increases slightly from 85% to 89% (significant at the 1% level), whilst those containing sessions in the afternoon also increases from 80% to 82% (not significant), largely as a result of more students desiring taught sessions on during Wednesday PM.

This data largely supports the qualitative comments that students would prefer a greater proportion all sessions in the morning and earlier in the week, with more free days towards the end of the week, and particularly on Friday.

The qualitative data suggests that for some students playing competitive sports is an important part of the university experience and that time free on a Wednesday afternoon is important. Students also commented that they like to travel at the weekend and having time free on a Friday allows them to begin their trips ahead of the afternoon peak commuting period.

At UoL the timetable planners recognise these needs and attempt to keep the scheduling of sessions on both Wednesday and Friday afternoons to a minimum. However, these constraints remove at least 8 one hour teaching slots from the weekly timetable and as a consequence both Wednesday's and Friday's are timetable low days (TTL) with a fewer sessions overall compared to TTH days.

This has a knock-on effect in terms the institutional space utilisation rates and requires additional timetabling effort to fit the displaced sessions into the remaining slots.

The quantitative data can reveal preferences in terms of how students value the provision of a free afternoon on Wednesday's and Friday's, as student preferences to these two afternoons can be classified into one of three categories: they value the free time in the afternoon, they actively dislike the free time, or they are indifferent towards it. Since the assignment of a timetable to an individual is a random process these preferences will be independent of whether their current timetable meets this desire, whilst the ideal timetable allows them to express their true choice.

Students who value the free time would be expected to keep the afternoon slots free in their ideal timetable, whilst those who actively dislike it may schedule sessions within this period so that they can take a benefit elsewhere in their ideal timetable. Calculating the proportion of students who switch from a timetabled afternoon in the current timetable to a free afternoon in the ideal timetable relative to the total for whom the afternoon is timetabled in the current timetable gives an estimate of the mean probability that any student will value free time during the afternoon. The probability for students who actively dislike the free time may be calculated in a similar way, whilst the remainder will represent the probability for those who are indifferent.

A student can be said to have a free afternoon if all their sessions finish by 13:00 and a busy afternoon otherwise. Analysis of the current and ideal timetables allows two 2x2 contingency tables to be constructed comparing the busy/free status for Wednesday and Friday afternoons, Figure 7, whilst the 95% confidence interval for P(x) can be derived from +/- 1.96 of the standard error of the estimate.

		Ideal Timetable				
	Wednesday	Busy	Free	Total	P(x)	95% CI
Current Timetable	Busy	96	53	**149**	0.36	0.28-0.43
	Free	220	635	**855**	0.26	0.23-0.29
	Total	**316**	**688**	**1004**		

		Ideal Timetable				
	Friday	Busy	Free	Total	P(x)	95% CI
Current Timetable	Busy	197	208	**405**	0.51	0.46-0.56
	Free	50	549	**599**	0.08	0.06-0.11
	Total	**247**	**757**	**1004**		

Figure 7 – TQS: Wednesday and Friday Afternoon Preferences

This data suggests that whilst between 28-43% of students value free time on a Wednesday afternoon, a further 23-29% would give it up for benefits elsewhere in the timetable. The similar figures for Friday are 46%-56% valuing the free time, and between 6-11% prepared to give it up. These figures imply that a minimum of 57% of students receive no advantage from timetabling efforts to keep this afternoon free.

Chi squared tests on four 4x2 contingency tables linking each respondent's travel time category to their preference for a free Wednesday/Friday PM given a currently busy afternoon and vice versa show no significant relationships suggesting that travel time has no influence on these preferences.

A further Chi squared test on a 4x4 contingency table linking each respondent's Wednesday afternoon preference to their preference for Friday PM shows a significant relationship χ^2 (9) = 23.899, p=0.004 suggesting that students may wish to trade free time between Wednesday PM and Friday PM.

Given the likelihood of a student receiving a session on a Wednesday (Friday) afternoon in the current timetable is 15% (40%), these preferences suggest that 4-6% of all students desire free time on a Wednesday but must attend timetabled sessions, whilst on a Friday the equivalent figure is 18-22%. This imbalance may explain why poor Friday afternoon attendance levels are widely reported (Van Blerkom, 2001).

The data suggests that overall students would benefit from a timetable policy which regarded Wednesday as a normal timetable day (TTH) in return for a reduction in timetabled sessions on a Friday and in particular on Friday afternoon, although this would be very unpopular with the minority who pay sports and politically very difficult to implement.

6.6.10 Between-Day: The Desire for a Convenient Timetable

The qualitative feedback included comments from 7% of respondents indicating a preference for more timetabled hours/day in return for fewer TTDs per week. As suggested in 4.3.3 this approach may result in fewer commuting trips to campus, and has been proposed as a potential university travel plan measure (Forum for the Future, 2003, p. 41).

Graph 10 – TQS: Timetabled Days Per Week

A single indicator can be derived from the quantitative data to examine respondent preference in this area, the number of TTDs specified in the current and ideal timetables, Graph 10. The current timetables show that 35% (43%) of respondents receive their contact hours over 4 (5) days, whilst in the ideal timetables this reduces to 34% (30%). Overall respondents desire an 8% reduction in the number of TTDs, decreasing the proportion of all students days containing timetabled sessions from 83% to 75%.

The distribution of the differences between TTDs in each pair of timetables is negatively skewed and leptokurtic with a high proportion (66%) of respondents indicating no change. However, a paired samples t-test is significant at the 1% level suggesting that the remaining respondents do desire timetables with fewer TTDs.

An OLR model can be built to examine how parameters, particularly travel time, affect this preference. As few respondents prefer timetables containing either one or two TTDs (11%), the measure can be converted into a categorical variable with three levels: 1-3, 4 and 5 TTDs for use as the dependant variable, with independent categorical variables for timetable contact hours, travel time and gender. The considerations when building this model are similar to those for single session days described in section 6.6.7 and the results obtained from fitting the model to the data are shown in Figure 8.

The empty cells in the model (7%) are accounted for by low counts associated with two unpopular timetable day/contact hours preference combinations: 4-7 contact hours spread over 5 days and 15-21 contact hours over 3 days. These combinations represent impractical timetable solutions and the low counts indicate genuine dislike rather than suggesting that the data is unrepresentative.

Whilst the model fits the data well (significant model fit and non-significant goodness of fit test) the test for the proportional odds assumption fails ($p<0.018$). If the model is rerun excluding the highest contact hours category, this test passes, suggesting that it is the choices associated with this category which contribute most of the non-proportionality. However it was decided to retain the category since the coefficients in the reduced model didn't differ to any great extent. All the coefficients are significant suggesting that preference for more TTDs increase with contact hours and that both travel time and gender also have an effect. Males appear to prefer more days in their timetables compared to females, whilst preference for compact timetables increases with travel time.

<table>
<tr><td colspan="2" rowspan="6">Test Statistics</td><td colspan="2">Total Samples</td><td colspan="5">1004</td></tr>
<tr><td colspan="2">% Cells With Zero Expected Value</td><td colspan="5">7 cells (7.3%)</td></tr>
<tr><td colspan="2">Model Fit p Value</td><td colspan="5"><0.001 (Chi square: 399.386, df=7)</td></tr>
<tr><td colspan="2">Pearson Goodness of Fit, p Value</td><td colspan="5">0.936 (Chi square: 40.012, df=55)</td></tr>
<tr><td colspan="2">Nagelkerke Pseudo R^2</td><td colspan="5">0.370</td></tr>
<tr><td colspan="2">Test of Parallel Lines, p Value</td><td colspan="5">0.018 (Chi square: 16.890, df=7)</td></tr>
<tr><td rowspan="13">COEFFICIENTS</td><td colspan="3"></td><td>Estimate</td><td>Std. Err.</td><td>Wald</td><td>df</td><td>Sig.</td></tr>
<tr><td rowspan="2">Threshold</td><td colspan="2">1-3 timetabled days</td><td>-1.710</td><td>0.217</td><td>61.891</td><td>1</td><td><0.001</td></tr>
<tr><td colspan="2">4 timetabled days</td><td>0.265</td><td>0.208</td><td>1.623</td><td>1</td><td>0.203</td></tr>
<tr><td rowspan="4">Timetabled Contact Hours</td><td colspan="2">4-7 contact hours</td><td>-3.536</td><td>0.217</td><td>264.517</td><td>1</td><td><0.001</td></tr>
<tr><td colspan="2">8-10 contact hours</td><td>-2.096</td><td>0.187</td><td>125.862</td><td>1</td><td><0.001</td></tr>
<tr><td colspan="2">11-14 contact hours</td><td>-1.066</td><td>0.179</td><td>35.623</td><td>1</td><td><0.001</td></tr>
<tr><td colspan="2">15-21 contact hours</td><td>0</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="4">Travel Time</td><td colspan="2">0-7.5 minutes</td><td>1.070</td><td>0.250</td><td>18.369</td><td>1</td><td><0.001</td></tr>
<tr><td colspan="2">7.5-15 minutes</td><td>0.654</td><td>0.204</td><td>10.221</td><td>1</td><td>0.001</td></tr>
<tr><td colspan="2">15-30 minutes</td><td>0.730</td><td>0.199</td><td>13.461</td><td>1</td><td><0.001</td></tr>
<tr><td colspan="2">>30 minutes</td><td>0</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Gender</td><td colspan="2">Male</td><td>0.416</td><td>0.141</td><td>8.660</td><td>1</td><td>0.003</td></tr>
<tr><td colspan="2">Female</td><td>0</td><td></td><td></td><td></td><td></td></tr>
</table>

Figure 8 – TQS: Preference for the number of timetabled days

The model can be used to predict the mean number of TTDs preferred by male and female students at varying levels of contact and for different travel times from campus by multiplying the proportion in each of the three output categories suggested by the model by the number of TTDs represented by each category. For the first category, 1-3 TTDs, estimates of the relative proportions of 1,2 and 3 day timetables within this group were obtained by counting the actual number of timetables with 1,2, and 3 days in the dataset.

The results are shown in Table 26. For presentational simplicity, students with travel times in the middle two travel time categories have been combined into one group, since the model gave similar coefficients for both categories.

Male Students							
Contact Hours	Preferred Timetable Days			Current Timetable Days	Proportion of Current %		
	0-7.5 minutes	7.6-30 minutes	>30 minutes		0-7.5 minutes	7.6-30 minutes	>30 minutes
4-7 hours	3.31	3.16	2.96	3.44	96.2%	91.8%	86.0%
8-10 hours	3.96	3.77	3.47	4.14	95.6	91.0%	83.8%
11-14 hours	4.4	4.23	3.94	4.61	95.4%	91.7%	85.5%
15-21 hours	4.72	4.61	4.4	4.76	99%	96.8%	92.4%
Female Students							
4-7 hours	3.16	3.03	2.88	3.24	97.5%	93.5%	88.8%
8-10 hours	3.77	3.58	3.29	4.03	93.5%	88.8%	81.6%
11-14 hours	4.23	4.05	3.75	4.45	95.0%	91.0%	84.2%
15-21 hours	4.61	4.48	4.23	4.75	97%	94.3%	89.0%

Table 26 – TQS: Preference for TTDs by Contact Hours and Travel Time

The model shows that for students living on or near campus, mean preferences for TTDs almost match the TTDs supplied by the current timetable, with students desiring a mean reduction of 5%, whilst those students living more than 30 minutes travel time from campus prefer timetables with 15% fewer days on average. Students enrolled on courses with a mid-range numbers of contact hours (8-14) demand a larger decrease compared to those from low or high contact hours courses.

The desired reduction to TTDs can be attributed to both a general desire for a more convenient timetable, and a specific need to reduce the amount of travel associated with attending on campus. The reduction in mean TTDs at each level of contact and travel time can be divided into the part common to all (represented by the preferences of those living on campus) and the preference for further reductions expressed by those who live remotely, where the overall reduction in TTDs is weighted by the proportion of the population at each level of contact and in each travel time band, Table 27.

This analysis suggests that around 50% of the preference for fewer TTDs can be attributed towards a desire for a more convenient timetable, and that 50% is associated with practical concerns around saving time/money by reducing trips to campus. This contrasts sharply with the preferences for fewer days containing a single timetabled session, section 6.6.7, in which 95% of the preference is general and only 5% related to travel.

Male Students				
Contact Hours		Timetable Day Reduction common to all students	Reduction associated with travel time	
			7.6-30 minutes	>30 minutes
	Population %	100%	75%	10%
4-7 hours	19%	0.13	0.15	0.35
8-10 hours	22%	0.18	0.19	0.49
11-14 hours	26%	0.21	0.17	0.46
15-21 hours	33%	0.04	0.11	0.32
Reduction in Total Timetabled Days (Population * Reduction)		**0.132 (46%)**	**0.153 (54%)**	
Female Students				
		100%	72%	16%
4-7 hours	25%	0.08	0.13	0.28
8-10 hours	29%	0.26	0.19	0.48
11-14 hours	27%	0.22	0.18	0.48
15-21 hours	20%	0.14	0.13	0.38
Reduction in Total Timetabled Days (Population * Reduction)		**0.180 (50%)**	**0.181 (50%)**	

Table 27 – TQS: Analysis of Preferences for reductions in TTDs

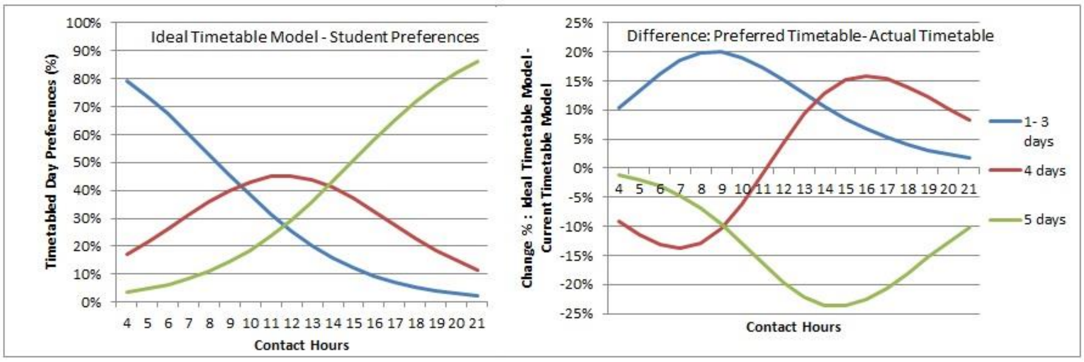
To further explore the distribution of students across each possible choice of timetabled day category, the OLR model was rerun with a single continuous independent variable representing contact hours. This allows the degree of preference for timetables with 1-3, 4 and 5 days treated as a function of contact hours. A second equivalent model was also created to show the similar distribution within the current timetables Table 28.

		Distribution of Timetable Days/Week by Contact Hour					
Test Statistics		Current Timetable			Ideal Timetable		
Model Fit p Value		<0.001			<0.001		
Pearson Goodness of Fit, p Value		<0.001			<0.001		
Nagelkerke Pseudo R^2		0.417			0.353		
Test of Parallel Lines, p Value		0.079			0.068		
		Est	Std. Err.	Sig.	Est.	Std. Err.	Sig.
Threshold	1-3 timetabled days	2.264	0.202	<0.001	2.532	0.192	<0.001
	4 timetabled days	4.474	0.242	<0.001	4.482	0.230	<0.001
Location	Contact Hours	0.369	0.021	<0.001	0.301	0.018	<0.001

Table 28 – TQS: Distribution of Timetabled Days/Week by Contact Hour

Both models fit the data and pass the test of proportionality, but give significant (failing) p values for the goodness of fit test. However, when an OLR model includes a continuous variable this can create many empty cells, resulting in an unreliable goodness of fit test (Norušis Marija J, 2011, p. 78).

The proportions of students preferring (receiving) their sessions spread over 1-3, 4 or 5 TTDs as suggested by the ideal (current) timetable model were enumerated for all contact hours, Graph 11 (left), whilst the difference between the TTDs desired by students, and that currently being given to students was calculated, Graph 11 (right).



Graph 11 – TQS: Preferred Distribution of the number of timetabled days

The preference data suggests that the most popular choice for timetables with ≤9 contact hours is 1-3 TTDs, for between 9-14 contact hours it is 4 TTDs, and for timetables with ≥14 contact hours, 5 TTDs are preferred. These preferences identify three potential timetable design classification groupings: Relaxed, Ideal and Intense. Students with ideal timetables will receive their contact hours over the number of days suggested above, whilst those with relaxed (intense) timetables will have the hours are spread over more (fewer) days. The categorisation of each combination of contact hours and TTDs is shown in Figure 9.

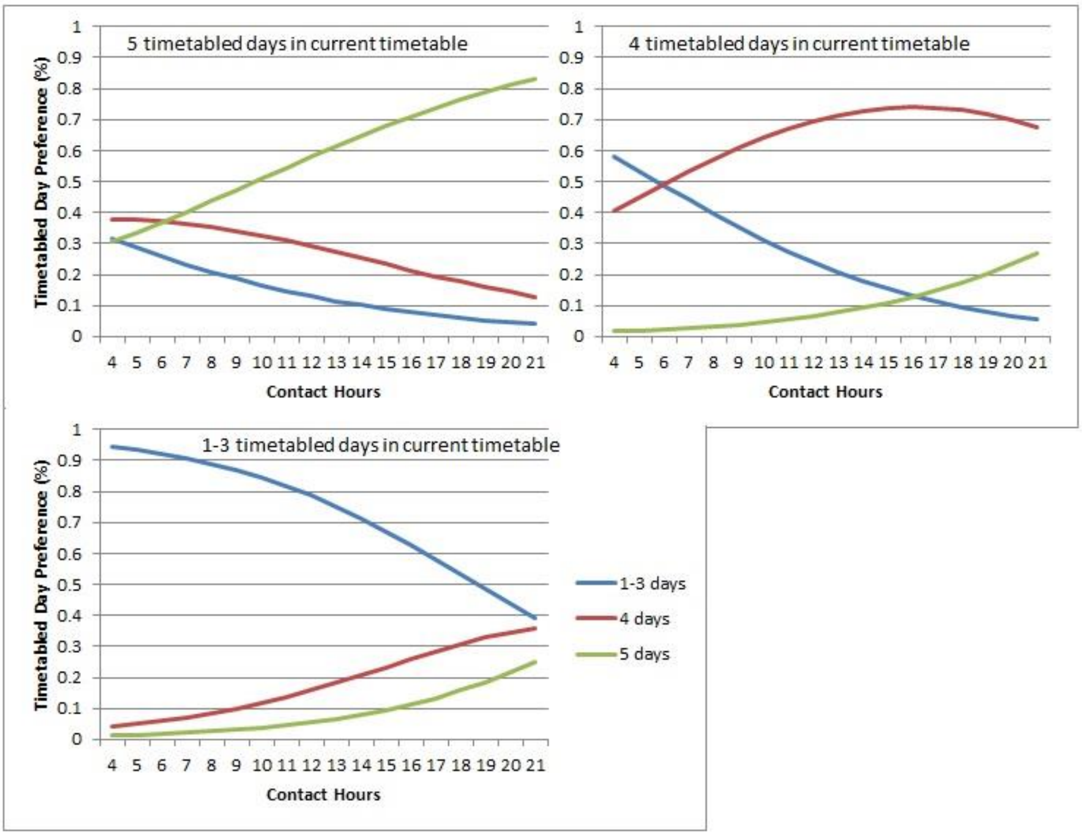
<table>
<tr><td></td><td colspan="17">Contact Hours</td></tr>
<tr><td>TT Days</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td><td>18</td><td>19</td><td>20</td></tr>
<tr><td>5</td><td colspan="10">Relaxed</td><td colspan="7">Ideal</td></tr>
<tr><td>4</td><td colspan="5">Relaxed</td><td colspan="6">Ideal</td><td colspan="6">Intense</td></tr>
<tr><td>1-3</td><td colspan="6">Ideal</td><td colspan="11">Intense</td></tr>
</table>

Figure 9 – TQS: Classification of TTDs by Contact Hours

Analysis of the differences between the current and ideal timetables show that the respondents at all levels of contact would prefer fewer timetables with 5 TTDs with this desire reaching a peak for those students on courses with between 13-15 hours, where almost 25% would prefer timetables with 4 days or less. Students enrolled on courses with ≤11 contact hours would prefer up to 20% more timetables with between 1-3 days.

These broad preferences for fewer TTDs mask the desire of a minority of students for more TTDs. Whilst in other areas of student timetable preference (break length, minimum sessions per day) there is a clear consensus amongst the respondents in terms of what constitutes a high quality timetable in this area the choice is less homogenous and there appears to be no single ratio linking timetable contact hours with the optimal number of TTDs. Whilst some of this preference can be explained by travel time, other unobserved factors mean that some students prefer to receive their course material in a more diluted way (fewer contact hours per day) whilst others prefer an intensive delivery (more contact hours per day), perhaps to minimise their presence on campus.

The analysis carried out at the start of this section identified that the number of TTDs in 66% of respondent ideal timetables matched the number in their current timetables. To explore the distribution of this apparently satisfied 66% a further OLR model was developed to examine the relationship between preference for TTDs and contact hours, after controlling for the effect of the number of TTDs in the current timetable, by including this in the model as an independent categorical variable. A single parsimonious model failed the test of significance for proportional odds and therefore the samples were split into three strata, representing those respondents with 1-3, 4 and 5 TTDs in their current timetable. The revised models fit the data well, and all pass the goodness of fit and proportional odds tests. The preferences suggested by each model were enumerated across the range of contact hours and plotted, Graph 12.



Graph 12 – TQS: Choice of ideal TTDs given current TTDs

The models show that the predominant preference appears to be for a timetable with the same number of days as exists within the current timetable, with 58% of students who have their sessions spread over 5 days desiring a timetable spread over five days, and this figure increases to 64% (73%) for those with timetables spread over 4 (1-3) days. In all cases the second most popular choice is for a timetable with one fewer day to the current arrangement. Very few students desire a timetable with more days than in their current timetable, even as contact hours increase.

6.7 Institutional Timetable satisfaction

The TQS identifies attributes of the timetable that are of importance to the students at UoL but gives no any indication of whether their experiences are typical of the wider UK undergraduate student population. To determine if student dissatisfaction with their timetable can be detected at the institutional level, a further analysis was conducted using data extracted through both the UK National Student Survey (NSS) and the Higher Education Statistics Agency (HESA).

The NSS, which is distributed to all UK final year undergraduates, contains one question that simply askes whether *"The timetable works efficiently as far as my activities are concerned".* The responses to this question, which are defined using a 5 point Likert scale, and aggregated by institution were obtained for the 2012 NSS survey (Higher Education Funding Council England, 2013).

From the data collected from the NSS dataset, seventy higher education institutions were selected for analysis. Institutions that broadly matched the profile of UoL were chosen, whilst half of those chosen were pre-1992 (traditional) universities, with the other half being post-1992 (new) universities. Across the 70 institutions, there were 179,717 student responses and from these the percentage of students agreeing with the timetable question, and those disagreeing were calculated. Overall the mean (standard deviation) across all institutions for respondents who agreed was 80% (5%) compared to 10% (3%) who disagreed. At UoL, 86% of respondents agreed, whilst 8% disagreed, suggesting that the Leeds figures are within the 80% confidence interval (1.2 standard deviations) around the overall sample agreement mean, and within the 68% confidence interval (1 standard deviation) of the mean for disagreement.

The differences in the institutional means for agreement/disagreement in the pre and post 1992 institution groups were found to be statistically significant at the 1% level (independent samples T test) suggesting that students at the newer universities are significantly less satisfied with their timetables than those at traditional institutions. It is not immediately apparent why the post-1992 institutions are generating timetables that are significantly less satisfactory compared to those served by the pre-1992 universities. It could be related to differences in the demographic profile of the students attending these institutions or it could be due to differences within the institutions themselves.

The Higher Education Statistics Agency collects data about university estates including the Gross Internal Area for all non-residential space utilised by the institution (m^2) and the total number of Full Time Equivalent (FTE) students and staff employed by the institution. Figures for GIA, Student-FTE and Staff-FTE for all institutions were obtained for the academic year 2011-2012 (Higher Education Stastics Agency, 2012). The ratios of floor-space (GIA) and FTE staff to FTE students across institutions show that the mean area (and standard deviation) available per student in pre-1992 institutions is 15.2 m^2 (4.1) compared with 7.4 m^2 (1.45) for post-1992 ones, whilst there are 4.7 (1.26) students per member of staff in the traditional universities compared with 9 (1.3) in the newer ones. This suggests that there is a range of space/student and student/staff ratios spread across the old and new institutions.

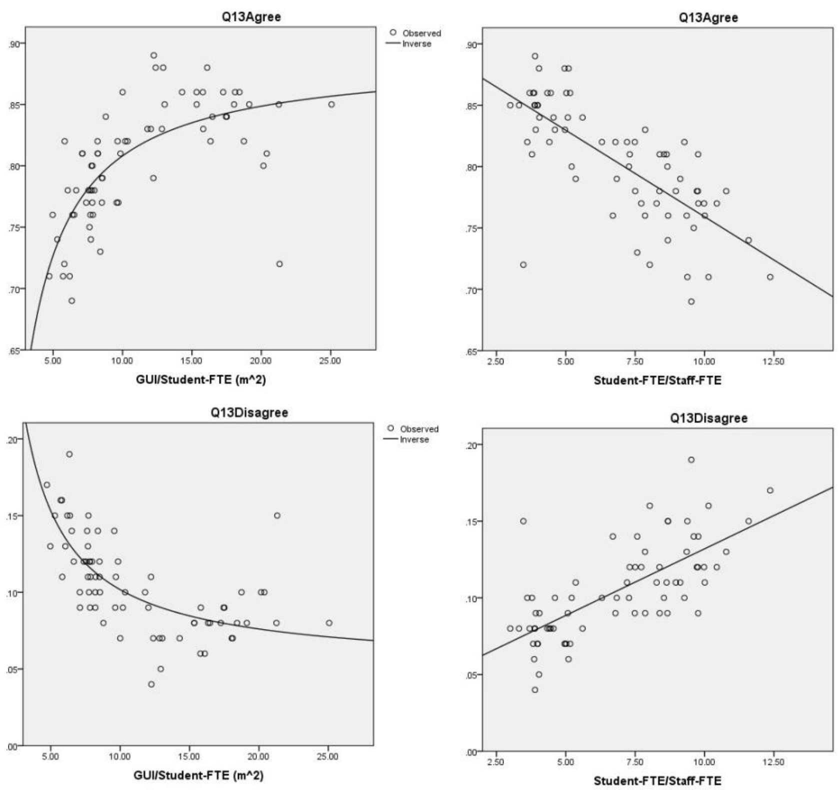


Figure 10 – NSS: Timetable Quality Question Curve Fit

[NSS Timetable Quality Question Responses Against Institutional Floor-Area and Staff-Student Ratios]

Curves were fit between each institutional agree and disagree percentage and the corresponding ratios for space and staff, Figure 10. A linear relationship was found to give the best fit for the student/staff ratio (R^2= 0.5 for Q13Disagree and R^2=0.53 for

Q13Agree), whilst the inverse of the space ratio resulted in a good fit for this data (R^2=0.51 for Q13Disagree and R^2=0.52 for Q13Agree). The parameters associated with all four curves were significant at the 1% level. Using the inverse for the space ratio and the student-staff ratio as independent variables, two LRMs were built with the institutional agree and disagree percentages as the dependant variables, Table 29.

Dependant Variable	Constant	Unstandardised Coefficients		Standardised Coefficients		R^2
		1/Space	Staff	1/Space	Staff	
Q13Disagree	0.044	0.299*	0.044*	0.415	0.342	0.537
Q13Agree	0.901	-0.388*	-0.008*	0.344	0.430	0.560

* Coefficient significant at the 5% level

Table 29 – NSS: Timetable Satisfaction Model Parameters

The fitted curves and the regressions show that as the space and staff available per student decreases timetable dissatisfaction increases, and similarly as space and staff per student increase so do overall levels of timetable satisfaction. These relationships are particularly apparent for low space ratios (below 10m^2 per student) where the rate of change in dissatisfaction levels accelerate. The standardised coefficients suggest that the staff ratio is more important in timetables that are satisfactory, whilst the space ratio is the primary driver behind timetables that are unsatisfactory.

This model suggests that the reason why post-1992 institutions have significantly lower timetable satisfaction ratings and significantly higher timetable dissatisfaction levels is due to them having smaller estates and fewer staff per student compared to the traditional pre-1992 universities. The work of the space management group prompted universities to examine their teaching estates and suggested that low room utilisation rates represented an avoidable opportunity cost (UK HE Space Management Group, 2006a) and could be improved through aggressive timetabling approaches. Every entry in an academic timetable represents an association between resources and entities: a room, a member of staff and a group of students. If it is assumed that lower space and staff ratios are indicative of higher levels of demand placed on individual institutional resources (rooms and staff) then this suggests that the consequence of generating feasible timetables in which resources are constrained in one dimension (rooms, staff or both) results in a fragmentation of the timetable in the remaining dimension (student timetable quality).

Beyrouthy suggested that there is a critical room utilisation value below which timetable allocations nearly always succeed and above which they nearly always fail (Beyrouthy et al., 2009) and these real-world datasets appear to replicate these results and show that since feasible timetables always have to be generated the phenomenon is manifest in terms of poorer quality timetables for students. The model suggests that although space (room) constraints are driving the relationship with student timetable quality they are a necessary but not a sufficient condition, and that to achieve a high quality timetable constraints imposed by staffing levels must also be considered.

Cheng advises caution when making comparisons between institutions using data from the NSS (Cheng and Marsh, 2010) and suggests that around two thirds of the variation in satisfaction rates are attributable to the course being studied rather than the institution attended. However, if it is assumed that the level of resource available to the timetable are broadly harmonised across an institution, then in this case this is less of a concern.

The UoL respondents to the NSS ranked Leeds in 5th position in terms agreement with the timetable question amongst the 70 institutions studied, suggesting that the timetable at Leeds is a relatively good example compared to the UK as a whole. If the timetable quality attributes identified as important in the TQS are representative this suggests that timetables containing early starts, late finishes, short days with a single session, long gaps between sessions and session imbalances across the days of the week are common in many UK universities.

This analysis suggests that the narrative of waste and conflict identified in section 6.4.15 is at least partially being caused by an institutional focus on timetable optimisation for space management and room utilisation purposes (RQ8). If timetable quality is important, then the institutions that have larger estates available to the timetable (relative to student numbers) are at a competitive advantage to those with lower space/student ratios. The results also indicate that potentially the pre-1992 (traditional) universities should be able to achieve higher quality timetables simply as a result of their legacy of having less well utilised buildings.

6.8 Summary of Timetable Preferences

The qualitative and quantitative data-sets obtained through the timetable quality survey ultimately provide a consistent picture of student preferences with regards to their timetable.

The most striking feature highlighted across both datasets is that current timetabling practice generates the wrong type of break. Students dislike breaks that are of one hour or longer in duration, as they equate non-contact hours spent on-campus with wasted time. Simultaneously though, students would welcome shorter sub one hour breaks between their sessions to allow them to arrive on time, to give them time to take a quick comfort break, to refresh themselves and to mentally prepare for the next class.

The most inconvenient time for sessions is from 09:00-10:00 and students express a strong preference for a slightly later daily start time to encourage a larger and more attentive audience. However, there is also a consistent desire for timetabled days starting in the morning and finishing earlier than currently, primarily through the removal of the inter-session breaks. Students would prefer their sessions to be front-loaded in the week, and some would trade additional sessions on a Wednesday in return for a freer Friday. Students almost universally dislike TTD's containing a single session day, and prefer every TTD to include at least two sessions.

Student preferences for the number of TTDs per week indicate a lesser degree of homogeneity. External time-constraints and concerns around commuting influence this preference, as does their current sessional arrangement. However, within the number of TTDs chosen by the student (individual preference) there is a more universal preference for a balanced timetable, with contact hours evenly distributed across and within all the TTDs (whatever their number). Depending on the number of contact hours scheduled on any given day, students prefer the sessions are either taken back-to-back (with short breaks), or in two equal sized blocks separated by a single (lunch) break (analogous to a school day).

Therefore, the survey suggests that student timetable preference can be split into two elements: firstly, the individual preference for a specific number timetabled days and secondly, a shared preference for a balanced timetable, with few breaks, no single session days and limited early starts (answering RQ3, supporting H3).

6.8.1 Timetable Preferences and Travel Behaviour

The TQS qualitative analysis suggests that students generally adopt a contemporary view of their timetable, and this is supported by the quantitative analysis which demonstrates that some of their preferences are connected with student trip-making behaviour (answering RQ1, supporting H1).

Students exhibit a general preference for fewer TTDs per week, and this preference increases with travel time. The survey suggests that overall students wish to see a 7% reduction overall in the total number of TTDs. Half of this reduction is attributable to concerns around commuting, whilst the qualitative data suggests that students also value days away from campus to take stock and to catch up on work.

Students exhibit a strong desire for fewer single session days with a halving in the total number of such days in the ideal timetables. Concerns around commuting are again a factor in this preference and students with the longest travel times exhibit a greater desire for fewer such days. However, overall 95% of the reduction identified through the survey is independent of travel time and this suggests that students see a day containing a single timetabled session as a sub-optimal allocation of their time and a wasted opportunity to undertake some other activity.

It could be argued that a dislike of single session days is driving the reduction in number of TTDs per week. However the survey shows that whilst there are 523 fewer single session days in the respondent ideal timetables, there are only 328 fewer TTDs. This means that although this may be the case for some, respondents also appear to want to redistribute sessions from other days to add to their single session days to create a more balanced timetable overall.

The preference for the start time of the timetabled day appears to be weakly related to travel time to campus with those students who have the longest travel time preferring an early start and those living locally a later one. Given the higher proportion of car drivers amongst students with longer travel times this preference may be related to the local situation at UoL where high levels of peak-time traffic encourage commuters to distribute their trips over an extended peak-period.

Walking students who live some distance from campus also demonstrate a significant preference for an earlier finish compared to those who live on-campus, and this is explained through concerns related to dark-walking home in the winter months.

The difference between respondent preferences expressed through their ideal timetables and the reality of the current timetable counterintuitively suggest that for students who live remotely it will be those who are enrolled on the higher contact hours courses that will feel the least frustration with their timetable. As contact hours increase TTDs begin earlier, include fewer days with a single session and have more contact hours per TTD, meaning that even when the sessions are spread over five days this distribution will not appear unreasonable for the commuting student. Students enrolled on lower contact hours courses are almost as likely to have sessions spread over the same number of days and are much more likely to have more single session days, a later start time and fewer hours per day.

Chapter 7 – Uncovering Student Trip-Making Behaviour

7.1 Introduction

This chapter will examine data from the second part of the TQS designed to definitely establish the relationship between the academic timetable and student trip-making behaviour. As already discussed in Chapter 4 university travel planners see student study-place trips as being equivalent to workplace commuter trips, with the effect of the timetable on this behaviour being largely ignored. The qualitative data reviewed in the previous chapter suggested that students hold a contemporary view of their timetable and the aim of this chapter is to explore and quantify real student trip-making behaviour through the responses given in the TQS to questions that specifically asked participants to summarise their study-place trips to campus.

The material presented in this chapter completes the delivery of research objective O3 (conduct a survey of student timetable preferences) and addresses research questions RQ2 (do students attend campus less frequently on NTD's?) and RQ4 (do students exhibit leave-and-return behaviour?).

7.2 Methodology

This section outlines the methodology used to obtain the necessary data and includes a discussion of the survey instrument, how the data was pre-processed and introduces the ordered logistic regression (OLR) model, which is used to analyse the data described in this chapter.

7.2.1 Survey Instrument

The TQS included a group of questions that asked the respondent to describe their trip-making behaviour.

When eliciting information about trip frequency university travel surveys typically include a single question asking respondents to state either the number of trips they make to campus during a typical week, or to list the days of the week which included a trip to campus, (see section 4.3.4). This approach is based on assumption that a trip is equally likely across all days, or that the day of the week determines the likelihood of a trip. Neither of these question styles allow for any recognition that students might regard trip-making on timetabled and NTDs differently.

To account for this hypothesised dichotomy in trip-making behaviour the TQS included two questions about student study-place trips. The first asked students to consider on how often they had missed coming to campus on TTDs, whilst the second requested an estimate of the frequency of trips to campus on NTDs. To provide some background on student motivation for staying away from campus, the survey also asked students to list the activities they would consider undertaking on NTDs that didn't include a trip to campus.

The survey requested that students consider three hypothetical situations, a day when their first session was scheduled to start at 11:00, a day when their last session was scheduled to end at 15:00 and a day with a three hour gap between 12:00 and 15:00. They were then asked to consider their likely arrival time, their likely departure time and the activities they would consider undertaking during the extended break.

When examining travel behaviour, travel time and mode are both important attributes and consequently the TQS included two travel related questions asking respondents to list their typical travel time to campus in minutes and their regular travel modes.

The survey was administered during the 8th teaching week of the first semester of the 2012/2013 academic year, meaning that when considering their answers students had to recall their behaviour over the first seven teaching weeks of the semester. A full copy of the timetable quality survey is shown in Appendix B.

7.2.2 Data Pre-processing

The analysis of trip making behaviour was restricted to those survey respondents who were undergraduates, in the first three years of their course, reducing the dataset available for analysis to 1,380 responses out of a population of 20,659 students, giving a response rate of 6.6% for this part of the TQS.

Categorical variables to represent the number of TTDs in the respondent's academic timetable and the average number of contact hours/day were derived from other TQS responses. As before, TTDs were split into three levels:: 1-3 TTDs (21%), 4 TTDs (32%) and 5 timetables days (47%), whilst average contact hours per day was processed into a second categorical variable, based on the analysis described in section 6.6.10 again with three levels representing : Intense timetables (18%), Ideal timetables (53%) and Relaxed timetables (29%).

As the TQS data only provides information for the survey week, the simplifying assumption was made that all students used similar timetables in the previous seven weeks, even though it is known that some timetables vary across the weeks.

The survey requested that students list their faculty of study, and this was processed into a categorical variable with three levels: Arts Based (54%), Science Based (36%) and Medical (10%).

Respondents were requested to provide the typical travel time to campus in minutes. Inspection of data showed a Poisson-like distribution, with a mean travel time of 22 minutes and with a small number of samples (4%) with travel times in excess of 60 minutes. To facilitate the analysis of this data, responses were recoded into a categorical variable with four levels: 0-14 minutes (29%), 15-29 minutes (48%), 30-44 minutes (14%) and ≥ 45 minutes (9%).

The survey requested that respondents specified all the travel modes they used regularly for their trip to campus using the list taken from the UoL travel survey (University of Leeds, 2010b). For this analysis these choices were considered to be too broad and were recoded into a categorical variable with three levels: Private, representing car and motorcycle (4%), Public transport, representing bus and train (24%) and Active, representing walking and cycling (72%). Where a respondent specified multiple modes public transport took precedence over a private mode which itself took precedence over an active mode. Categories were prioritised in this way because it was thought that respondents would generally specify all the modes they used on a trip to campus, and with this ordering typical modal combinations, such as car and walk, would cause the mode category used for the majority of a trip to be selected. It was assumed that the modes specified as being used during the survey week were also the modes used during the preceding seven weeks.

7.2.3 Survey Validity and Bias

Section 6.3 outlined general points about the validity of the TQS and its apparent bias towards younger female undergraduate students. Since this analysis includes variables representing travel time and mode further checks were performed to compare the data in TQS with that from the UoL travel survey (University of Leeds, 2010b). It was found that public transport users were significantly over-represented in the TQS and this could be due to an effect from the mode categorisation method described in section 7.2.2. However, a similar comparison of the proportion of respondents in each travel time category categorical showed no significant differences between the TQS and the UoL travel survey.

7.2.4 Ordered Logistic Regression

Ordered logistic regression (OLR) modelling is a technique that allows the effect of one or more parameters on a distribution of choice probabilities across a population to be examined. Consider the binary choice regarding whether to come to campus on a particular day. If it is assumed that students will always be observed when they come to campus, then over a period of T days, the student will be seen on campus on t of these days ($0 \leq t \leq T$). From these observations it is possible to calculate an aggregate probability P of daily attendance over the entire period as $P=t/T$. This probability can be assumed to be constant for all T days, even if in reality the individual may be more likely to attend on some days rather than others. The challenge is to model the effect of the factors that can be observed and which might influence the attendance decision of an individual over the population as a whole.

The LRM, see section 6.5.3, is not appropriate when the dependant variable is specified as a probability since the result from the linear model is not constrained to the range 0 to 1. A logistic link function, equation 7-1, may be used to map a continuous index value, z, ($\infty \leq z \leq \infty$)onto a probability value in the range 0 to1 (Kleinbaum and Klein, 2002, p. 5).

$$f(z) = \frac{1}{1 + e^{-z}} \qquad 7\text{-}1$$

When z is zero, $f(z)$ is 0.5, with positive values causing $f(z)$ to tend towards 1 and negative values towards zero. The LRM may be substituted for the parameter z, equation 7-2, thereby allowing an unbounded linear relationship between terms to derive a bounded probability value (Field, 2013, p. 762).

$$P(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots \beta_k X_k)}} \qquad 7\text{-}2$$

The odds ratio (OR) for a specific outcome is defined as being the likelihood of occurrence of that outcome relative to all other outcomes. If the outcome of interest has probability P then the odds ratio is as defined in equation 7-3, (Field, 2013, p. 767).

$$OR = \frac{P}{1 - P} \qquad 7\text{-}3$$

The odds ratio function will asymptotically approach zero as P tends to zero and infinity as P tends to one. Taking the natural log of the odds ratio converts the ratio onto a linear scale, whilst at the same time introducing $P(x)$ for P in equation 7-4, (Kleinbaum and Klein, 2002, p. 17).

$$logit\ P(X) = ln_e \left[\frac{P(x)}{1 - P(x)}\right] \qquad 7\text{-}4$$

Through simplification the complementary natural log and e terms cancel out leaving the log odds ratio for the probability $P(x)$ expressed as the linear sum, equation 7-5, (Kleinbaum and Klein, 2002, p. 18).

$$logit\ P(X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots \beta_k X_k \tag{7-5}$$

Equation 7-5 represents a form of a binary logistic regression (BLR) model which can be used to model preferences between two choices, where the function values of 0 and 1 describe each of the choices, and in which intermediate values define the degree of certainty with which a given observation represents a specific choice. When the classification of individual observations is required a cut-off value, typically 0.5, divides the probability range into two discrete choices (Pardoe, 2006, p. 225). The effect of different sets parameter values on an outcome may also be determined, using the function to calculate the relative odds of each outcome and then by using an odds ratio to express the likelihood of one outcome relative to the other.

The BLR model can be extended to represent situations when multiple choice outcomes are to be modelled. In cases where the individual choices have no natural order, for example when choosing between different transport modes, the Polytomous Universal Model (PLUM) can be used, whilst when a natural order exists then the technique is known as ordered logistic regression (OLR). Consider asking students a question related to how many days they have missed coming to campus. Respondents may be invited to respond using a seven point scale in which the responses range from ‘never’, through ‘1-2 days’ and up ‘more than 10 days’. For each response category, d_j will represent the mean number of days missed by respondents who specified the j^{th} category as their response. If there are R responses in total, then the i^{th} response, r_i, will be in the range 1 to 7. The cumulative probability that a respondent will have specified a response less than or equal to j, $P(j)$ $(1 \leq j \leq 7)$ will be as shown in equation 7-6.

$$P(j) = \frac{\sum_i^R \begin{bmatrix} r_i \leq j : 1 \\ r_i > j : 0 \end{bmatrix}}{R} \tag{7-6}$$

The equation 7-5 can be used to model six of these seven cumulative response probabilities but in which the coefficients associated with each of the independent variables β_1 to β_k are held constant across all the equations and with a unique intercept term β_{0j} being defined in each equation. The equations can be solved using maximum likelihood estimation techniques, after which values for the j-1 β_{0j} threshold terms, and the k common β_1 to β_k location terms will be fit to the model. Each threshold term β_{0j} represents the log odds of the likelihood of a response less than or equal to j, in the case when all the independent variables, X_1 to X_k are zero. Each term can be converted back into the equivalent probability of a response $\leq j$ through equation 7-7.

$$P(j) = \frac{1}{(1 + e^{\beta_{0j}})} \qquad 7\text{-}7$$

These probabilities represent the cumulative attendance distribution function of the subset of the total population that can be represented by zeroes in each of the X_1 to X_k parameters. For this segment of the population the mean number of days missed, $\bar{d}$, will be the sum of the product of the probability of each response and the d_j terms, equation 7-8.

$$\bar{d} = \sum_j d_j \left(P(j) - P(j-1)\right) \qquad 7\text{-}8$$

The β_{0j} terms define the shape of a cumulative distribution function which maps a linear term derived from the independent variables onto a mean value for days missed defined by the d_j terms. When one or more of X_1 to X_k is non zero the model assumes that the β_1 to β_k coefficients apply equally over all the j-1 equations. However, whilst the effect on the odds ratios is proportional the effect on $\bar{d}$ is not, since the slope of the cumulative distribution function defined by the β_{0j} terms varies across the distribution. The sum of a set of coefficients represents the log of the odds ratio between the reference category (in which all the coefficients are zero), and a composite category represented by the non-zero coefficients. This ratio is constant across the range of threshold values. In this context the odds ratio has little meaning in terms of determining the effect of specific coefficient values on non-attendance rates and it is necessary to use the combined coefficients to calculate categorical response probabilities.

The OLR model may be used to represent both continuous and discrete independent variables and in the case of the latter each unique discrete value of X_k will have a corresponding unique coefficient. Where the discrete values themselves have an implied order, then the change in the coefficients across the range of discrete values allows the underlying relationship between the parameter and the response variable to be examined. The OLR model can be thought of as a method for explaining the variation between the cells in a contingency table that represent all combinations of the K independent variables at all J levels of the dependant variable. If each independent variable k has L_k levels then the contingency table will have $J\prod_k^K L_k$ cells.

An expected count for each cell can be calculated using the probability calculated by the model multiplied by the number of observations with the corresponding combination of independent variable values. The coefficients used to estimate the cell probabilities are based on all the observed data, smoothing it and dampening the observed within-cell variability (Agresti, 2007, p. 108). The goodness of fit of the model can be determined by calculating a Pearson Chi squared statistic based on the proportional difference between the observed and expected counts in each cell, equation 7-9, (Agresti, 2007, p. 35).

$$\chi^2 = \sum_i \sum_j \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{7-9}$$

Where

O_{ij}, E_{ij}	Observed and expected counts for cell [i,j]
$H0: O - E = 0$	Null Hypothesis: Observed and Expected values are similar

This statistic becomes unreliable if there are many empty cells or cells with low expected probabilities (Norušis Marija J, 2011, p. 78) and it may wise to accept a lower significance threshold or ignore the measure (ESRC Restore, 2011, section 5.4).

The Pearson Chi squared statistic describes how well the model fits at an aggregate level, whilst Nagelkerke's R^2 measure is analogous to the coefficient of determination in the linear model. This describes the proportion of the variation in the model that is explained by the coefficients, and a low value does not invalidate the overall fit at an aggregate level (Norušis Marija J, 2011, p. 83) nor does it invalidate any statistically significant coefficients (ESRC Restore, 2011, section 5.4).

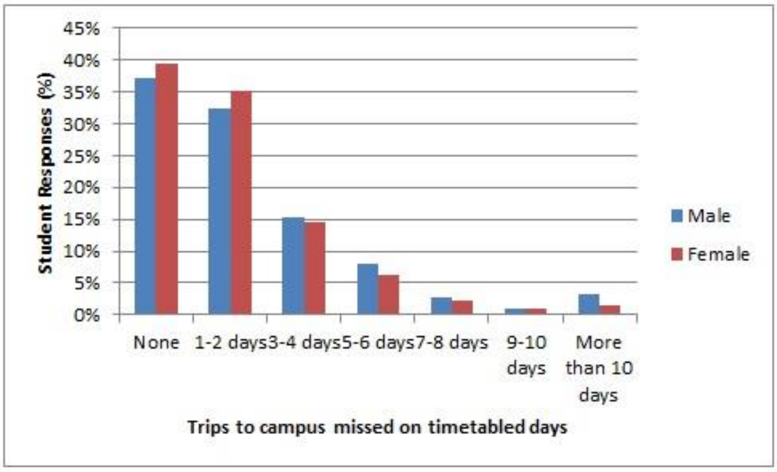
Since the model defines a single set of coefficients X for each independent variable they are assumed to make the same additive adjustment to the log-odds across all levels of the dependant variable Y. This assumption is tested through the proportional odds test. This test compares the fitted model with one that has separate coefficients for each X at each level of Y, with the null hypothesis being that the two models are equivalent. When a significant result is found to this test the proportional odds assumption has to be rejected. However, this test has been described as anti-conservative in that it is almost always likely to give a significant result, particularly if the sample size is large (ESRC Restore, 2011, section 5.9).

7.3 Survey Result and Analysis

This section contains a presentation of the results from the survey, and some analysis of their content.

7.3.1 Trips Missed to Campus on Timetabled Days

Participants were asked to specify how often they had missed coming to campus on TTDs during the seven weeks prior to the survey, Graph 13.



Graph 13 – TQS: Distribution showing student absence on TTDs

On average male (female) respondents had missed 2.1 (1.8) TTDs during the 7 weeks of the semester prior to the survey week. Converting these figures into rates suggests that males attended on 94.1% of TTDs, whilst females attended on 94.6% of days.

National workplace absence surveys indicate that on average employees are absent for 6.8 days per year (The Chartered Institute of Personnel and Development (CIPD), 2012). This equates to a daily employee attendance rate of just over 97% (assuming 6 weeks of holiday entitlement). It could be expected that students would attend slightly less frequently than employees, given that there are fewer short-term sanctions that can be applied by the university for non-attendance, and that the manditoriness of student trips to campus will be lower than those of employees going to work.

Given that students are at university to obtain a degree, and that attendance at timetabled sessions is generally recognised as a prerequisite of success, it would be expected that students will make an effort to attend on-campus on TTDs, and that most factors that influence attendance rates (student health levels, fatigue, family circumstances) will be out of the scope of this study. An OLR model (section 7.2.4) was used to identify any factors observable in the dataset that influence attendance rates. In fitting the model all variables were initially included, after which those that were not statistically significant were removed. The coefficients and summary statistics for the resultant model, including just the significant independent variables, are shown in Table 30.

The model just misses passing the goodness of fit test, although the test for proportionality across the categories is successful.

Test Statistics		Total Samples	1380				
		Model Fit p Value	<0.001 (Chi square: 48.397, df=6)				
		Pearson Goodness of Fit, p Value	0.049 (Chi square: 179.737, df=150)				
		Nagelkerke Pseudo R^2	0.037				
		Test of Parallel Lines, p Value	0.865 (Chi square: 21.680, df=30)				
COEFFICIENTS			Estimate	Std. Err.	Wald	df	Sig.
	Threshold	No days missed	-0.804	0.137	34.201	1	<0.001
		1-2 days missed	0.688	0.137	25.189	1	<0.001
		3-4 days missed	1.673	0.147	129.940	1	<0.001
		5-6 days missed	2.558	0.169	228.476	1	<0.001
		7-8 days missed	3.178	0.198	257.568	1	<0.001
		9-10 days missed	3.595	0.226	252.921	1	<0.001
	Timetabled Design	Intense	-0.622	0.152	16.746	1	<0.001
		Ideal	-0.348	0.113	9.491	1	0.002
		Relaxed	0				
	Travel Mode	Private	0.350	0.250	1.964	1	0.161
		Public Transport	0.344	0.118	8.574	1	0.003
		Active					
	Year of Study	1^{st} Year	-0.457	0.136	11.255	1	0.001
		2^{nd} Year	0.061	0.130	0.222	1	0.637
		3^{rd} Year	0				

Table 30 – TQS: Model Results, Absences from campus trips on TTDs

The model does suggest a relationship between timetable intensity and attendance, indicating that as contact hours/day increase students will make more effort to attend. There is a similarly significant but small effect between first year students and attendance, suggesting that this group attends slightly more frequently than the 2^{nd} and 3^{rd} year cohorts. However since the survey was conducted during week nine of the first semester, it is difficult to draw any definite conclusions, as students might still be determining their long-term behaviour patterns.

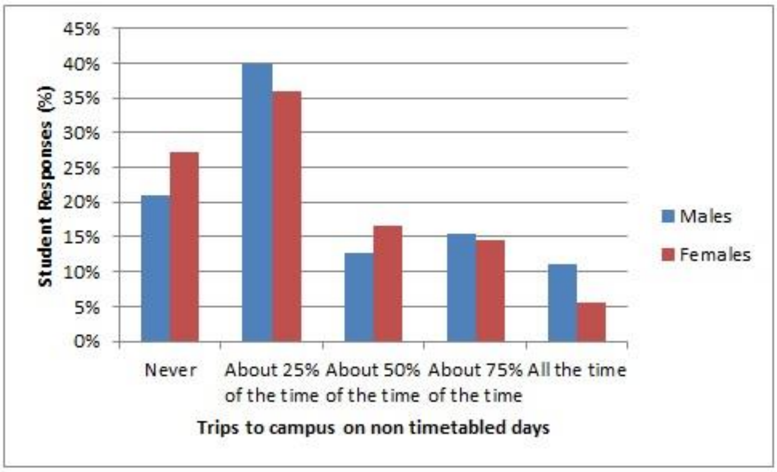
The model suggests that students who use public transport are statistically less likely to attend on TTDs compared to those who walk. This finding mirrors that of Richbell who found that employees using public transport for workplace commuting trips exhibited higher levels of absence compared to those using other modes, especially private car (Richbell and Minchin, 2012). For students a similar, but not statistically significant, coefficient is also estimated for those who drive, and it could be that given these modes are more common for students who live further from campus that travel distance is the determinant of this relationship, rather than mode. However, no significant relationship could be found between travel time and attendance rates.

The coefficients can be used to calculate the proportion of the sample in each dependant variable category for different combinations of independent variables. These proportions can then be multiplied by the number of days absence represented by each dependant variable category to obtain a mean level of absence.

The model suggests that students in their third year who drive or use public transport, (and who are perhaps living further away from campus), with relaxed timetables (fewer contact hours/day) will miss 1 in 10 TTDs, compared with first year students who walk or cycle to campus and who have intense timetable (more contact hours/day) who will miss less than 1 in 20 TTDs.

7.3.2 Frequency of Trips to Campus on Non Timetabled Days

It was hypothesised that students attend campus less frequently on NTDs and the survey aimed quantify this by asking participants directly how often they had attended campus on NTDs in the weeks prior to the survey week. Around 47% of respondents indicated that they had timetabled sessions scheduled across all five days and consequently their possible behaviour on NTDs was censored in the data, meaning this analysis was necessarily limited to the remaining 728 respondents. The distribution of their responses is shown in Graph 14.



Graph 14 – TQS: Student Attendance on NTDs

Combining this distribution with the NTDs available in each student's schedule shows that overall males are more likely to make trips to campus on NTDs, attending on 39% of them, compared to 34% of days for females. 21% (27%) of males (females) stated they never came to campus on NTDs, whilst 11% (6%) of males (females) attend campus everyday irrespective of whether they have classes or not.

An OLR model was used to examine how non-timetabled day attendance rates varied over the sample, with the categorical non-timetabled day response as the dependant variable. The categorical variable representing the number of TTDs in an individual timetable becomes a binary variable in this analysis given the exclusion of all respondents with five day timetables. The results for the model, listing all the significant coefficients, are shown in Table 31.

<table>
<tr><td colspan="2" rowspan="6">Test Statistics</td><td colspan="2">Total Samples</td><td colspan="4">720</td></tr>
<tr><td colspan="2">% Cells With Zero Expected Value</td><td colspan="4">29.6% (71)</td></tr>
<tr><td colspan="2">Model Fit p Value</td><td colspan="4"><0.001 (Chi square: 95.386, df=7)</td></tr>
<tr><td colspan="2">Pearson Goodness of Fit, p Value</td><td colspan="4">0.209 (Chi square: 196.139, df=181)</td></tr>
<tr><td colspan="2">Nagelkerke Pseudo R^2</td><td colspan="4">0.131</td></tr>
<tr><td colspan="2">Test of Parallel Lines, p Value</td><td colspan="4">0.235 (Chi square: 25.297, df=21)</td></tr>
<tr><td rowspan="16">COEFFICIENTS</td><td colspan="2"></td><td>Estimate</td><td>Std. Err.</td><td>Wald</td><td>df</td><td>Sig.</td></tr>
<tr><td rowspan="4">Threshold</td><td>Never Attend</td><td>0.292</td><td>0.275</td><td>1.128</td><td>1</td><td>0.288</td></tr>
<tr><td>Attend 25% of time</td><td>2.037</td><td>0.285</td><td>51.063</td><td>1</td><td><0.001</td></tr>
<tr><td>Attend 50% of time</td><td>2.858</td><td>0.292</td><td>95.966</td><td>1</td><td><0.001</td></tr>
<tr><td>Attend 75% of time</td><td>4.216</td><td>0.316</td><td>178.395</td><td>1</td><td><0.001</td></tr>
<tr><td rowspan="4">Travel Time</td><td>0-14 minutes</td><td>1.920</td><td>0.274</td><td>49.183</td><td>1</td><td><0.001</td></tr>
<tr><td>15-29 minutes</td><td>1.771</td><td>0.260</td><td>46.557</td><td>1</td><td><0.001</td></tr>
<tr><td>30-44 minutes</td><td>1.090</td><td>0.299</td><td>13.287</td><td>1</td><td><0.001</td></tr>
<tr><td>≥45 minutes</td><td>0</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="3">Travel Mode</td><td>1st Year</td><td>-0.582</td><td>0.187</td><td>9.659</td><td>1</td><td>0.002</td></tr>
<tr><td>2nd Year</td><td>-0.460</td><td>0.168</td><td>7.463</td><td>1</td><td>0.006</td></tr>
<tr><td>3rd Year</td><td>0</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Timetabled Days</td><td>1-3 timetabled days</td><td>0.524</td><td>0.147</td><td>12.470</td><td>1</td><td><0.001</td></tr>
<tr><td>4 timetabled days</td><td>0</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Gender</td><td>Male</td><td>0.245</td><td>0.158</td><td>2.416</td><td>1</td><td>0.120</td></tr>
<tr><td>Female</td><td>0</td><td></td><td></td><td></td><td></td></tr>
</table>

Table 31 – TQS: Model Results,Campus Attendance on NTDs

The model explains 13.1% of the individual variation between respondents (Nagelkerke Pseudo R^2) and passes the tests for proportionality and goodness of fit.

The model suggests that discretionary trips to campus decrease as student travel time increases, and that students in the first year make fewer discretionary trips than 2nd and 3rd year students. Those with timetables that have a single free day per week are less likely to make a discretionary trip on that free day, compared to students with two or more free days in their timetable. Male students make more discretionary trips than female students (not significant) but included since this characteristic is demonstrated in the aggregate data. The finding that students with one free day in their timetable seem to be less willing to attend on campus during that day appears to match the timetable preferences discussed in section 6.6.10 in which students with four TTDs are very unlikely to want to give up their free day. Jointly this suggests that students value one free day per week for non-academic activities. The coefficients for travel time are large relative to those for the other variables suggesting that travel time is the major driver behind variation in attendance rates on NTDs.

To test the relative effect of these coefficients in both isolation and combination the response probabilities for each attendance level predicted by the model were calculated for a range of category combinations, Table 32.

Gender	Year Of Study	Travel Time to Campus (minutes)	Attendance on NTDs (%) Timetabled Days/Week	
			1-3 days	4 days
Male	1st Year	0-14	45%	36%
		≥45	17%	12%
	3rd Year	0-14	55%	46%
		≥45	24%	18%
Female	1st Year	0-14	41%	32%
		≥45	15%	10%
	3rd Year	0-14	51%	41%
		≥45	21%	15%

Table 32 – TQS: Factors affecting attendance on NTDs

These results demonstrate the high degree of variation in attendance rates caused by all three factors. A student with a travel time in excess of forty five minutes will make less than half the visits to campus compared to one living nearby, whilst students in their third year will make between 25% and 40% more visits compared to their counterparts in the first year. Similarly students who have their timetable spread over three or fewer days will make between 25% and 40% more trips to campus on NTDs, compared to those whose sessions are scheduled across 4 days/week. The students with the lowest attendance rate on NTDs will be first year females who live remotely and have their classes scheduled over four days/week. These students will attend on one day in every ten NTDs, with their male equivalents attending once in every eight and a third NTDs.

7.3.3 Examination of the reasons for not coming to Campus

The university offers a range of on-campus resources to support students in their studies. If students aren't making use of these facilities because they have decided to absent themselves from campus it is important to investigate the reasons behind their non-attendance decision. Consequently the TQS asked participants to list the range of activities they undertook on days when they decide to not to come to campus, Table 33.

Reasons for not coming to campus on NTDs (n=1319)	Cited		Main Reason		By Gender	
	%	Rank	%	Rank	Male	Female
I have a part-time job (<=16 hours per week)	21.7	8	6.4	7	18.3%	23.2%
I have a full-time job (>16 hours per week)	2.7	10	1.9	10	2.3%	2.9%
I have childcare commitments	1.8	11	1.3	11	1.5%	2.0%
I have family commitments	9.6	9	2.7	9	9.0%	9.9%
I have other commitments on my time	45.6	5	10.4	3	45.1%	45.9%
I find I can work better away from the University campus	**52.2**	3	**20.5**	1	48.4%	53.9%
I like to go out at socialising at night and need time to recover	27.4	7	2.0	8	**34.6%****	24.3%
I want time during the week for leisure activities	52.0	4	7.1	5	**60.4%****	48.4%
I want some time for myself	62.1	2	8.7	4	63.7%	61.4%
I need some time for domestic tasks such as shopping, washing, cleaning	66.3	1	7.1	5	59.1%	**69.5%****
Travelling to university takes time and/or costs money that I would rather use in other ways	**36.8**	6	**12.5**	2	32.8%	38.5%

Table 33 – TQS: Student Reasons for not coming to campus

Whilst the most common reason given for staying away from campus was due to maintenance activities, more than 50% of students stated that being able to work better away from campus was a reason for not attending (ranked 3rd), whilst 36% stated that the travel time/costs of getting to campus was a concern which limited the trips they made (ranked 6th). Only 4% of participants gave no reasons suggesting that most students regard spending some part of the week away from campus as being important to them.

The survey requested that participants identify the main reason why they chose to stay away from campus, and of the 80% of participants who indicated that there was a single main reason, more than 20% suggested that this was due to being able to work better away from campus (ranked 1st), whilst 12% indicated that was due to concerns about travel time/costs (ranked 2nd) .

Just over 21% of respondents indicated that time away from campus was spent on part-time work, suggesting that a sizeable minority of student now need to do some kind of paid work to support their studies, and that free days in the timetable allows them to fulfil this need.

Analysis of the cited reasons by gender indicates significant differences in the motivation for staying away from campus. Females cite the need for time for maintenance tasks or part time work, working better away from campus, and concerns about travel time and costs more frequently, whilst males cite the need for time for leisure activities, or to recover from nights out more frequently. This suggests that even when making the decision not to come to campus females are more conscientious than males in terms of their studies.

The apparent preference of females towards working away from campus might be explained through a tendency in females to select courses with lower contact hours, which generally involve fewer TTDs. However, analysis of this preference by faculty shows that in each one (excluding Business and Mathematics/Physical Sciences) at least 7% more females cite this reason when compared to their male counterparts.

Analysis of the results of the TQS shows that students demonstrate a weak desire for fewer TTDs (section 6.6.10). By combining the reasons stated for not to come to campus with the individual student preferences for fewer TTDs on campus, it is possible to discern the student motivation behind these preferences.

The number of trips in each participant's current and ideal timetables were grouped by gender and analysed by the reasons stated for not coming to campus, and from this the mean difference in trips between those who specified each reason and those who didn't was calculated, Table 34.

If a particular reason is a motivator for fewer TTDs and trips to campus then the desired reduction should be higher for those students who specify the reason compared to those who don't, and consequently the difference in the trip rate will be shown as a negative value. This analysis shows that reducing travelling times/costs and working better away from campus are significant motivators for both genders when desiring fewer TTDs. Male students also want more time off-campus to pursue "other commitments" whilst females consider substituting trips to campus with part-time work.

Reasons for not coming to campus on NTDs	Δ trip rate reduction between those specifying the reason and those who didn't	
	Male	Female
I have a part-time job (<=16 hours per week)	-0.12	**-0.14***
I have a full-time job (>16 hours per week)	Not available, insufficient samples	
I have childcare commitments		
I have family commitments	-0.10	-0.13
I have other commitments on my time	**-0.13***	-0.03
I find I can work better away from the University campus	**-0.14***	**-0.17****
I like to go out at socialising at night and need time to recover	-0.03	-0.06
I want time during the week for leisure activities	0.02	0.07
I want some time for myself	-0.10	-0.02
I need some time for domestic tasks such as shopping, washing, cleaning	-0.07	*0.11**
Travelling to University takes time and/or costs money that I would rather use in other ways	**-0.43****	**-0.28****

Table 34 – TQS: Motivation behind desire for less TTDs

[**(*): Difference significant at 1% (5%) level using a one sided two sample z-test (since change must always be a reduction) with null hypothesis: no difference in trip-rate reduction level between those specifying a preference and those who don't]

The preferences around working better away from campus were explored further using an OLR model. A three level categorical dependant variable was calculated based on responses to statement "I work better away from campus", and classified as either: no response, agree with statement or statement specified as main reason. Each successive level of response can be assumed to indicate a stronger preference towards working away from campus. However, the model was unable to find any significant differences between the response levels of students by either residential distance or year of study.

7.3.4 The Overall Frequency of Trips to Campus

Analysis of the two survey questions eliciting absence from campus on TTDs and presence on campus on NTDs detailed in sections 7.3.1 and 7.3.2 indicate that the student decision to attend on campus is driven by two distinct probabilities as shown in Table 35, (answering RQ2, supporting H1a))

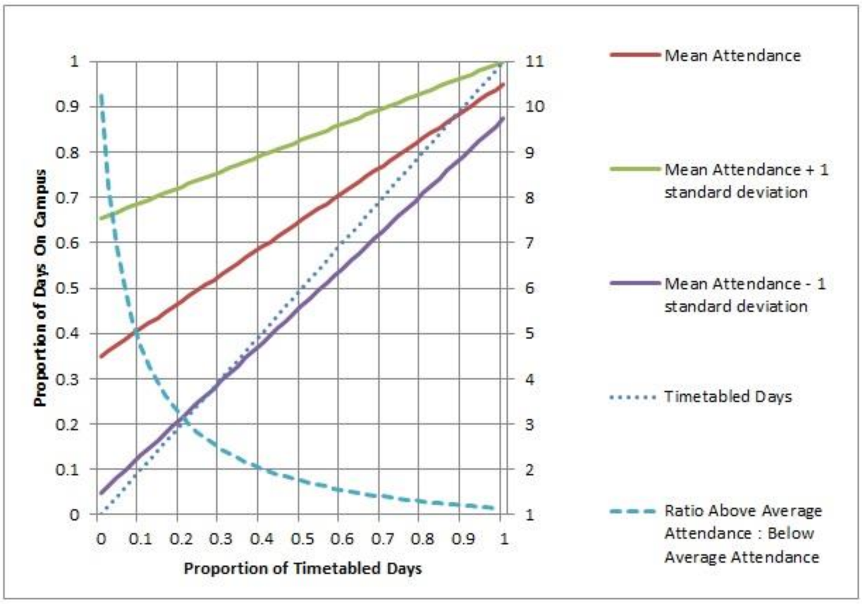
	Probability of Attendance					
	Males		Females		Overall	
	μ	σ	μ	σ	μ	σ
Timetabled days (mandatory trip)	0.946	0.080	0.951	0.074	0.95	0.076
NTDs (discretionary trip)	0.390	0.321	0.338	0.296	0.351	0.303

Table 35 – TQS: Student Probability of On-campus Attendance

Female students will attend slightly more regularly on TTDs, whilst male students will visit campus more often on NTDs. Assuming these probabilities are normally distributed then given the overall mean probability for attendance on timetabled (tt) and NTDs (ntt), the value at which the two probabilities will be equal can be expressed as multiple (x) of their standard deviations, equation 7-10.

$$\mu_{tt} - x \cdot \sigma_{tt} = \mu_{ntt} + x \cdot \sigma_{ntt} \quad (7\text{-}10)$$

Equality occurs when x=1.58, at which point 11.5% of the two distributions will overlap. This means that for at least 88% of the sample the main determinant of their total number of trips to campus will be their number of TTDs/week, and that although discretionary attendance on NTDs will increase their total attendance, this increase will be insufficient to take the total attendance above the level achieved by adding an further timetabled day to the timetable (supporting H1a). The linear relationship suggested by these probabilities between TTDs and attendance is shown in Graph 15..



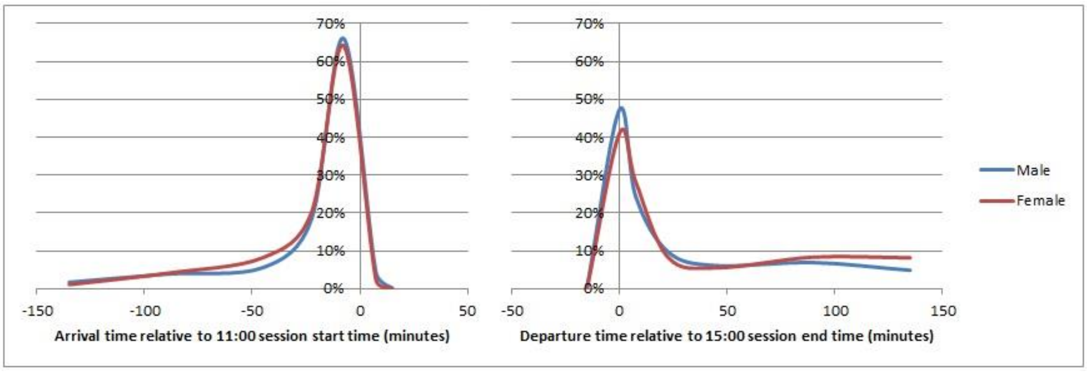
Graph 15 – TQS: On-campus attendance vs TTDs

This plots the likely proportion of days that will include a trip to campus relative to the proportion of days containing timetabled sessions for a typical student (mean attendance), a student predisposed to more regular trips (plus one standard deviation) and a student less likely to make trips to campus (minus one standard deviation). The overall level of attendance in each case is calculated using a combination of these TTD and NTD attendance probabilities.

The differential between the mean probabilities of attendance on timetabled and NTDs causes the absolute difference in overall attendance levels to reduce as the number of TTDs increase. The ratio of the proportion of days spent on campus between an above average student and a below average student is also displayed on the graph demonstrating this effect. When the timetable includes just two TTDs per week (proportion = 0.4) the more conscientious student will spend twice as many days on campus compared with the less conscientious student. However, when the timetable includes sessions over four days per week the difference falls to less than one day in every three (RQ6).

7.3.5 Campus Arrival and Departure Times

Participants were asked to specify their likely on-campus arrival and departure times for hypothetical TTDs starting at 11:00 and finishing at 15:00, with the aim of determining the degree to which the timetable influences on-campus arrival and departure times and consequently the timing of their commuting trips. These arrival and departure times were chosen because they are both some distance from nominal workday arrival (09:00) and departure (17:00) times, whilst still clearly being in the morning and afternoon. It was thought that these choices would allow commuting behaviours driven by the timetable to be distinguished from those influenced by fixed arrival and departure times. Interpolated arrival and departure time profiles for the two hypothetical sessions are shown in Graph 16.



Graph 16 – TQS: TTD Sample Arrival and Departure Time Profiles

These profiles show that over 60% of respondents indicated that they would arrive on-campus in the 15 minutes immediately prior to the start of the first session at 11:00, whilst over 40% of respondents indicated that they would leave campus as soon as their final session finished at 15:00. The departure distribution is more dispersed (relative to arrival on-campus) and indicates that around 10% of those attending remain on-campus after 17:00.

On average male students will arrive on campus 17 minutes before the start of the session, whilst females will arrive a minute earlier. On departure males will leave campus on average two minutes after their session finishes whilst females will leave about five minutes after the end of the session.

An OLR model was fit to the arrival time data, Table 36. Although the model is a good fit, the significant parameters are limited to the travel time and the timetable days categories.

Test Statistics		Total Samples	1379				
		% Cells With Zero Expected Value	6.9% (5)				
		Model Fit p Value	<0.001 (Chi square: 105.302, df=5)				
		Pearson Goodness of Fit, p Value	0.792 (Chi square: 41.685, df=50)				
		Nagelkerke Pseudo R^2	0.083				
		Test of Parallel Lines, p Value	0.753 (Chi square: 15.404, df=20)				
COEFFICIENTS			Estimate	Std. Err.	Wald	df	Sig.
	Threshold	Arrival before 09:00	-2.723	0.251	118.152	1	<0.001
		Arrival 09:00-10:00	-1.560	0.193	64.991	1	<0.001
		Arrival 10:00-10:30	-0.601	0.179	11.273	1	0.001
		Arrival 10:30-10:45	0.743	0.180	16.931	1	<0.001
		Arrival 10:45-11:00	5.229	0.251	435.644	1	<0.001
	Travel Time	0-14 minutes	1.827	0.198	84.731	1	<0.001
		15-29 minutes	1.748	0.186	88.702	1	<0.001
		30-44 minutes	1.269	0.217	34.090	1	<0.001
		≥45 minutes	0				
	Timetabled Days	1-3 timetabled days	-0.222	0.146	2.319	1	0.128
		4 timetabled days	-0.139	0.128	1.182	1	0.277
		5 timetabled days	0				

Table 36 – TQS: Model Results, Arrival Time for 11:00 AM Session

The model complements the findings discussed in section 6.6.4 and suggests that those students with the longer travel times will arrive on-campus earlier, whilst the arrival time of those who live within 15 minutes of campus are significantly shifted towards a just-in-time arrival. The model suggests that there is limited evidence of a relationship between timetabled contact days and arrival time, with students who have their timetable scheduled over fewer days perhaps arriving slightly earlier than those whose timetable extends across all the days of the week. Other parameters also appeared to also give significant coefficients, although due to the number of limited samples in the survey they resulted in many zero frequency counts, preventing the calculation of accurate goodness of fit statistics and limiting confidence in the model as a whole. However, these other model trials suggested that older students arrive earlier as do first year students, whilst second year students arrive slightly later overall.

An OLR model was also fit to the departure time choice data, and the results are shown in Table 37.

<table>
<tr><td colspan="2" rowspan="6">Test Statistics</td><td>Total Samples</td><td colspan="5">1380</td></tr>
<tr><td>% Cells With Zero Expected Value</td><td colspan="5">8.3% (12)</td></tr>
<tr><td>Model Fit p Value</td><td colspan="5"><0.001 (Chi square: 35.871, df=6)</td></tr>
<tr><td>Pearson Goodness of Fit, p Value</td><td colspan="5">0.036 (Chi square: 136.952, df=109)</td></tr>
<tr><td>Nagelkerke Pseudo R^2</td><td colspan="5">0.027</td></tr>
<tr><td>Test of Parallel Lines, p Value</td><td colspan="5">0.001 (Chi square: 51.856, df=24)</td></tr>
<tr><td rowspan="16">COEFFICIENTS</td><td colspan="2"></td><td>Estimate</td><td>Std. Err.</td><td>Wald</td><td>df</td><td>Sig.</td></tr>
<tr><td rowspan="5">Threshold</td><td>Depart Immediately</td><td>-0.422</td><td>0.192</td><td>4.841</td><td>1</td><td>0.028</td></tr>
<tr><td>Depart 15:00-15:15</td><td>0.695</td><td>0.192</td><td>13.048</td><td>1</td><td><0.001</td></tr>
<tr><td>Depart 15:15-15:30</td><td>1.101</td><td>0.194</td><td>32.237</td><td>1</td><td><0.001</td></tr>
<tr><td>Depart 15:30-16:00</td><td>1.428</td><td>0.196</td><td>53.076</td><td>1</td><td><0.001</td></tr>
<tr><td>Depart 16:00-17:00</td><td>2.274</td><td>0.206</td><td>121.486</td><td>1</td><td><0.001</td></tr>
<tr><td rowspan="2">Gender</td><td>Male</td><td>-0.244</td><td>0.108</td><td>5.087</td><td>1</td><td>0.024</td></tr>
<tr><td>Female</td><td>0</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="3">Year of Study</td><td>1st Year</td><td>-0.667</td><td>0.134</td><td>24.819</td><td>1</td><td><0.001</td></tr>
<tr><td>2nd Year</td><td>-0.386</td><td>0.129</td><td>8.986</td><td>1</td><td>0.003</td></tr>
<tr><td>3rd Year</td><td>0</td><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="4">Travel Time</td><td>0-14 minutes</td><td>0.350</td><td>0.193</td><td>3.290</td><td>1</td><td>0.070</td></tr>
<tr><td>15-29 minutes</td><td>0.446</td><td>0.183</td><td>5.901</td><td>1</td><td>0.015</td></tr>
<tr><td>30-44 minutes</td><td>0.274</td><td>0.216</td><td>1.608</td><td>1</td><td>0.205</td></tr>
<tr><td>≥45 minutes</td><td>0</td><td></td><td></td><td></td><td></td></tr>
</table>

Table 37 – TQS: Model Results, Departure time after 15:00 finish

Even though the model is built on a matrix containing only 8% of zero frequency cells both the goodness of fit and test for proportionality fail at the 5% significance level and combined with the lower R^2 value suggests that the explanatory power of the model is limited.

However, the model suggests that male students are likely to leave before female students and that as student’s progress through their course they are more likely to remain on-campus for a period of time after their last session. The coefficient estimates related to the travel time category are interesting, though not significant, and suggest that students with longer travel times will depart soonest, whilst those who have the shortest travel times are most likely to extend their stay on-campus. This is the opposite of the arrival time behaviour, and suggests that those students with longer travel times skew their days towards to the morning, potentially giving them discretionary free time prior to their first session, whilst those with the shorter travel times spend discretionary time on-campus after their last session. The estimated coefficients between travel time are not consistent and suggest that the students who reside within 15 and 29 minutes of campus remain on campus the longest after the end of timetabled sessions.

The survey questions on arrival and departure time preferences also included options to allow participants to specify if their on-campus arrival and departure times were fixed and not influenced by the timing of their first and last sessions. Those students who use a car to get to campus are most likely to operate to a fixed schedule with over 12% (19%) of car users specifying that they had a fixed arrival (departure) time against a sample mean of 6.1% (14%).

Although the results for arrival and departure behaviour are applicable only to TTDs which begin at 11:00 and finish at 15:00 they do suggest that to a large extent that the timing of student commuting trips is determined by their timetable. It would be expected that the arrival time distributions for students commencing their first session earlier than 11:00, at either 9:00 or 10:00, would show a smaller deviation from a mean arrival time just before the start of the session, and that a similar compression amongst choices would be apparent in the departure time distributions for students whose final sessions finish at 16:00 and 17:00.

The survey asked respondents to list their likely arrival and departure times, but does not elicit information about late arrivals and early departures. This means that these distributions are somewhat idealised in that they do not encompass any element of unplanned behaviour, and as such give no information about whether some session start and end times result in higher levels of late arrivals or early departures compared to others.

7.3.6 Leave-and-return Behaviour

The comments made by respondents to the TQS suggest that when some students have longer breaks they leave campus before returning again in advance of their next timetabled session. An earlier study found that attendance at sessions following an extended break was lower due to students going home and then not returning (Fjortoft, 2005).

This part of the TQS investigated the degree to which leave-and-return behaviour exists by asking participants to list the activities that they would consider undertaking if they had a hypothetical three hour gap in their timetable from 12:00-15:00. The alternatives listed included three on-campus study related activities, three off-campus activities (including returning home) and three on-campus non study related choices. The activities that would be considered to be undertaken by the survey respondents are shown in Table 38.

The activity cited most frequently is that of going to the library with around two thirds of all respondents stating that they would consider this choice, and with females being significantly more likely to consider this activity. Males appear more likely to consider leaving-and-return behaviour though not significantly so.

Activities considered during 3 hour break (n=1380)	Cited		Cited By Gender	
	%	Rank	Male	Female
Go to the library	67.6%	1	58.5%	**71.7%****
Go to somewhere quiet to study	45.1%	6	42.0%	46.4%
Go to a computer cluster	50.8%	2	48.3%	51.9%
Go to the refectory/students union	46.4%	3	42.9%	48.0%
Go for lunch somewhere other than the refectory/students union	45.7%	4	47.9%	44.8%
Go to the sports centre	17.2%	8	18.9%	16.5%
Leave campus and return to home/hall of residence	45.7%	5	**50.9%**	43.3%
Leave campus and go into the city	32.5%	7	31.1%	33.1%
Leave campus and do something else	9.6%	9	12.0%	8.6%

Table 38 – TQS: Activities considered to take place during 3 hour gap

[**(*): Difference significant at 1% (5%) level using two proportion z-test with null hypothesis: no difference in preference between males and females]

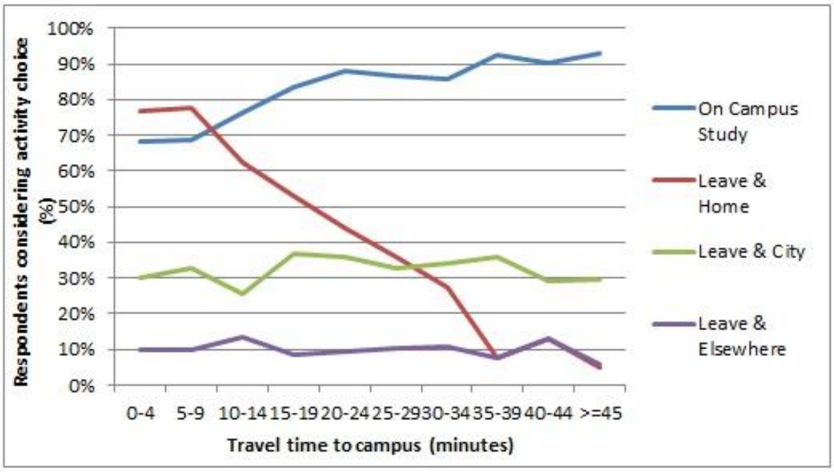
To consider the effect of other parameters on the choice of activity during timetable gaps, each respondent was classified as being either non-campus centric (if they only listed off-campus activities, 7%), campus-centric (if they only listed on-campus activities, 39%) or partially campus centric (if they listed both, 54%). An OLR model was fit to the survey data, using the campus centric category classification as the dependant variable. The results are shown in Table 39.

Test Statistics		Total Samples	1365				
		% Cells With Zero Expected Value	22.2% (32)				
		Model Fit p Value	<0.001 (Chi square: 170.731, df=7)				
		Pearson Goodness of Fit, p Value	0.481 (Chi square: 86.958, df=87)				
		Nagelkerke Pseudo R^2	0.142				
		Test of Parallel Lines, p Value	0.527 (Chi square: 6.108, df=7)				
COEFFICIENTS			Estimate	Std. Err.	Wald	df	Sig.
	Threshold	Off-campus centric	-4.941	0.289	292.313	1	<0.001
		Partially campus centric	-1.605	0.257	38.972	1	<0.001
	Year of Study	1st Year	-0.538	0.154	12.207	1	<0.001
		2nd Year	0.010	0.149	0.005	1	0.944
		3rd Year	0				
	Travel Time	0-14 minutes	-1.978	0.230	73.814	1	<0.001
		15-29 minutes	-1.207	0.217	31.058	1	<0.001
		30-44 minutes	-0.611	0.249	6.037	1	0.014
		≥45 minutes	0				
	Gender	Male	-0.168	0.120	1.938	1	0.164
		Female	0				
	Age Category	18-21 years	-0.713	0.185	14.770	1	<0.001
		22 years and older	0				

Table 39 – TQS: Model Results for Timetable Gap Activity Choice

The model appears to fit the data passing the tests for goodness of fit and the parallel lines assumption. The model shows that younger students, those in the first year, and those who have shorter travel times to campus are less likely to be campus centric compared to those who are older, in the later years of their course or who have greater travel times. These are the largest coefficients in the model and suggest that travel time is a major influence on student's timetable break period activity choice.

To investigate this further the survey responses were grouped into strata based on travel time to campus, using a 5 minute classification size, beginning with those students with travel times of 0-4 minutes and extending to those with travel times of 45 minutes or more, giving 10 bins in total. The percentage of respondents in each bin who reported they would consider an on-campus study activity or who indicated they would undertake any of the activities involving a trip away from campus were calculated, Graph 17. This demonstrates that although the percentage of respondents who would consider leaving campus to go into the city or elsewhere remains constant, the proportion that would consider leave-and-return behaviour decreases as travel time increases, whilst those considering on-campus study exhibits the opposite trend. This suggests that for students who have the longer travel times on-campus study is a substitute for being able to return home. As shown in section 7.3.3 more than 50% of survey respondents believed that they can work better away from campus, and so it seems reasonable to assume that one reason why students would wish to return home is to continue studying. Students will be motivated to return home if the utility they can derive from making the trip is greater than that which can be obtained from staying on campus. The main disutility of any trip away from campus will be the travel time involved and a simple way to represent the utility of the activity performed at the end of the trip is using an activity time ratio, equation 7-11 (Dijst and Vidakovic, 2000).

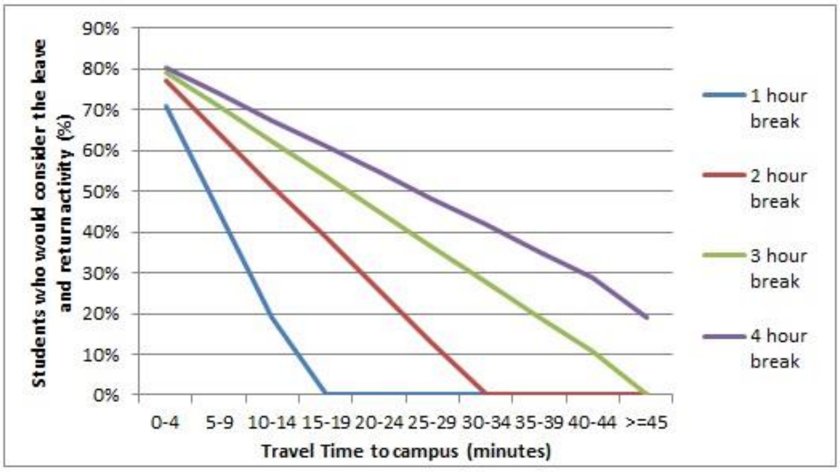


Graph 17 – TQS: Timetable Break Activity Choice by Travel Time

$$Activity\ Time\ Ratio = \frac{(Total\ Time\ Available - Travel\ Time)}{Total\ Time\ Available} \qquad 7\text{-}11$$

This ratio was calculated after assuming that students left campus immediately their hypothetical timetabled session finished at 12:00 and returned immediately prior to their next session at 15:00. A linear relationship was found between the activity time ratio (independent variable) and the proportion of students who would consider the leave and return activity (dependant variable).

A regression line fitted to this data suggests a slope of 1.54, an intercept of -0.71 and with an R^2 value of 0.96. This indicates that for a 3 hour break, when residential travel time is reduced by one minute a further 1.7% of the sample will consider a leave-and-return trip. These coefficients suggest that no trips will be made when the activity time ratio is approximately 0.5 (0.46), and travel time equals the time available for other activities. Similarly even when students live in halls on-campus a maximum of 84% of the sample will consider going back to their room.



Graph 18 – TQS: Estimate of Leave and Return Activity Consideration

Assuming that these coefficients hold constant across all timetable break durations, then by calculating the activity time ratios for different combinations of travel time and break length estimates the proportion of the sample who would consider leaving-and-return behaviour for different lengths of break can be derived, Graph 18. For students whose travel time is negligible, break length has little effect, but as break length increases the proportion of students with longer travel times who consider it increases.

The analysis of the survey data suggests that leave-and-return trips during the breaks in the timetable are often considered by students. However, the survey data says nothing about the frequency of leave-and-return trips and although a student may frequently consider this alternative they may not always convert the intention into an actual trip (RQ4, partially supporting H1b).

7.4 Discussion

Analysis of the data from the TQS shows clearly that student trip-making behaviour is different on TTDs compared to NTDs. On TTDs females are slightly more likely to attend (though not significantly so) and amongst the student population overall attendance appears to be regarded as a mandatory activity, with campus attendance rates almost equivalent to those for the workplace. Timetables that are designed to offer a higher number of contact hours per timetabled day, with fewer TTDs overall attract a slightly higher attendance rate compared to those with fewer sessions per day. This behaviour appears logical as students will have more to lose if they absent themselves on days when they have more sessions.

On NTDs the mean attendance rate is less than half that associated with TTDs, with males being significantly more likely to make discretionary trips to campus. Travel time to campus also has significant effect on attendance, with those students who have the longest travel time attending less frequently. Academic maturity (year of study) also encourages presence on campus, whilst those students who have their sessions compressed into fewer days attend more frequently on NTDs compared to those who have sessions on four days per week.

The main factor determining the overall number of trips made by a student to campus over a period of time, is simply the number of TTDs contained within the period, and increasing (or decreasing) the number of TTDs will have a direct impact on the number of trips made.

Student arrival and departure times are linked to session start and end times, with this being particularly the case for the arrival time. Students who travel the longest arrive the earliest and those with the shortest travel time the latest. Those who travel by a private mode are more likely to have fixed arrival and departure times.

Students often contemplate leave-and-return behaviour during timetabled breaks, with males considering these more frequently than females. The proportion of students who consider such a trip decreases as travel time increases, reaching zero when the time for a return trip from campus to home is approximately equivalent to the time available to be spent at home.

The category of faculty of study: arts; sciences or medical was not found to be a significant factor in determining the trip-making or arrival/departure behaviour of students. It could be that the categorisation of faculties was too crude to identify the subtleties of this behaviour or alternatively the variation in contact hours across faculties is already reflected in the timetable days and timetable design style variables.

The results of this part of the TQS are important for university travel planners as they show that current student travel survey and modelling methods are inadequate as they do not generally take into account the differential trip rates on TTDs and NTDs, nor recognise the effect of timetable session start and end time on campus arrival and departure patterns. Leave-and-return behaviour appears to be common and represents a hidden source of trips, undetected in student travel surveys and unidentified within university travel plans.

The results suggest that changes to the design of the timetable will influence student travel behaviour in the following ways. Firstly, an increase in the intensity of the timetable, more contact hours per day, would reduce the number of student TTDs across a semester and due to the lower discretionary trip rate reduce the overall number of student trips to campus. Secondly, removal of the longer breaks from the timetable would reduce the supply of (and demand for) leave-and-return trips, although since these trips are currently hidden the impact of this change would also be hidden. Thirdly, changing the time of the first session so that it occurs later, with fewer sessions starting at 9:00 would offset the student commuting AM peak away from the workplace commuting peak. Similarly distributing the first session start time over a wider part of the day would result in a smoother student arrival pattern across the morning. The results of this analysis demonstrate that the university could use timetable design as a travel planning soft measure to influence student behaviour.

At the same time theories of student engagement, persistence and involvement are jointly underpinned by the desire to foster and develop the connections between the student and their studies. Included within this is the simple idea that the more time students spend on-campus the greater their feelings of engagement and involvement and their desire to persist. If this is indeed the case then this analysis identifies three barriers which are preventing student attendance on-campus.

Firstly, more than half the students in the survey indicate that they believe that they work better away from campus and that non-contact time on-campus is wasted time. This is manifest in: lower attendance rates on NTDs; the desire for leave-and-return behaviour and the preferences stated in 6.4.15 for fewer breaks and fewer days including timetabled sessions. If students felt they could be more effective when on-campus all of these behaviours would be reduced.

Secondly, long travel times to campus appear to discourage attendance on NTDs, although they also force students to remain on campus during longer timetabled breaks, as there is insufficient time to make a return trip home.

Thirdly and most importantly, the design of the student's individual timetable will encourage or discourage attendance on campus. Timetables which compress sessions into fewer days may be felt to be more convenient by students, but the fact that they allow the taught part of the student's course to be fitted in around other activities means that less time will be spent on-campus compared to those students whose timetable is spread over more days of the week.

The contact hours within a student's curriculum is a contributory factor in this process, since the production of a compressed timetable becomes more likely as contact hours decrease. Over the last 20 years universities have moved towards student centred learning approaches that have reduced overall levels of contact. This is a sensitive subject for the HE sector, being the cause of negative publicity and of claims of the 'dumbing down' of university education (Times Higher Education Supplement, 2008). In response the Quality Assurance Association for Higher Education (QAA) has published guides aimed at educating students (Quality Assurance Agency, 2011a) and commentators (Quality Assurance Agency, 2011b) about the diverse range of activities that can be classed as student contact. Similarly whilst 45% of students who have fewer than nine contact hours per week express dissatisfaction at the low level of contact (Bekradnia, 2012, p. 4) other studies have found no link between contact hours and educational quality (Gibbs, 2010, p. 21) or contact hours and learning outcomes (Ramsden, 2008, p. 15) whilst excessive contact hours can obstruct the deep learning achievable through self-study (Schmidt et al., 2010).

However, perhaps the focus should not be on the absolute number of contact hours, but rather on the timetabling implications of a curriculum containing fewer contact hours. What the TQS shows is that when a course has less contact hours, it becomes more difficult to create a timetable which is meaningful in terms of full-time study. A low contact hours timetable is more likely to include multiple days with either a single session or no sessions at all, and the TQS demonstrates that single session days are universally unpopular, whilst NTDs reduce motivation to attend. In this context the focus of the QAA on educational arguments in support of low contact hours courses misses the key point which is that minimally filled timetables discourage attendance on-campus.

It could be that the number of trips to campus is not a good indicator of student engagement and that other mechanisms are at work to reinforce the bond between student and institution. Use of the VLE could be one such element and for this students need not be physically present on-campus and that virtual presence is sufficient to create a feeling of engagement. This is investigated in Chapter 8.

7.5 Summary And Conclusions

Student trip-making behaviour has been investigated using a traditional survey technique which has confirmed that whilst the student population as a whole exhibits a wide range of behaviours the general trend is for students to link their trip-making to their timetable. The trip-making behaviour reported by students in the TQS confirms the contemporary view of the timetable, and suggests that students wish to minimise the time they spend on campus (RQ1, supporting H1). The survey shows that students are less likely to attend on NTD's (RQ2, supporting H1a) and that many students often consider leave-and-return behaviour (RQ4, supporting H1b).

However, whilst the survey shows that on-campus attendance is linked to timetable it does not show if attendance on-campus is a good thing, and whether those who decide to spend less time on-campus are placing themselves at a disadvantage. This will be explored further in the subsequent chapters.

The TQS methodology is itself problematic in some respects and this raises questions with regards to the reliability of the findings. Firstly, the survey relies on students recall of past behaviour potentially leading to incorrect reporting of attendance on-campus. Secondly, the timetable data collected through the survey represents a snapshot of one week and doesn't take into account variability in both the timetable and student preferences across a longer time period. Thirdly, the survey asks students about their hypothetical trip-making behaviour and this may not reflect their actual behaviour. The survey is unable to quantify key behavioural elements such as the level of leave-and-return trips. Finally, the survey may be unrepresentative of the overall population and subject to bias. It could underrepresent those students who are less engaged with their studies since they may also be those who are least likely to respond to a survey like the TQS, and consequently discretionary trip rates may be even lower than those reported in the survey.

Chapter 8 – The Observational Dataset

8.1 Introduction

Chapter 7 described a traditional travel survey method and discussed the results which identified a tentative relationship between the academic timetable and student trip-making behaviour. This chapter introduces the datasets used in an observational student survey (OSS) method that utilises existing data sources to make inferences about student trip-making and can be used to study changes in behaviour over a longer time-frame than is possible with a traditional survey technique. The chapter includes descriptive statistics and reveals some findings about the behaviour of students attending UoL, whilst Chapter 9 describes the OSS method in detail and the results obtained from its application.

The material presented in this chapter begins the delivery of research objective, O4 (develop an observational student survey method).

8.2 Data Specification and Collection

The OSS studied a population consisting of all non-medical[1] full-time undergraduate students enrolled on years 1-3 of a taught (timetabled) degree programme at the UoL, and who were under 50 years of age at the time of enrolment. This population was observed over three distinct time periods (A, B, C) each corresponding to one academic semester (Figure 11). Data was collected over the core 10 week teaching period within each semester, providing 50 days of data in each period. The data for time periods A and C both include the last week of the spring term (week 10 in semester A, and week 8 in semester C) and a reduction in student activity during these weeks can be observed in the datasets.

Period	Academic Year and Semester	From	To	Notes
A	2010-2011 – Semester 2	24/01/2011	03/04/2011	Spring term ended on 01/04/2011
B	2011-2012 – Semester 1	26/09/2011	04/12/2011	Autumn term continued for one further week
C	2011-2012 – Semester 2	23/01/2012	29/04/2012	Includes Easter break between weeks 8 and 9

[1] Students in the faculty of medicine and dentistry were excluded as their study programmes include academic constraints on their time which are not listed in the published University timetable.

Figure 11 – OSS: Time Periods

The population was generally observed whilst on-campus at UoL and where possible each individual observation is tagged with a code representing the location or building in which the observation was made. Each dataset used within the OSS will now be described.

8.2.1 Student Demographic Data

The University stores all student related data in a Student Information System (SIS) known locally as BANNER. Data was exported from this system defining the demographic attributes of the students in the study population: gender, age at enrolment (17-70), nationality (British, European Union, Overseas). This was supplemented with time period specific information: year of study (1, 2 or 3), faculty of study, Cartesian distance in miles between the student's residential location and campus, and the student's type of residential accommodation - hall, home or other.

8.2.2 Academic Performance Data

The academic demands placed on each student are specified by the number of modules they are to study in a semester, the credits associated with those modules and the number of examinations that they must sit. The outcome of taking this diet of modules can be assessed from the overall mark awarded for each module studied. SIS provided a credit weighted mean module mark (and standard deviation) for each student across each semester.

8.2.3 Timetable Data

The full timetable for every session scheduled during each of the three study periods was obtained from the UoL's Student Systems Administration group. This consisted of each session's time period (A,B or C), week number (1-10), day number (1-5), start time, end time and zone code. This dataset was very similar to that described in section 6.2.4 and again all sessions of an indeterminate length were excluded.

8.2.4 Library Data

Access to the three libraries at UoL is controlled by a turnstile entry system, and all users must scan their university Id card to gain access. The library administration estimates that 98% of all student library entries are recorded through this system (Salter, 2013). When a student enters the library a record is made of: their student number, the date/time of the event, and the name of the library to which entry was requested. There are no corresponding exit turnstiles so the duration of each visit is unknown. When a student borrows a book the details are recorded on the library's book lending system, and from this system the total books borrowed by each student in each time period was extracted.

8.2.5 On Campus Fixed Computer Usage Data

UoL provides students with access to a network of 1,550 desktop PC workstations organised into computer clusters around the campus. This provision is supplemented with 55 workstations located in the refectory and cafeterias, plus a limited number of other standalone PC’s also available for student use. Access to this network of workstations is controlled through a login/logout system and all students are issued with a university supplied user name. When a student logs in or out of a fixed PC, their user name, the date/time of the event, and the location of the workstation (where this is known) are recorded.

8.2.6 Wireless Device Usage

The University provides a comprehensive network of almost 800 wireless hot-spots around the campus allowing students to connect their own wireless enabled devices to the campus network and to give them access to the UoL intranet and the Internet. To use this network a student must first verify that they are registered to study at UoL by providing their university supplied login name and password the first time they connect to the wireless network. Once a device has been authenticated each time it subsequently connects to the campus wireless network a record is made of: student username, the date/time of the connection and disconnection events and the media access control (MAC) address for the device.

The MAC address is a unique identifier taken from an address space of 2^{48} different addresses, that is assigned to each and every network enabled device. The first 24 bits of the address contain an Organisationally Unique Identifier (OUI) which identifies the manufacturer of the device or its internal components. The Institute for Electrical and Electronic Engineers (IEEE) maintains a list of manufacturers and the OUI’s assigned to devices produced by them (IEEE Standards Association, 2013).

Many students use the wireless capability of their smart-phone to browse the Internet when on-campus. Identification of the OUI address ranges for the mobile phone manufacturers: Apple, Blackberry, HTC, Samsung, Nokia and Sony Ericson allowed the wireless activity associated with mobile phones from these manufacturers to be separated from all other wireless activity held in the dataset.

8.2.7 Portal Usage

The University provides students with access to an extensive online study support system. This includes the provision of an email account, information about the student’s course and a connection to the University’s Virtual Learning Environment

(VLE). Access to this system is provided through the UoL portal which is implemented through a web based interface, meaning that students may connect it from any Internet browser on any device, from any location and at any time of the day or night. Students login to the portal using their standard user name at which time this login name and the date/time of the event is recorded. A student will remain connected to the portal until they explicitly terminate session or it disconnects automatically after 45 minutes of inactivity. Neither of these events are recorded so the duration of each portal session is unknown. When the portal is used on-campus it will be accessed from either a fixed PC or a device connected to the campus wireless network. Therefore each on-campus portal login event will be bracketed in time by either login/logout or association/disassociation events in other datasets, meaning that a general location (either on-campus or off-campus) can be associated with the event. The Portal provides access to a remote PC desktop. This facility allows students to access software owned by the University from off-campus locations. Every time a student starts up a remote desktop session the login name of the student and the date/time of the event is recorded.

8.2.8 Sports Facility Usage

The UoL has two on-campus sports facilities and access to these is controlled through a turnstile entry system. User of these facilities must scan their university Id card to gain entry, after having prepaid for a single session or a longer term membership subscription. When a user scans their Id card the entry system records; their id card number, the date/time of the event, the turnstile at which the card was scanned, and an indicator showing whether access was granted or denied.

8.2.9 Refectory Usage

UoL provides on-campus residential accommodation to over 700 students, these places being provided on a fully catered basis with students taking their meals in the main university refectory. Students are given a meal card which is topped up with a predetermined amount of credit each day, which can then be redeemed against food and drink purchased in the refectory. Meal cards are inserted into a reader at a payment station which debits the cost of the food and drink purchased from the card. Each time a pre-paid meal card is used the meal card number, date/time of the transaction and the payment station at which the transaction took place are recorded.

8.2.10 A Note on Data Protection

In their raw form the datasets used in the survey contain sensitive personal information that could be used to identify the location and activities of specific individuals. Consequently the use of this data falls under the auspices of the Data Protection Act (HM Government, 1998). The act contains provision to allow this type of data to be used for study purposes if any personal information can be aggregated out of the dataset. Following advice from the University's Legal Officer a method to anonymise the data using a unique random number to represent each student across all of the datasets was developed, and institutional approval to use the data for the OSS was granted.

8.3 Dataset Representation

The activity datasets contain a partial record student presence on-campus and provide a rich source of study activity, the scope of which is apparent from Table 40.

Dataset	Time Period		
	A	B	C
Number of Students	16,088	16,021	15,998
Timetabled Sessions	1,632,391	1,761,142	1,651,916
Library Entries	272,458	283,244	301,562
Sports Centre Entries	93,358	85,310	99,293
Fixed PC Logins	646,984	543,706	639,349
Portal Logins	1,938,096	2,016,959	2,015,290
Desktop Anywhere Logins	9,225	10,548	17,300
Wireless Devices Authentications (Of which mobile phone activity %)	717,791 (71%)	878,855 (73%)	1,466,693 (76%)
Meal Card Usage	56,998	64,382	56,449
Total Activity Data Records	**3,736,241**	**3,883,004**	**4,595,936**
Activity Data Records/Student/Day	**3.3**	**3.5**	**4.1**

Table 40 – OSS: Count of Activity Records

The data was initially collated into three Access databases. However, the volume of records contained in each database meant querying the data was slow and cumbersome. Furthermore using SQL queries to join tables on timestamp based criteria is difficult, since the temporal precision of the data itself is too great. Therefore a decision was taken to simplify the structure of the data by reducing the chronological precision with which activities were held.

For each time period of 50 days a fixed length vector was defined with each element in the vector representing a one hour timeslot. One vector was associated with each student in the dataset effectively creating a two dimensional matrix of activity data. Each element within each vector in the matrix contains a collection of Boolean markers, each representing either an activity that took place in the timeslot, its location or the location of any timetabled session scheduled for that timeslot. When a student is found to have performed a specific activity, been at a specific location or had a timetabled session in any given hour, the corresponding

Boolean markers within cell representing that student and hour are set to true. Figure 12 shows the data organised in this way, and identifies that in timeslot y student x entered the library (EBL), logged into a fixed PC and used the Portal, whilst at the same time missing a timetabled session in the Geography building (GEOG).

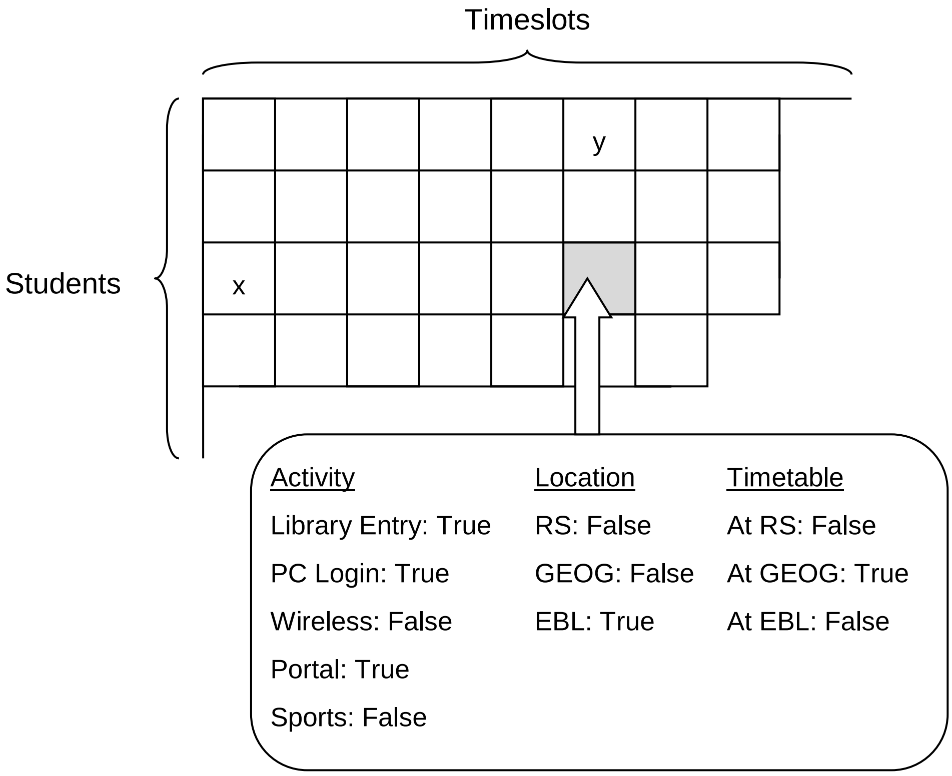


Figure 12 – OSS: Activity Data Representational Structure

A compressed storage format was selected which allowed each element to be represented using 3x32 bit words which provided capacity for 32 distinct activities, 32 potential locations and for one scheduled session at one of 32 locations. This format allowed all the activity data for all students and across all time periods to be represented in a single 750MB structure meaning that all the data could be held simultaneously within the working memory of a desktop computer. The bit-wise representational format also meant that Boolean logic operators could be used when querying the data simplifying the process of selecting specific activities or particular locations. Overall the compact data representation and the efficient Boolean query method resulted in reduction of at least one order of magnitude in the time needed to query the data, when compared to the original Access database.

A bespoke application was written using the DELPHI programming language to query the data and provide results in Excel spreadsheet format. This application included standard queries to count activities by hour, day or semester and to produce hourly distributions of activity participation (for screenshots, see Appendix C).

8.4 Analysis

The observational dataset contains a partial record of the activities performed by each undergraduate student whilst on and off campus over three time periods. The record of on-campus activity can reveal differences in the student trip-making behaviour between TTDs and NTDs. This data can be examined at an aggregate level, over the days of each time period and at the individual student level.

8.4.1 Resource Usage Profile Snapshots

Before beginning the formal analysis of the OSS datasets the three figures below reveal an interesting picture around the on-campus resource usage and student behaviour contained within the datasets. Figure 13 shows an aggregation of student activity: on-campus and off-campus portal logins and library, fixed PC and sports centre access across the hours of a typical weekday in period C.

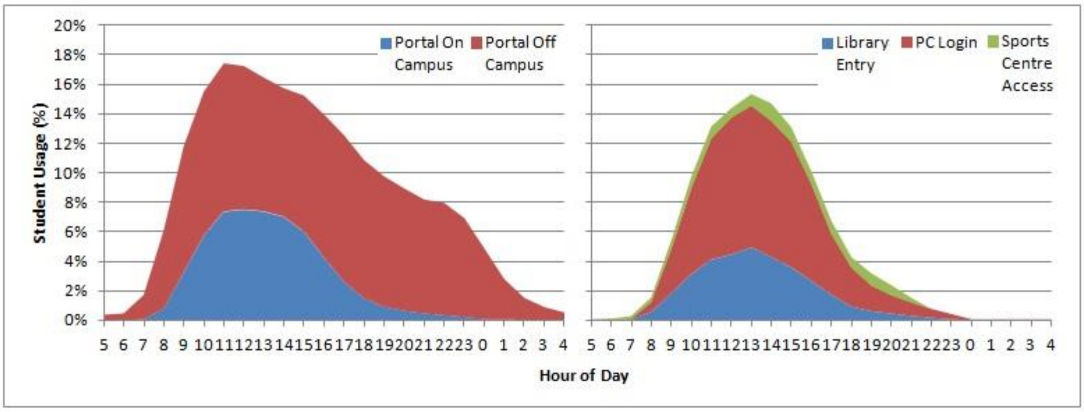


Figure 13 – OSS: Hourly Resource Usage Profiles

[Percentage of student population using the Portal: On and Off-Campus, Library Entry, PC Login and Sports Centre Entry during Period C]

The plots suggest that in the hours around lunchtime about 25%[2] of the population are engaged in one of these five activities either on or off campus. The data also reveals that students work late into the evening with about 8% still being logged into the portal after 23:00 on a weekday.

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[2] On-campus Portal access will normally be performed through a fixed PC and therefore the plots include an element of double counting

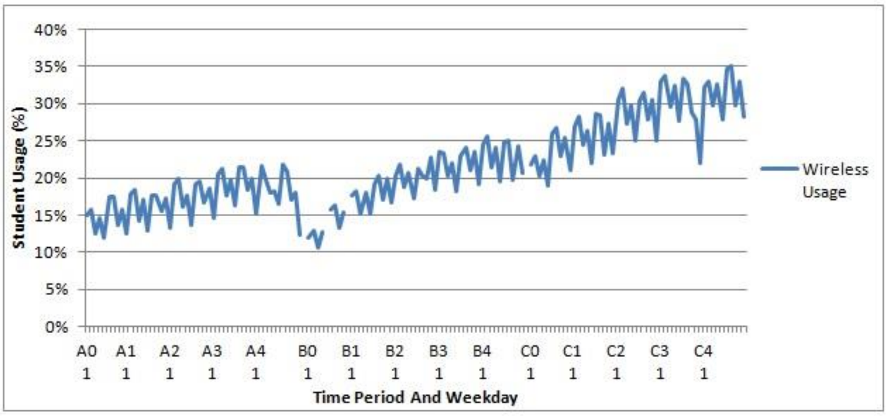

Figure 14 – OSS: Daily On-Campus Wireless Device Usage

[The key on the X axis refers to the day number, in the range 1-50, within each of the three time periods A, B and C]

Figure 14 shows the proportion of students who used a wireless enabled device to access the on-campus network across each weekday of each time period (150 days). A cyclic usage pattern over the days of the week and long-term upward trend in usage is apparent. This trend potentially presents problems for the university in terms of the provision of sufficient capacity to meet this constantly increasing demand.

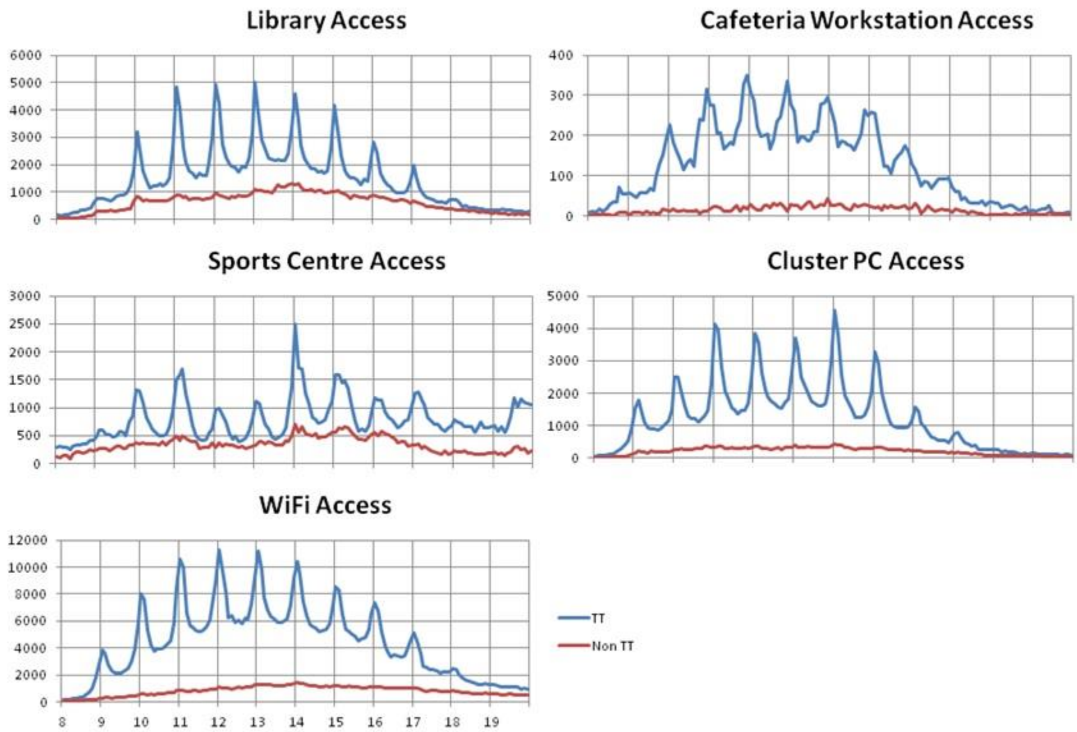

Figure 15 – OSS: Minute By Minute Demand for On-Campus Resources

[TTDs: blue, NTDs: red]

Finally, Figure 15 demonstrates peaks in demand for on-campus resources caused by the timetable. For each resource type, peak demand occurs around the hour mark, corresponding with the changeover period between one timetabled session and the next. The same peak-driven demand profile also applies to other (non-electronic) on-campus resources such as catering outlets and shops. The university must provide capacity to meet these peaks even if the underlying level of demand is lower. Demand on NTDs is both lower and more evenly spread across the day, although slight peaks are noticeable in library entries in the morning, suggesting perhaps that some non-timetabled students may accompany their timetabled peers on the trip to campus.

8.4.2 Aggregate Levels of Student Activity

Each time period includes fifty weekdays on which timetabled activities can occur, each weekday dividing the student population into two groups based on whether their day contains at least one timetabled session or not. For each day and within each of these groups the number of students who are recorded performing the activities identified in the datasets can be counted and expressed as a percentage of the total students in each group, Table 41. There is a degree of consistency between the activity figures across the three time periods. For example, on average more than 25% of students with a TTD log into a fixed PC on that day, whilst over 20% of them enter a campus library. The equivalent figures for NTDs show around 15% of students with a NTD both login and enter the library.

The increasing popularity of smart-phones for wireless access to the on-campus network is apparent, with average usage figures which increase over the time periods. This is matched by a small reduction in on-campus PC usage between periods A and C suggesting that students may be using their own devices as a substitute for the fixed IT infrastructure. The use of Desktop Anywhere to provide off-campus access to on-campus IT resources also appears to be increasing, albeit from a low base level.

The combined datasets detect activity for more than 50% of the population on-campus on TTDs and over 30% on NTDs. Not only do these figures give a lower bound for the real student attendance, but they also provide a degree of confidence in terms of the level of coverage of the population that can be achieved through monitoring electronic resource usage.

	Percentage of student days that include each type of monitored activity					
	Timetabled Day			Non Timetabled Day		
	Period A μ (σ) %	Period B μ (σ) %	Period C μ (σ) %	Period A μ (σ) %	Period B μ (σ) %	Period C μ (σ) %
On Campus Fixed PC Login	28.5 (3.73)	27 (3.29)	27.1 (3.68)	16.8 (3.69)	14.5 (3.08)	16.1 (4.08)
Library Entry	21.2 (4.61)	23.1 (4.32)	21.9 (4.62)	16.5 (4.14)	17.5 (4.63)	18.6 (4.76)
Wi-Fi Enabled Mobile Phone Usage	15 (1.25)	17.3 (3.02)	25.5 (2.38)	8.4 (1.9)	9.7 (2.42)	17.1 (3.68)
Sports Centre Entry	7.7 (1.23)	7.1 (1.02)	8.2 (1.17)	7 (1.21)	6.7 (1.31)	7.6 (1.24)
Wi-Fi Enabled Device Usage	4.5 (1.25)	4.6 (1.11)	5.9 (1.64)	4.2 (1.48)	3.9 (1.21)	5.7 (2.01)
Meal Card Usage	3.9 (0.22)	4.1 (0.12)	3.6 (0.26)	1.8 (0.53)	2.1 (0.59)	1.9 (0.57)
Student Activity Detected On Campus	**49.6 (5.43)**	**51.4 (5.15)**	**54.9 (5.19)**	**32.2 (5.58)**	**31.7 (5.36)**	**36.9 (6.6)**
On Campus Portal Login	30.9 (4.45)	31.5 (4.31)	34.1 (4.76)	18.8 (4.4)	17.7 (4.24)	21.2 (5.54)
Off Campus Portal Login	57.5 (5.04)	59.1 (4.69)	57.4 (4.75)	55.4 (5.68)	57.4 (5.56)	54.9 (5.39)
Desktop Anywhere Usage (On or Off campus)	1.2 (0.24)	0.6 (0.2)	1.1 (0.36)	1.2 (0.33)	0.7 (0.31)	1.1 (0.38)

Table 41 – OSS: Student Daily Activity

[Shaded Cells: No significant difference at the 1% level (p value>0.01) between activity level on TTDs and NTDs using independent samples t-tests with null hypothesis: activity levels the same on TTDs and NTDs]

A higher proportion of the population perform most types of activity on TTDs (non-significant differences highlighted in Table 41). Given that student activity choice on NTDs is largely unconstrained it might be expected that a higher percentage of non-timetabled students would participate in the monitored activities compared with TTDs. The percentages are based on the total population and not on the subset who might visit campus on any given day, and therefore if a number of students are absent from campus on NTDs the associated percentages will under-estimate the true level of activity.

While student behaviour may differ between TTDs and NTDs the differences in on-campus activity levels provide some supporting evidence for the differential trip rates reported in section 7.3.4. The figures for meal card usage are particularly interesting. These cards are held by a maximum of 4% of the population and who use them in the refectory to pay for all their meals. On NTDs the average level of meal-card usage is around half that for TTDs, and although these students could be too busy participating in other activities to take their meals this perhaps suggests that even some of the students who live very close to campus do not consider visiting it on NTDs. The differences between the figures for off-campus activity on TTD's and NTDs, for both the Portal and Desktop Anywhere are non-significant and possibly suggest that students engage in similar levels of academic activity off-campus on both types of day. This supports the main reason given by students in the TQS for not attending on-campus, that they work better away from it, section 7.3.3.

The deviations reported with each mean activity level suggest that student activity participation varies across the days within each time period. To examine this variation in more detail LRMs were built to describe the aggregate level of activity participation on any given day using three parameters to represent temporal variation within the dataset (time period, week number and day of week) and a fourth parameter to differentiate TTDs from NTDs. The parameters for time period and day of week were coded using 6 dummy variables (3 periods and 5 days) whilst the week number was coded using 2 variables, the first being active for weeks 1-5, and the second for weeks 6-10. The aim of this coding was to identify changes in the rate of weekly change in activity levels between the first and second half of the time period. A final dummy variable was used to represent day type with TTDs coded as 1 and NTDs as 0. The results of fitting a LRM to the day-by-day level for each type of activity can be seen in Table 42.

			On Campus PC	Library Entry	Mobile Use	Sports Entry	Wireless Use	Meal Card Use	Full Activity	Portal On Campus	Portal Off Campus	DTAW
Adjusted R Square			0.904	0.797	0.946	0.5	0.813	0.867	0.925	0.912	0.793	0.681
Standard Error of Estimate			2.15564	2.29857	1.44562	0.71592	0.71592	0.38591	3.00689	2.39423	2.43023	0.21769
Durbin Watson Test Statistic			1.942	1.169	1.486	0.866	0.89	2.503	1.638	1.79	1.32	1.77
COEFFICIENTS	(Constant)		14.584	15.451	4.094	8.184	2.358	1.904	28.418	16.897	65.094	0.642
	Day Type	Non Timetabled	0	0	0	0	0	0	0	0	0	0
		Timetabled Day	11.774	4.581	7.529	0.579	0.381	1.909	18.388	12.922	2.055	-0.037**
	Time Period	A	0	0	0	0	0	0	0	0	0	0
		B	-1.913	1.425	1.598	-0.438	-0.226*	0.253	0.179**	-0.271**	1.814	-0.349
		C	-1.053	1.383	9.608	0.548	1.476	-0.094**	5.016	2.783	-0.318**	0.051**
	Week Number within Period	Weeks 1 to 5	1.155	1.153	0.938	0.05**	0.442	-0.058	1.752	1.219	-0.802	0.076
		Weeks 6 to 10	0.727	0.796	0.744	-0.081	0.414	-0.027	1.159	0.847	-0.719	0.074
	Day of Week	Monday	0	0	0	0	0	0	0	0	0	0
		Tuesday	-0.96*	-1.112	0.602*	-0.553	0.129**	0.012**	-0.764**	-0.985*	-3.701	0.075**
		Wednesday	-3.863	-5.005	-0.993	-0.688	-0.697	0.383	-5.536	-5.356	-4.693	0.061**
		Thursday	-1.328	-3.387	-0.186**	-1.335	-0.341	0.208	-2.887	-3.042	-7.235	-0.01**
		Friday	-6.191	-9.449	-2.107	-1.925	-1.68	0.459	-10.717	-9.227	-12.312	-0.243

Table 42 – OSS: Daily Activity Levels Linear Regression Model

[All coefficients significant at 1% level, except: *(**)=5% (not significant), using coefficient test of significance (section 6.5.3, equation 6-12)]

In each model the constant term represents the percentage level of activity expected for a non-timetabled Monday of a notional week 0 in time period A, whilst the coefficients describe the change in this value for other time periods, weeks, days of the week and on TTDs. The models fit the data reasonably well with adjusted R^2 values of greater than 0.7 in all cases apart from for the Sports and Desktop Anywhere datasets. The residuals are normally distributed with no evidence of heteroscedasticity (checked by visual inspection of scatter plots of the standardised residual against the standardised predicted value and of P-P plots of the regression standardised residual, not shown). However, there is evidence in some of the models of a positive correlation between the residuals since the Durbin Watson test statistic falls below 1.6 (library entry, mobile use, sports entry, wireless use and off-campus portal access) whilst the model for meal card usage is subject to a negative correlation amongst the error terms. When positive correlation is present the model coefficients remain valid, but are not optimal (Field, 2013, p. 176).

The coefficients show that activity levels are higher on TTDs, that they increase with each successive week throughout the time period (although the greatest increases are recorded in the first half) and that whilst activity levels on Monday and Tuesday are largely equivalent, they fall as the week progresses. The good fit of the models suggests that although the absolute levels of activity differs between TTDs and NTDs, other influences on student behaviour appear to be equivalent irrespective of whether a student has timetabled sessions on a particular day.

Examining the coefficients for all detected on-campus activity (the column labelled full activity), and assuming that overall on-campus student behaviour is the similar on both TTDs and NTDs, then the difference between the base activity level on NTDs of 28%, and TTDs of 47%, can only be explained through differential attendance rates. If mean attendance on TTDs is assumed to be around 92% (section 7.3.4) then on-campus student attendance on NTDs should be around 54%. This is higher than the level reported in the TQS of 36% (section 7.3.2). Using on-campus portal logins to perform the same calculation supports this hypothesis and suggests that student attend of 52% of NTDs.

If mean attendance on NTDs is around 50% then this suggests that around 30% of the students attending campus on NTDs enter a library, compared to around 21% of timetabled students. This too seems reasonable given that the library is one of the primary on-campus locations for private study. Similarly sports centre entry rates on NTDs would be around 16% as against 10% on TTDs suggesting that for some performing sports is a motivation to attend on-campus when they have no classes scheduled.

The model for the meal card activity data is interesting in that it includes weekday coefficients that have an opposite sign to those shown in the other models. This suggests that more meal card holding students use the refectory as the week progresses and that Friday is the busiest day for timetabled and non-timetabled meal card holders alike. Two reasons are suggested; firstly that students find they have more free time towards the end of the week, and that secondly, unused credit builds up on the card during the week, and students are more likely to use their cards when there is more available to spend.

8.4.3 Individual Levels of Student Activity

Every student within the population will have different preferences in terms of the activities that they wish to perform whilst on-campus. Distributions of the number of days each student has performed each activity should reveal these preferences, Table 43. For each activity type the mean number of days over which that activity was performed by the population as a whole is shown, together with the standard deviation around this mean, Pearson's first skewness coefficient and the modal value for the distribution. The percentage of the population that undertook the activity over the number of days described by the modal value is also given.

The most striking feature of these figures is that the distributions from which they are taken are highly positively skewed and that with the exception of the portal usage, all other activities seem to regarded as discretionary by sizable minority of the population. This is demonstrated through the low mean values, the degree of skew, and modal values which correspond to zero days of use.

Around 10% of the population never enter the library, more than 28% never borrow a book[1], 8% never use a UoL provided on-campus PC and the facilities available through the sports centres are only used by 40% of students. Similar observations have been made in other studies examining the relationship between electronic resource usage (specifically library resources) and student attainment or retention (Haddow, 2013, Goodall and Pattern, 2011, Soria et al., 2013, Crawford et al., 2004).

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[1] It might be assumed that the low level of book borrowing amongst the student population is a recent phenomenon, however, a 1961 study at UoL found that 23% of students didn't borrow a single book during their whole time at the university. In MANN, P. H. 1974. *Students and Books*. (page 34).

		Mean number of weekdays on which a student undertakes each type of monitored activity. Minimum: 0 days, Maximum: 50 days		
		Period A	Period B	Period C
Library Entries	μ (σ, skew) days	10.3 (9.4, 1.09)	11.2 (9.5, 1.18)	10.8 (9.7, 1.11)
	Mode (% pop.)	0 days (11.2%)	0 days (7.7%)	0 days (9.8%)
Books Borrowed	μ (σ, skew) books	10.1 (12.7, 0.8)	9.4 (12.4, 0.76)	9.8 (12.8, 0.76)
	Mode (% pop.)	0 books (27.6%)	0 books (29.2%)	0 books (30.4%)
On Campus PC Usage	μ (σ, skew) days	13.2 (10.6, 1.25)	12.4 (10, 1.24)	12.5 (10.5, 1.19)
	Mode (% pop.)	0 days (6.2%)	0 days (5.7%)	0 days (8.1%)
Sport Centre Entries	μ (σ, skew) days	4.2 (7.7, 0.55)	3.9 (7.2, 0.54)	4.5 (8.1, 0.56)
	Mode (% pop.)	0 days (60.8%)	0 days (60%)	0 days (59.6%)
On Campus Portal	μ (σ, skew) days	14.2 (10.3, 0.98)	14.6 (10.2, 0.95)	15.8 (10.9, 1.45)
	Mode (% pop.)	4 days (4.3%)	5 days (4.1%)	0 days (3.7%)
Off Campus Portal	μ (σ, skew) days	33.4 (11.5, -1.45)	34.7 (10.5, -0.31)	33.6 (11.2, -1.46)
	Mode (% pop.)	50 days (3.6%)	38 days (3.6%)	50 days (3.8%)
Portal Overall	μ (σ, skew) days	38.1 (10, -1.2)	39.6 (8.6, -1.22)	38.9 (9.5, -1.16)
	Mode (% pop.)	50 days (7%)	50 days (7.4%)	50 days (8.3%)
Desktop Anywhere	μ (σ, skew) days	0.4 (1.2, 0.29)	0.4 (1.4, 0.31)	0.7 (2.1, 0.32)
	Mode (% pop.)	0 days (84.7%)	0 days (82%)	0 days (79.4%)
Mobile Phone	μ (σ, skew) days	7.2 (12.7, 0.57)	8.1 (13.4, 0.6)	12.4 (16.6, 0.75)
	Mode (% pop.)	0 days (55.1%)	0 days (57.4%)	0 days (50.2%)
Wireless Device Usage	μ (σ, skew) days	2.9 (7.2, 0.4)	2.7 (7.3, 0.38)	3.6 (8.6, 0.42)
	Mode (% pop.)	0 days (63.9%)	0 days (69.8%)	0 days (66.5%)
Mealcard (only card holders)	μ (σ, skew) days	39.3 (17.4, -0.61)	41.1 (15, -0.6)	39.8 (15.3, -0.67)
	Mode (% pop.)	50 days (32.2%)	50 days (34.5%)	50 days (31.1%)

Table 43 – OSS: Student Activity Distribution Over Time Period

In contrast to this picture of discretionary resource usage access to the portal is seen as being important across almost the entire population, with over 7% of students logging into the portal at least once (either on-campus or off-campus) on every weekday in each time period. The rise in the popularity of wireless devices to access the on-campus network is apparent with almost 50% of students using such a device at least once during time period C, whilst there is also a corresponding decrease in the number of students using fixed PC's on-campus with the percentage of students never using this resource increasing by 2% between periods A and C. The popularity of Desktop Anywhere also appears to be increasing, with more than 20% of students using this facility in time period C.

Changes in the way the library is being used are also apparent. More books and journals are becoming available online and this is reflected in a decline in books borrowed, whilst the library's secondary function, as a self-study space, appears to becoming more significant given the slight upward trend in the number of students who use it.

8.4.4 Electronic Inactivity as a Proxy for Disengagement

Theories around student engagement suggest that when students are more closely connected with their institution then they are less likely to drop-out from their studies (Tinto, 1998). Furthermore academic time-use studies suggest a connection between time spent on meaningful academic tasks and attainment level (Stinebrickner and Stinebrickner, 2004). If the data collected through the OSS captures meaningful information related to the students time-use behaviour then the frequency and duration of on-campus student activity should provide an indication of the degree of the connections between engagement/time-use and attainment.

The use of electronic records of student activity as a "proxy for engagement" has been suggested by others, in the context of the relationship between library use and retention (Crawford et al., 2004, Haddow, 2013). However, whilst highly significant positive correlations between activity frequency and academic attainment are evident in this dataset, student participation in any one activity alone is insufficient to reliably describe their academic performance since both successful and unsuccessful students alike may choose not to participate in that activity (Goodall and Pattern, 2011).

An alternative approach is to look for symptoms of disengagement within the population by identifying those students who rarely or never perform each type of activity. As shown in Table 44, five activity types were examined, with each student's preference for the activity, as represented through the dataset, being classified as either being positive (they perform the activity regularly) or negative (they perform the activity rarely or never).

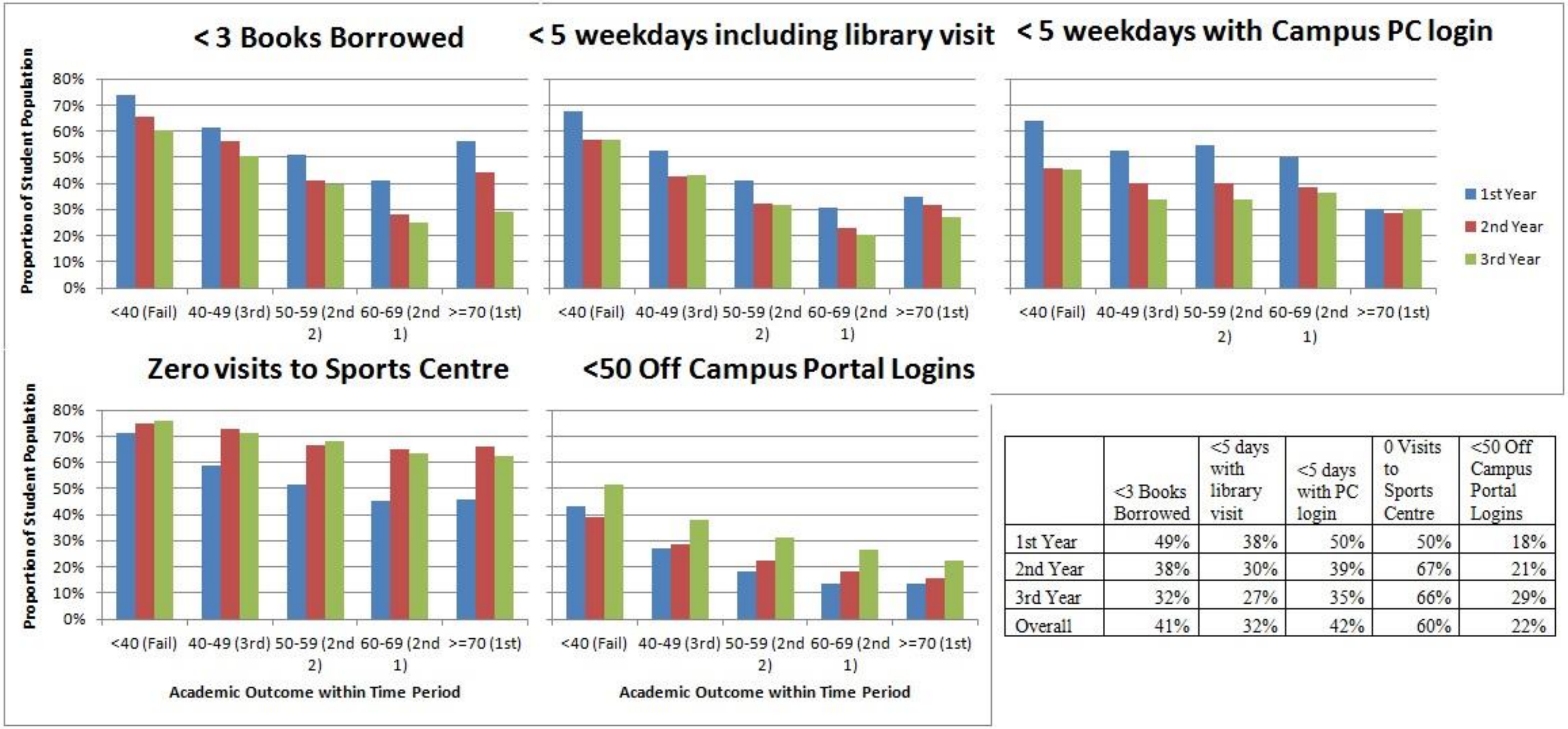
The population was then grouped by academic year and attainment level as represented by the semester end mean module mark with 5 groups corresponding to the standard degree classification levels. The proportion of students with a negative preference towards each activity type in each year and at each degree classification level was then plotted, Figure 16. Chi squared tests were conducted on the contingency tables from which the plots were taken, and all were found to be significant at the 1% level, suggesting relationships between negative activity preference and academic performance.

Activity Type	Individual Activity Preference		Proportion of Population indicating a negative preference
	Positive	Negative	
Library Books Borrowed	3 or more books borrowed	2 or fewer books borrowed	41%
Library Entries	A library was entered on five or more weekdays	A library was entered on fewer than five weekdays	32%
On-Campus PC Logins	An on-campus PC was logged into on five or more weekdays	An on-campus PC was logged into on fewer than five weekdays	42%
Sports Centre Entries	The sports centre was used at least once	The sports centre was never used	60%
Off-Campus Portal Logins	The Portal was accessed 50 or more times whilst off-campus	The Portal was accessed fewer than 50 times whilst off-campus	22%

Table 44 – OSS: Classification Key for Individual Activity Preference

For the activities related to the library (library entries and books borrowed) and for on-campus PC logins the proportion of students with a negative preference reduces with each successive academic year, and with improved academic performance. However, these figures highlight that even in the third year of their studies around 30% of all students who attain a first class mark borrow fewer than 3 books and enter the library on less than 5 days over the time period.

More first year students have a positive preference for sports centre use compared to second and third years, whilst the significant relationship between a non negative preference towards sports activities and attainment perhaps supports the idea that all types of student engagement, including participation in sports activities, support the academic process. The proportion of students with a negative preference towards off-campus portal access increases with academic year and given that more students in these groups also have a positive preference towards on-campus activities (library entry and PC logins) this perhaps suggests that later years students spend more time on-campus compared to those in the first year.



	<3 Books Borrowed	<5 days with library visit	<5 days with PC login	0 Visits to Sports Centre	<50 Off Campus Portal Logins
1st Year	49%	38%	50%	50%	18%
2nd Year	38%	30%	39%	67%	21%
3rd Year	32%	27%	35%	66%	29%
Overall	41%	32%	42%	60%	22%

Figure 16 – OSS: Distribution of Student Negative Activity Preferences

Whilst each of the five indicators demonstrate that negative preferences for an activity reduce as academic performance improves, the data shows that many students still perform well despite holding a negative preference, again suggesting that no single activity is vitally important in achieving a successful academic outcome. By examining activity preferences in combination it was found that overall around 2.5% of the population in each of the three academic years exhibit a negative preference across all 5 indicators (NEG) , whilst 10% of the population in each year have a positive preference for all five activity types (POS). The distribution of the students appearing in these two combined indicators are shown in Figure 17. Across all three academic years, the students in the NEG group predominate in the category representing a failing mark, whilst very few appear in the top mark category. Conversely the proportion of students in the POS group increases with academic outcome.

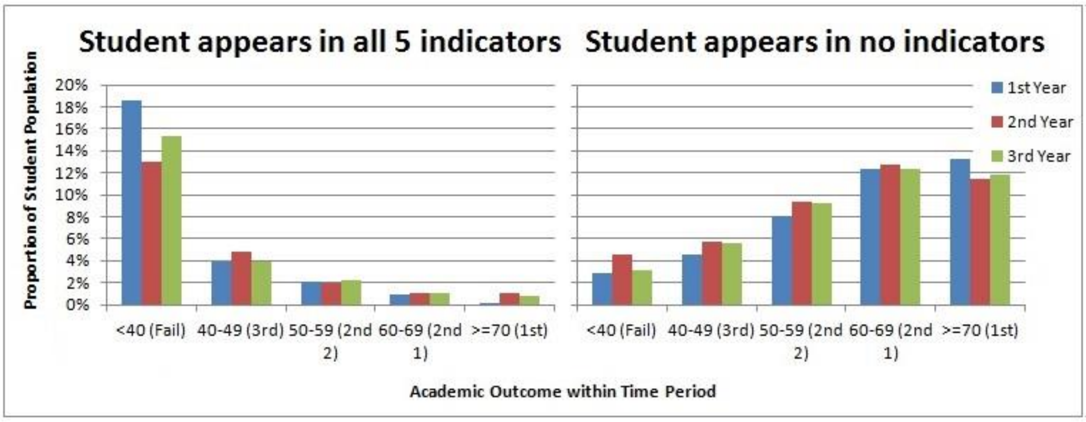


Figure 17 – OSS: Combined Activity Indicator Distributions

Given that student engagement with education purposeful activities has positive and statistically significant effect on persistence (Kuh et al., 2008) then those who fail to engage are less likely to persist and more likely to achieve a failing mark, and therefore it could be said that the students in the NEG group are more likely to be disengaged from their studies compared to those not in this group.

Bayes rule provides a mathematically rigorous method for combining prior and conditional probabilities in order to derive the likelihood of a specific conditional outcome, equation 8-1.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad \text{8-1}$$

If P(A) is the prior probability of achieving a certain academic outcome, and P(B) is the prior probability of a student having a negative preference for all five indicators, then the calculation of the conditional probability that a student will achieve a specific outcome given they express a negative preference in all indicators suggest that first year students who appear in the NEG group have almost a 40% chance of not achieving a passing mark. The odds ratio for 1st year students in the NEG group suggest they are only 1.5 times as likely to achieve a passing mark as opposed to a failing one, in comparison with the ratio for the whole population where a pass is over 19 times as likely as a fail.

An OLR model was built to examine the proportion of students present in the NEG group across different segments of the population. An OLR model that has a dependant variable with just two categories is equivalent to binary logistic model (although the signs of the coefficients are reversed) but the OLR model was chosen in this case as it more closely matches a contingency table interpretation of the data. Independent categorical variables were introduced into the model to represent time period, academic year, student gender, TTDs per week and the residential distance from campus.

An initial run of the model failed to produce a sufficient fit to the data, and after investigation it was found that the coefficient values differed across the academic years. The data was segmented and three models built instead. These models were found to fit the data, with non-significant goodness of fit tests. The values of the coefficients for each categorical variable and for each academic year are shown in Table 45.

			NEG Group Membership Probability		
			1st Year	2nd Year	3rd Year
	Pseudo R Squared	Nagelkerke	0.044	0.019	0.055
	Goodness of Fit	Pearson Chi-Square	47.254	40.291	36.282
		df	40	40	40
		Significance	0.2	0.457	0.638
COEFFICIENTS	Constant		2.389	2.606	2.068
	Gender	Male			
		Female	-0.224*	-0.511	-0.849
	Distance	0-0.5 miles	-1.024	-0.302**	-1.391
		0.5-2 miles	-0.461	-0.732	-1.332
		2-4 miles	-0.94	-0.337**	-0.877
		>4 miles			
	Timetable	1-3 days/week			
		4-5 days/week	-0.687	-0.27*	-0.535
	Time Period	A	0.118**	0.046**	-0.209**
		B	-0.798	-0.257**	-0.25**
		C			

Table 45 – OSS: NEG Group Membership OLR Model

[All coefficients significant at 1% level, except *=5%, and **=not significant]

Examination of the signs/values of the coefficients shows that males are more likely to be in the NEG group, as are those who live further away. Given the findings of the TQS both of these relationships might have been expected. However, students with between 1-3 TTDs/week are also more likely to be in the NEG group when compared to those with 4-5 TTDs/week and this is surprising, whilst the significant negative coefficient for first year students in period B, suggests that newly enrolled students are particularly at risk.

The NEG group membership probability suggested by the model for a first year male student who lives remotely and who has 1-3 TTDs per week in time period C is 0.084, whilst if the student lived on-campus this would drop to 0.032, and if they instead had 4-5 TTDs/week the probability would drop further to 0.016. Calculation of the odds ratios suggests that students living remotely and who have compressed timetables are over 5 times more likely to be members of the NEG group, when compared with those who live on-campus and have timetabled sessions on every day of the week (RQ6). This model provides the first hint of a more a malign relationship between the design of the academic timetable, and the student academic experience.

Chapter 9 – On-Campus Student Population Estimation

9.1 Introduction

The previous chapter introduced the observational dataset and demonstrated how different characteristics of the use of on-campus resources suggests differential trip rates on TTD's and NTDs, supporting the findings of the TQS. Whilst this aggregate analysis is useful, to obtain the precision necessary to fully understand trip-making behaviour on a student-by-student basis it is necessary to analyse individual records of student activity on-campus.

This chapter will outline a three stage process to produce a series of on-campus attendance estimates for each time period that are successively refined from an aggregate estimate of the total number of student days including a trip to campus, through estimates of the daily on-campus population before finally inferring trip probabilities at an individual level.

The work presented in this chapter continues the delivery of research objective O4 (develop an observational student survey method) whilst also delivering objective O5 (explore the trip making behaviour of students at an aggregate and disaggregate level) and addressing research questions RQ1, RQ2 and RQ7 (can an observational survey technique be developed?).

9.2 The On-Campus Population Estimation Problem

This section introduces the on-campus population estimation problem.

In the descriptions that follow the subscript i will represent the ith student out of a total population of I, and the subscript j will represent the jth day within an arbitrary time period consisting of J days.

The following additional symbols are also used.

d_{ij}	An activity detection matrix, identifying on-campus activity by each student over the time period, such that each cell contains 1 if student i performed a detected on-campus activity on day j, and 0 otherwise
t_{ij}	A trip record matrix, identifying all trips made by each student over the time period, such that

each cell contains 1 if student i made a trip to campus on day j and 0 otherwise.

htt_{ij}	The number of timetabled hours student i has on day j
$IsTT(i,j) = \begin{bmatrix} 0\ if\ htt_{ij} = 0 \\ 1\ if\ htt_{ij} > 0 \end{bmatrix}$	A function that returns 1 if student i has at least one timetabled session of day j.
$IsnTT(i,j) = 1 - IsTT(i,j)$	A function that returns 1 if student i has no timetabled sessions on day j
$dtt_j = \sum_i IsTT(i,j)d_{ij}$	The total number of students with timetabled sessions detected on campus on day j.
$dntt_j = \sum_i IsnTT(i,j)d_{ij}$	The total number of students with no timetabled sessions detected on campus on day j.

The individual probability of student i making a trip to campus on any timetabled or non-timetabled day within the time period can be calculated as shown in equations 9-1 and 9-2.

$$P(tt)_i = \frac{1}{J}\sum_j t_{ij} IsTT(i,j) \qquad 9\text{-}1$$

$$P(ntt)_i = \frac{1}{J}\sum_j t_{ij} IsnTT(i,j) \qquad 9\text{-}2$$

Unfortunately the observational dataset does not give direct access to the trip record matrix t and therefore this must be inferred from the activity detection matrix d which is available.

On any day j the trip-making behaviour of each student i can be classified into one of three states:

- State 1: No trip to campus: d_{ij}=0 and t_{ij}=0
- State 2a: Trip made to campus and a detectable activity performed: d_{ij}=1 and t_{ij}=1
- State 2b: Trip made to campus but no detectable activity performed: d_{ij}=0, but t_{ij}=1

The estimation problem involves disambiguating between states 1 and 2b and reassigning a proportion of cells in t_{ij} from 0 to 1 in cases where a trip has been made but not detected.

All trips to campus will be of an unknown duration, and whilst a student is on-campus they will have some, unknown, activity dependant probability of undertaking a detectable activity.

For a trip to campus by student i on day j the following quantities can be defined:

h_{ij}	The duration, in hours, of student i's stay on campus on day j. Zero if no trip is made to campus
$P(dntt)_i$	The probability that student i will be observed during any hour on- campus of a non-timetabled day j or during any hour on-campus containing a break between sessions on a timetabled day
$P(dtt)_i$	The probability that student I will be detected during any hour containing a timetabled session on day j

Given these definitions a binomial distribution defines the probability that the student will be detected at least once during their stay on campus.

For those students with no timetabled sessions on day j the total number that can be expected to be detected on-campus, $Dntt_j$ (which is known) is defined by equation 9-3.

$$Dntt_j = \sum_i t_{ij} IsnTT(i,j) \cdot \left[1 - (1 - P(dntt)_i)^{h_{ij}}\right] \qquad 9\text{-}3$$

A similar equation, but extended to include two detection probabilities, for those students who have at least one timetabled session on day j, Dtt_j, is defined according to 9-4.

$$Dtt_j = \sum_i t_{ij} IsTT(i,j) \cdot \left[1 - (1 - P(dtt)_i)^{htt_{ij}} (1 - P(dntt)_i)^{h_{ij} - htt_{ij}}\right] \qquad 9\text{-}4$$

These equations simplify the true situation since it is unlikely that the detection probabilities for an individual student will remain constant over all J days. Even if it is assumed that there is some regularity in a student's daily routine, the probabilities of detection almost certainly require an additional subscript, which if not defining a unique probability for each day j, might define a distinct probability for each day of the week, resulting in between 6 and 10 detection probabilities per student.

However, what the equations do show that the likelihood of being observed increases with the duration of stay on-campus.

The aim is to infer values for the trip record matrix, t_{ij}, from these equations or at least to obtain an estimate of the total number of trips to campus on any day, T_j. However, in the absence of further information these equations are intractable, in that for every possible combination of values that could exist within t_{ij} there are matching values for the other parameters, meaning that on any day j all possible values of Tj (the total number of students visiting campus on that day) are equally as likely from a lower bound of Dj (all students who visited on-campus were detected) to an upper bound of I (all students in the population visited campus and were detected with a probability of $(Dtt_j+Dntt_j)/I$).

Methods which attempt to estimate a more accurate value for Tj (or a similar quantity in a different context) are classified as belonging to what is known as the population estimation problem.

9.3 The Population Estimation Problem

The population estimation problem applies in situations in which only a sample of a whole population is observed and entails estimating the size of the whole population based on the size and characteristics of the sample. The motivation for developing estimation methods mainly emanates from the field of ecology where calculating accurate estimates of species of animal, plant or habitat is important for management or conservation purposes (Williams et al., 2002, p. 6). The problem is also encountered in non-ecological contexts with some examples being: the identification of hard to reach populations, like drug users (Chiang et al., 2007), the number of errors remaining hidden within a software package (Petersson et al., 2004), and the number of unreported maritime accidents (Hassel et al., 2011).

Population estimation methods rely on systematic sampling strategies where the target population is sampled multiple times or at multiple locations and typically employ a mark and recapture technique. This involves marking and releasing each object when it is initially encountered within a sample, and then observing how many times the marks reappear in the subsequent samples. Population estimates may then be calculated using a capture frequency distribution to approximate the capture probabilities for the whole population, or through ratios of marked to unmarked objects to make inferences about the whole population.

Population estimation methods fall into two classes, those associated with closed populations and those associated with open populations (Southwood and Henderson, 2000, p. 73). A closed population is one in which the number of objects within the population is assumed to be constant across all sampling periods, for example when estimating the number of black-taxicabs operating within a city over a short period of time (Carother.Ad, 1973). In contrast an open population is one in which the population is (or could be) changing during the course of the study (Amstrup et al., 2005, p. 5) and is subject to births, deaths and also sometimes temporary immigration and emigration. An open population is assumed in studies with a longer time frame, for example when estimating the size of a animal colony over a number of breeding seasons during which births and deaths will occur naturally.

These two classes of models can be thought of as providing a means to control the duration h_{ij} term in equations 9-3 and 9-4 through making it equivalent for all members of the population (closed and open populations), and then by accounting for any variation which occurs from one fixed time period to the next (open populations only).

If the campus is considered to be the study area, then the trip-making behaviour of the student population to or from campus can be thought of as being equivalent to observing the changing characteristics of an animal population over time.

Separate observations of the population would be made across each hour on a given day, with a student trip to campus during the hour being equivalent to a birth event, a student departure from campus the same as a death event, and leave-and-return behaviour thought of as being equivalent to temporary emigration and immigration.

The class of open population models are based around work done by Jolly and Seber (Jolly, 1965, Seber, 1965). Representing student trip-making behaviour using this class of model would involve choosing a monitoring time period, for example one hour, making an assumption that the population was locally-closed and not subject to change during that period, and then calculating the population on-campus during each hour of the day, with the total number of trips to campus (and hence the on-campus population) being equivalent to the sum of the births (arrivals) in the population assuming a zero on-campus population at the start of the day.

Although this application of the model to the university campus is intuitively appealing, the rate of change of the student population is much greater than would be expected in an animal population, in which the overall level may remain constant over the study period, even if births and deaths mean all the animals within the population change over time.

The model of the population estimated for any time period is solved using maximum likelihood estimation (MLE) techniques, with the likelihood equation being split into three components which calculate the conditional probabilities of associated with the first capture event, losses on capture (deaths) and the recapture of previously marked samples (Williams et al., 2002, p. 497).

The first capture event will include samples that were in the population during the previous time period and those that were born subsequently. However, because survivability between time periods, and not births, is the main focus of the model, in the Jolly-Seber model it is represented according to the (simplified) equation 9-5 where the number of births in period i is based on the difference between the size of the estimated population in periods i and i+1 after taking the number of deaths (departures) in period i into account; φ_i being the probability of survival from period i to i+1 (Williams et al., 2002, p. 499).

$$B_i = N_{i+1} - \varphi_i N_i \tag{9-5}$$

Shwarz states that this approach often leads to negative estimates of the number of births (arrivals) between two time periods (Schwarz and Arnason, 1996), and they propose an alternative method where births are specified as a fraction of a super-population of total births (total arrivals). Due to the large number of parameters which must be estimated in the original Jolly-Seber model and the revised Shwarz model they both include the simplifying assumption that the capture probabilities for all animals in each time period are equal.

Two examples of the use of the Jolly-Seber open population estimation method in a transportation context were found. In the first (abstract only, due to the document being in Portuguese) the method was used to estimate the number of vehicles parking daily in a city centre (de Oliveira and Bueno, 2004) . The point (daily) estimates were close to the expected value (number of parking spaces) but with a wide confidence interval. The authors suggest using more parsimonious closed population estimation methods. In the second, the method was used to estimate the number of vehicles used daily within Bejing (Chen et al., 2008). However, the authors erroneously assume the every active vehicle has an equal probability of detection (via fixed ANPR cameras) when this will depend upon the duration of the trip and route followed.

Although the trip-making characteristics of the student population appear to conform to the behaviour represented through the Jolly-Seber model, the approach is not appropriate for this estimation problem due uncertainty over the modelling of the arrivals rate, the large number of parameters in the model and the need for all objects within the population to have equal probabilities of capture. As discussed in section 8.4.3 students demonstrate heterogeneity in their use of on-campus resources and hence detection probabilities across students will vary.

The second class of models allows estimation of closed populations, those in which all members of the population can potentially be captured in all samples. In one sense the population of university students can be regarded as being closed across specific time periods if the number of students enrolling or dropping out midway through the period is assumed to be negligible, even if the population on-campus on a daily basis is potentially open due to differing individual stay durations.

The original and simplest method for obtaining an estimate of a closed population is through the use of the Lincoln-Petersen estimator (LP). This is based on a mark and recapture methodology in which members of the population are captured/observed over two periods (Williams et al., 2002, p. 290). At the end of the second sampling period each member of the population will have exhibited one of four capture histories:

- [0,0] : Not caught in either sample
- [0,1] : Caught in the first sample but not the second
- [1,0] : Caught in the second sample but not the first
- [1,1] : Caught in both samples.

The total population N will be the sum of the counts of all four capture histories with the number with capture history [0,0] being unknown. The number caught in the first sample can be labelled M (the sum of histories [0,1] and [1,1]), the number caught in the second sample labelled C (the sum of histories [1,0] and [1,1]), and the number caught in both (history [1,1]) labelled R. Then if the two samples are assumed to be independent the ratio of those caught in both samples to those caught in the first sample will be equivalent to ratio of those caught in the second sample to the population as a whole, equation 9-6, which can be rearranged to give N, equation 9-7.

$$^{R}/_{M} \approx {}^{C}/_{N} \qquad (9\text{-}6)$$

$$N = \frac{MC}{R} \qquad (9\text{-}7)$$

A simple and intuitive example is provided by Davies whereby the attendance at a free-to-view open-access sports event is determined by counting the number of event programmes sold (M), the number of event feedback questionnaires completed (C), and the number of positive responses to a question within the questionnaire that asks if the respondent purchased a programme (R), (Davies et al., 2010). This demonstrates the flexibility of the method in its application to human populations since neither of the counts need to be obtained using a traditional ecological field sampling method. However, it also demonstrates the method’s main limitation in that any correlation in spectator behaviour between purchasing a programme and completing the survey is undetectable and will lead to an unknown degree of bias in the estimate.

An advantage of this method is that the estimate can be derived directly, and it does not require an iterative approach or special software to solve. As such the estimator is very accessible and quick and easy to use. Southwood proposes it as a kind of default case against which all other more sophisticated methods should be judged (Southwood and Henderson, 2000, p. 75).

The first recorded application of the technique is normally credited to Laplace who used it to estimate the population of France in 1803, although a similar method was used 200 years earlier by Gaunt to determine the effect of the plague on the population of England (Amstrup et al., 2005,p. 2).

Although the field of closed population estimation has developed, particularly recently, this classic method is still used in some applications. A search of Web of Knowledge found 25 articles listed since 2008 that quoted the topic “Lincoln Petersen”. Furthermore, some of the other closed population methods, that often rely on more than two sampling periods, simplify to the LP estimator in the two sample case; Schnabel Censuses, (Southwood and Henderson, 2000, p. 85) and Chao’s lower bound estimator for model M_t when probability of capture varies with time (Chao, 1989).

The representation of the estimator given in 9-7 was found to be biased when data is sparse and an unbiased form defined by Chapman is shown in equation 9-8 with the variance as defined in equation 9-9 (Chapman, 1951).

$$N = \frac{(M+1)(C+1)}{(R+1)} - 1 \tag{9-8}$$

$$var(N) = \frac{(M+1)(C+1)(M-R)(C-R)}{(R+1)^2(R+2)} \tag{9-9}$$

Equation 9-9 demonstrates that the accuracy of the estimator is dependent on both the size R relative to the product of M and C and on the total number of observations (M+C-R). Designs which maximise the number of elements counted in R and which include higher numbers of observations overall will improve the accuracy of the estimator.

One alternative closed population estimator, Chao’s lower bound, calculates a bottom limit for the population estimate, and in the two sample case reduces to equation 9-10.

$$N \geq (M + C - R) + \frac{[(M - R) + (C - R)]^2}{4R} \qquad 9\text{-}10$$

Brittain et al compared the performance of the LP estimator with Chao's lower bound and other two sample closed population estimators (Brittain and Bohning, 2009). They found that Chao's lower bound performs slightly better than LP in both simulation studies and with real epidemiological data. However, as clearly stated in Chao's original paper her estimator is only valid when the heterogeneous individual probability of capture is constant across all sample periods (Chao, 1987).

The LP estimator relies on a number of important assumptions (Williams et al., 2002, p. 293):

- That the population is closed
- That each member of the population is equally likely to be captured, and that there is no heterogeneity between members of the population
- That no member of the population marked on sample occasion one, loses their mark before being observed during sample occasion two
- That there is no sample bias and that being observed on sample occasion one, does not either increase an individual's likelihood of being observed on sample occasion two (trap happy), nor does it decrease it either (trap shy).

If any of these assumptions are broken then the accuracy of the estimate falls, with most errors resulting in an underestimation of the size of the population (Chao and Huggins, 2005, p. 33).

Chao showed that the equal catchability assumption only applies to the second sample, and specified a theoretical correction for the bias in the estimator attributable to both heterogeneity or when the equal catchability assumption does not apply to the second sample, equation 9-11, (Chao et al., 2008)

$$N = \frac{MC}{R}\,(1 + \gamma) \qquad 9\text{-}11$$

When γ is zero the estimator is unbiased, when positive M is over-represented in R and when negative it is under-represented. However, as Chao notes, with only 3 quantities; M C and R, the true value of γ can-not be determined, and the estimator assumes that no bias is present (γ=0).

The LP estimator produces a estimate with a narrow confidence interval but is subject to a larger bias than more a general model which uses more parameters and controls for bias, but produces a wider confidence interval (Chao and Huggins, 2005, p. 70).

9.4 Estimation of the On-Campus Population and Student Trip Probabilities

The use of the LP estimator to calculate student attendance on-campus offers three advantages over its use with animal populations. Firstly, whilst a lower bound to the population estimate is always known (M+C-R), in this case since the number of students enrolled at the university within each time period is fixed (closed population) then there is also a known upper bound to the estimate. This means that bias can be detected in some cases when γ is negative. Secondly, the size of each sample is several orders of magnitude larger than for a typical animal survey, with around 800,000 student days in each time period and this reduce the standard error associated with each count since this will be proportional to $1/\sqrt{n}$. Finally, the narrow confidence interval provided by the LP estimator is important in this context since it is reasonable to assume that most TTDs include a trip to campus and hence the population will always be close to the theoretical maximum.

Care must be taken with the specification of the sampling period. If this is regarded as being a day, then the population on-campus over the day must be considered open, since each member of the population will have a different stay duration, and as shown in equations 9-3 and 9-4 those with shorter stay durations will have a lower probability of being detected relative to those who stay longer.

Within the context of estimating the number of students on campus two sampling occasions can be created as follows. Students will be members of the first sample group if they use a Wi-Fi enabled mobile phone on campus, whilst they will be members of the second sample group if they perform one of more of the following activities: enter a library, enter a sports centre, login to a fixed PC or use some other wireless device on-campus.

Chao shows that the assumption of equal catchability does not apply to the first sample (Chao et al., 2008), so it is not important if some students never use a Wi-Fi enabled mobile phone, whilst others use one on every visit to campus.

The population can be stratified to eliminate some sources of heterogeneity in the second sample (Chao and Huggins, 2005, p. 33). Since the TQS showed that student trips to campus differ between males and females and whether the day contains a timetabled session, the population can be split into 4 strata based on gender and day type (TTD or NTD).

The dispersed distributions of individual on-campus resource usage shown in section 8.4.3 suggest that some heterogeneity will remain in the second sample group. However, if the degree of heterogeneity expressed by mobile phone users, relative to non-mobile phone users is similar then the resultant effect on the estimate will be negligible. Table 46 shows the relationship, expressed as a LRM, between the number of students using mobile phones (the M term) and those using other detected resources (the C term) over each timetabled and non-timetabled day in each time period. Table 47 shows a similar the relationship between the mobile phone users usage of other on-campus resources (the R term) compared with the usage of non mobile phone users (C-R). If there is little heterogeneity in the use of on-campus resources between the mobile phone users and the non mobile phone users then the R^2 values for each fitted regression line will be high indicating that the ratio between the two quantities is constant across the range of usage values.

		Period A		Period B		Period C	
		Male	Female	Male	Female	Male	Female
	N	50	50	48	48	50	50
TT Day	Slope	2.61	2.61	1.67	1.83	1.95	2.29
	Intercept	-472.73	-472.73	545.63	1192.41	-713.21	-587.37
	R Squared	0.93	0.93	0.65	0.45	0.94	0.9
Non TT Day	Slope	2.45	4.2	2.03	2.21	1.46	1.74
	Intercept	42.62	38.58	60.4	148.52	51.96	73
	R Squared	0.94	0.88	0.93	0.85	0.95	0.92

Table 46 – OSS: Mobile phone usage vs On-campus resource usage

		Period A		Period B		Period C	
		Male	Female	Male	Female	Male	Female
	N	50	50	48	48	50	50
TT Day	Slope	0.28	0.14	0.21	0.11	0.48	0.33
	Intercept	-7.80	-36.63	138.43	139.49	7.43	0.37
	R Squared	0.76	0.78	0.23	0.18	0.61	0.60
Non TT Day	Slope	0.29	0.12	0.31	0.20	0.54	0.33
	Intercept	-6.68	4.60	-5.76	-5.28	0.58	29.62
	R Squared	0.82	0.64	0.81	0.62	0.70	0.55

Table 47 – OSS: Mobile phone users vs non mobile phone users

For NTDs high R^2 values are found in all cases except in Table 47 for females in period C. Intercept values close to zero in this table are also indicative of a fixed linear relationship. For TTDs, the relationships in period B (the autumn term), when one third of the population will be new to UoL, appear to be less well defined than they are for the spring terms (periods A and C). New student Wi-Fi registration will take place the first few weeks and hence the relationship will change over the period as students find they can use their phones to access the network.

The definition of the observational data-set, section 8.2.10, provides flexibility in terms of the way the M, C and R counts are provided for each strata. Figures can be extracted for any arbitrary combination of hour long time slots within the time period, so that counts can be generated by hour, day, week or time period, and can be filtered to include/exclude students based on criteria related to their timetables:

by contact hours, start time, before first session, after last session, during a session, or in a gap between sessions.

Given that in this study it is the student study-place commuting trips that are of interest, it is important that the effect of other trip types on the estimates is minimised. For this reason only activity recorded between 8:00 and 19:00 was used in the calculation of the estimates.

The method used to assign daily trip probabilities to individual students consists of three stages:

- Estimation of the overall number of student days which included a trip to campus across each time period.
- Estimation of the daily population on-campus across the time period
- Assignment of probabilities $P(tt)_i$ and $P(ntt)_i$ to each individual in the population.

Each of these three stages will now be described.

9.4.1 Estimating the overall population on campus

The population is divided into 4 strata by gender (male/female) and day type (timetabled day/non-timetabled day).

The total number of student days within each strata can be counted, as shown in equations 9-12 and 9-13 for timetabled and NTDs respectively.

$$DAYtt = \sum_i \sum_j IsTT(i,j) \qquad \text{9-12}$$

$$DAYntt = \sum_i \sum_j IsnTT(i,j) \qquad \text{9-13}$$

For each strata the aim is to produce a single figure giving the estimate of the proportion of the total student days that included a trip to campus.

Each student day can be regarded as an separate capture experiment, which generates one the four capture histories outlined in the previous section.

The estimate is obtained by summing the capture histories for each experiment and then by calculating the LP estimator for the totals, as shown in 9-14 for NTDs.

m_{ij} c_{ij}	Two matrices which contain 1 if student i used a Wi-Fi
$r_{ij} = m_{ij} \cdot c_{ij}$	enabled mobile phone (m) some other electronic device (c).

$$LPntt = \frac{(\sum_i \sum_j IsnTT(i,j)m_{ij} + 1)(\sum_i \sum_j IsnTT(i,j)c_{ij} + 1)}{\sum_i \sum_j IsnTT(i,j)r_{ij} + 1} - 1 \qquad 9\text{-}14$$

$$POPntt = \frac{LPntt}{DAYntt}$$

The LP estimator requires that all members of the population are equally available to be sampled even if they then have different individual probabilities of being detected. Since the likelihood of any individual being detected increases with time spent on campus, it is important that all individuals are sampled over a time period equivalent to the shortest duration of stay of any individual within the on-campus population.

It can be expected that most students who attend campus on a timetabled day will attend at their scheduled sessions on that day, and consequently a reasonable simplifying assumption is that all students who are on campus on a given day attend all their classes on that day.

Given this assumption, if the population is further grouped by the number of timetabled contact hours and if each student is then observed solely during the hours in which they have timetabled sessions then the population effectively becomes closed since all students with k hours of timetabled sessions on any day will contribute k hours of detection possibilities to the estimate.

The results of calculating an on- campus attendance LP estimate for the timetabled population in each time period, after grouping the TTDs by contact hours are shown in Figure 18. These estimates demonstrate a clear and changing bias, with values which seem too low when contact hours are low, (60% attendance on campus on TTDs containing one contact hour) and which are too high (over 100%) when there are more contact hours. The estimates also appear to become progressively less biased in each successive time period, and that those for male students seem to contain less bias than do the female estimates.

Two estimates of attendance are shown in each graph. One is calculated based on activity in the timetabled hours only, whilst the second is calculated using activity across the whole day. The estimates converge as contact hours increase since the timetabled hours take up a greater proportion of the day, whilst the bias appears to be less pronounced at low contact hours. The degree of bias appears to be related to the proportion of student days on which a mobile phone was used. This figure increases with the number of contact hours in the timetable, more male students use these devices and the absolute number of phones in use increases with each time period. Since the real level of attendance must lie between the extremes represented by one and six contact hours the sign of the bias must change somewhere on the continuum between these two estimates, and there will be a point at which the estimator is unbiased and gives an accurate value for attendance. As Chao shows theoretically bias occurs when the first sample is over(under) represented in the combined sample. In this case, the bias will represent differences in the proportion of detected mobile phone users who also use another electronic resource, compared with the proportion of the whole population who use an electronic resource. Whilst this ratio can-not be observed directly it should be related to the overall number of mobile phone and other electronic resource users in the on-campus population. The best estimate of the number of mobile users on campus can be obtained searching for activity across the whole day as opposed to just within timetabled sessions as this will include those students who have a mobile, but didn’t activate it during their timetabled session.

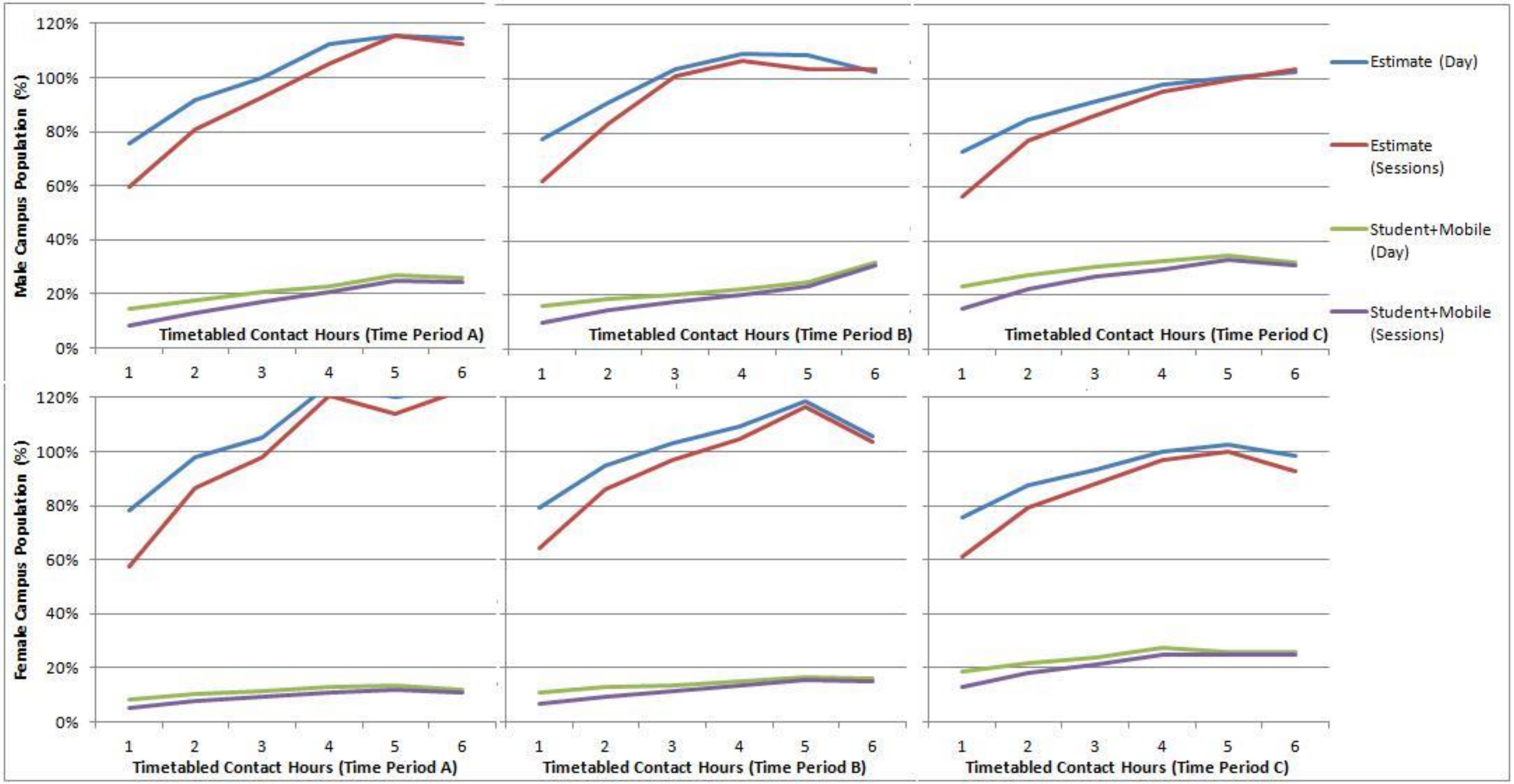


Figure 18 – OSS: Attendance On TTDs: Biased estimates

The proportion of the total number of student days on which a mobile phone or another electronic resource is used during time period C is shown in Figure 19. Mobile phone users predominate when contact hours are low whilst at higher contact hours, the students who use other electronic resources are dominant.

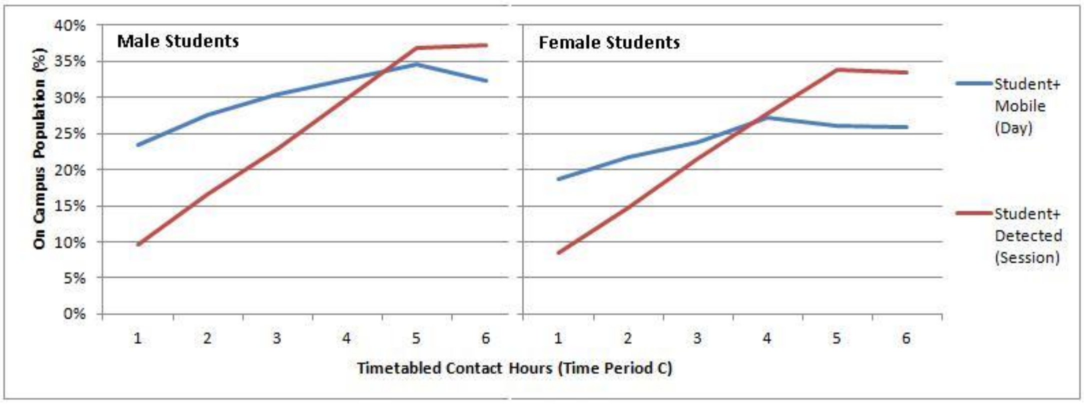


Figure 19 – OSS: Mobile Phone use vs usage of other resources

It is hypothesised that the point of intersection at which the proportion of mobile phone users matches the proportion of other resource users, α, corresponds to there being zero bias in the estimate and that Chao's γ can be estimated as shown in equation 9-15 where Mk is the proportion of student days with k contact hours on which a mobile phone was used.

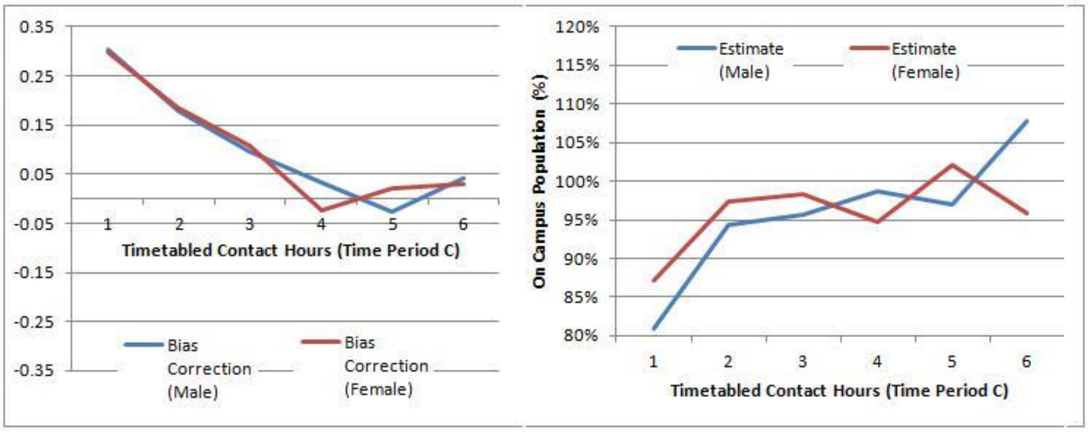
$$\gamma = \frac{\alpha - M_k}{\alpha} \qquad \text{9-15}$$

The hypothesised values for the point within the contact hours range when the bias in the estimator is zero are shown in Table 48.

	Male			Female		
Time Period	A	B	C	A	B	C
Contact Hours	2.64	3.03	4.53	1.14	1.68	3.26
Mobile Proportion	19.6%	20.4%	33.6%	9.0%	12.0%	26.6%

Table 48 – OSS: Hypothesised Point of Zero Bias

Using this bias correction factor the attendance estimates can be recalculated. The estimates for time period C are shown in Graph 19 together with the correction factors suggested by equation 9-15.



Graph 19 – OSS: Attendance Estimates for TTDs, Time Period C

These adjusted attendance estimates are simultaneously much closer to 100% and in all but two cases still below this theoretical upper bound. This suggests that the bias correction factor has improved the accuracy of the estimates. Overall attendance estimates by gender for all TTDs in time period C, calculated using this method and weighted by the proportion of days containing between 1 and 6 contact hours indicate that males (females) attended on 92.5% (94.3%) of days. Unfortunately estimates for time periods A and B showed similar instability to that demonstrated in the non-biased corrected version and consequently these estimates were discarded and those generated for time period C used in their place.

For NTDs the heterogeneity within the population in terms of stay duration and use of electronic resources is likely to be lower. Trips to campus on non-timetabled and weekend days are discretionary and individuals are only likely to make a trip if there is a specific on-campus activity which they want to undertake. This activity will typically involve them interacting with the university’s electronic systems and being detected as a result. On the basis of this assumption the calculation of overall attendance on all non-timetabled and weekend student days was performed using the simple non bias corrected LP estimator.

The final overall estimates for each subset of the population across all time periods is shown in Table 49. The 95% confidence intervals are calculated using the LP estimator standard deviation equation 9-9 with a weighted average across each level of contact hour being used for TTDs.

		Timetabled Days			
		Student Days	Attend	Standard deviation	95% confidence interval
Male	A B C	291,322	92.5% (Period C)	0.399%	91.7%-93.2%
Female	A B C	327,605	94.3% (Period C)	0.817%	92.7%-95.9%
		Non Timetabled Days			
		Student Days	Attend	Standard deviation	95% confidence interval
Male	A	72,957	51.9%	0.416%	51.1%-52.7%
	B	58,156	51.7%	0.472%	50.8%-52.6%
	C	71,578	54.3%	0.301%	53.7%-54.9%
Female	A	111,110	49.6%	0.502%	48.6%-50.6%
	B	94,643	48.1%	0.461%	47.2%-49.0%
	C	109,395	48.5%	0.276%	47.9%-49.0%

Table 49 – OSS: Overall On-Campus Attendance Estimates

The estimates appear to indicate that just over half as many students attend on campus on NTDs compared to timetabled ones. The high number of observations means a low standard error associated with each estimate and a similarly narrow confidence interval.

9.4.2 Estimating the daily population on campus

For each type of student day, timetabled, non-timetabled the LP estimator can be used to calculate the on-campus attendance on a daily basis, giving an indication of how the attendance fluctuates across the days of the week through each week of the time period.

If the LP estimator was completely accurate then the sum of the estimates for each day would equal the overall attendance estimates calculated in section 9.4.1. However, this is unlikely and the daily estimates must be adjusted so that they do match the overall totals.

For the NTDs each daily estimate for day j, $LPntt_j$ within the time period is calculated using the LP estimator according to equation 9-16. The estimate is then adjusted by the difference between the sum of the daily and overall attendance totals multiplied by a proportion that represents the day's contribution to the daily attendance total, 9-18.

$$LPntt_j = \frac{(\sum_i IsnTT(i,j)m_{ij} + 1)(\sum_i IsnTT(i,j)\, c_{ij} + 1)}{\sum_i IsnTT(i,j)r_{ij} + 1} - 1 \quad \text{9-16}$$

$$DAYntt_j = \sum_i IsnTT(i,j) \quad 9\text{-}17$$

$$LPntt'_j = LPntt_j + \left[\frac{LPntt_j}{\sum_j LPntt_j}\right]\left[LPntt - \sum_j LPntt_j\right] \quad 9\text{-}18$$

For each TTD the attendance is calculated in the same way as for NTDs, $LPtt_j$ 9-19. However, because some of the daily estimates yield values over the theoretical upper bound, the scaling operates differently. In this case the daily estimates are pivoted around the mean attendance value for TTDs, 9-22, by assuming that the busiest timetabled day corresponds to the highest daily estimate, and that on that day 99% of the population attended on campus, 9-21.

$$LPtt_j = As\ for\ LPntt_j \quad 9\text{-}19$$

$$DAYtt_j = \sum_i IsTT(i,j) \quad 9\text{-}20$$

$$f = \frac{(0.99 - \frac{LPtt}{\sum_j Daytt_j})}{(\max\left(\frac{LPtt_j}{Daytt_j}\right) - \frac{\sum_j LPtt_j}{\sum_j Daytt_j})} \quad 9\text{-}21$$

$$LPtt'_j = LPtt + (LPtt_j - \frac{\sum_j LPtt_j}{Daytt})f \quad 9\text{-}22$$

The percentage difference between each overall estimate and the sum of the corresponding daily estimates is shown in Table 50.

	Timetabled Day		Non Timetabled Day	
	Male	Female	Male	Female
Time Period A	4.80%	6.53%	-0.26%	-3.38%
Time Period B	9.13%	6.82%	-3.38%	-0.26%
Time Period C	-3.33%	-4.28%	-0.57%	-1.02%

Table 50 – OSS: Differences between alternative attendance estimates

The adjusted estimated daily attendance figures for TTDs ($LPtt'_j$) and NTDs ($LPntt'_j$), plotted as percentages of the total population are shown in Figure 20 and Figure 21 respectively. Each plot also shows the percentage of students detected on each day. Attendance fluctuates across the week, and on-campus attendance on TTL days is lower than for TTH days, whilst on NTDs attendance declines through the week and is lowest on Fridays. Within each time period timetabled attendance reduces as the weeks progress and this is mirrored by an increase in attendance on NTDs towards the end of each time period.

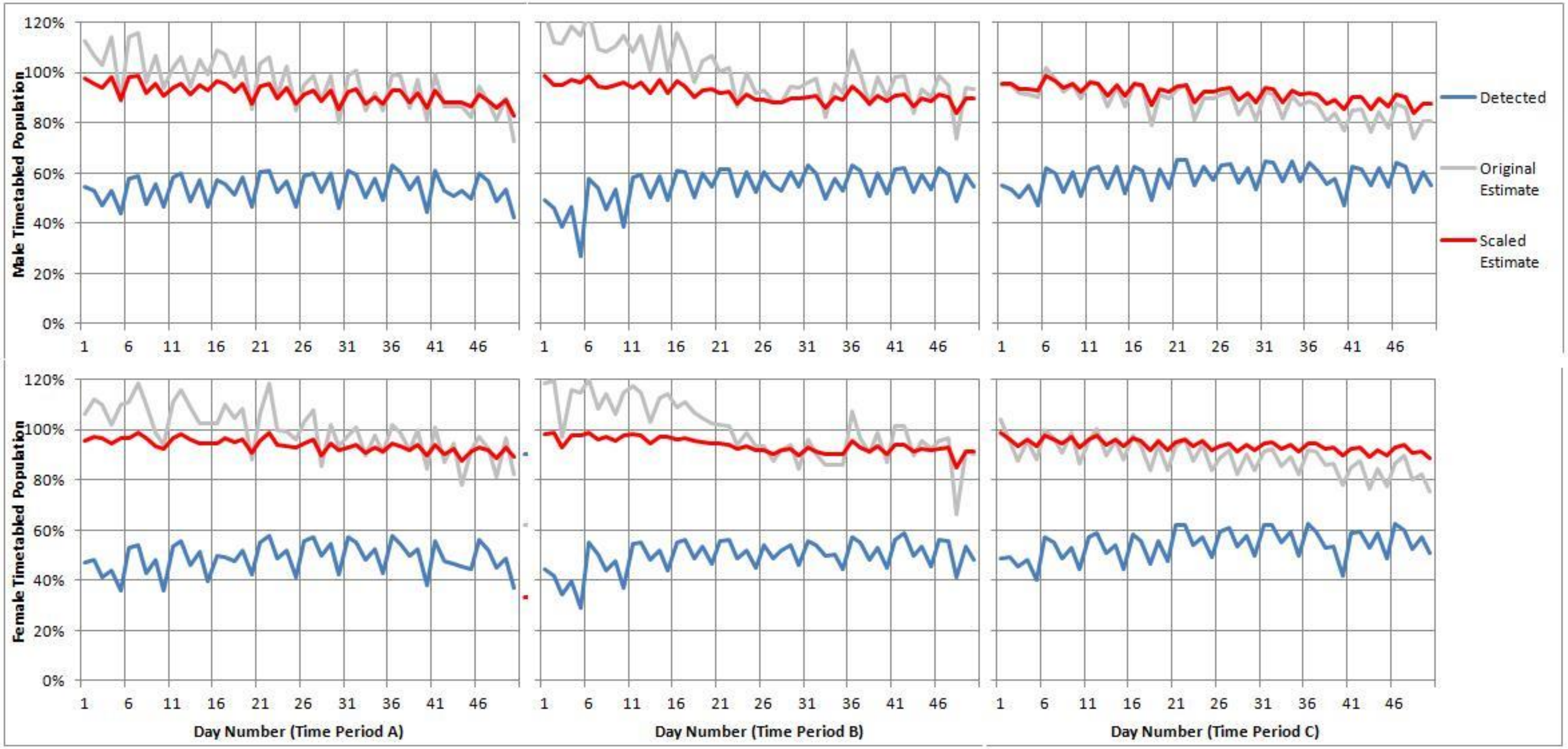


Figure 20 – OSS: Estimated on-campus daily attendance on TTDs

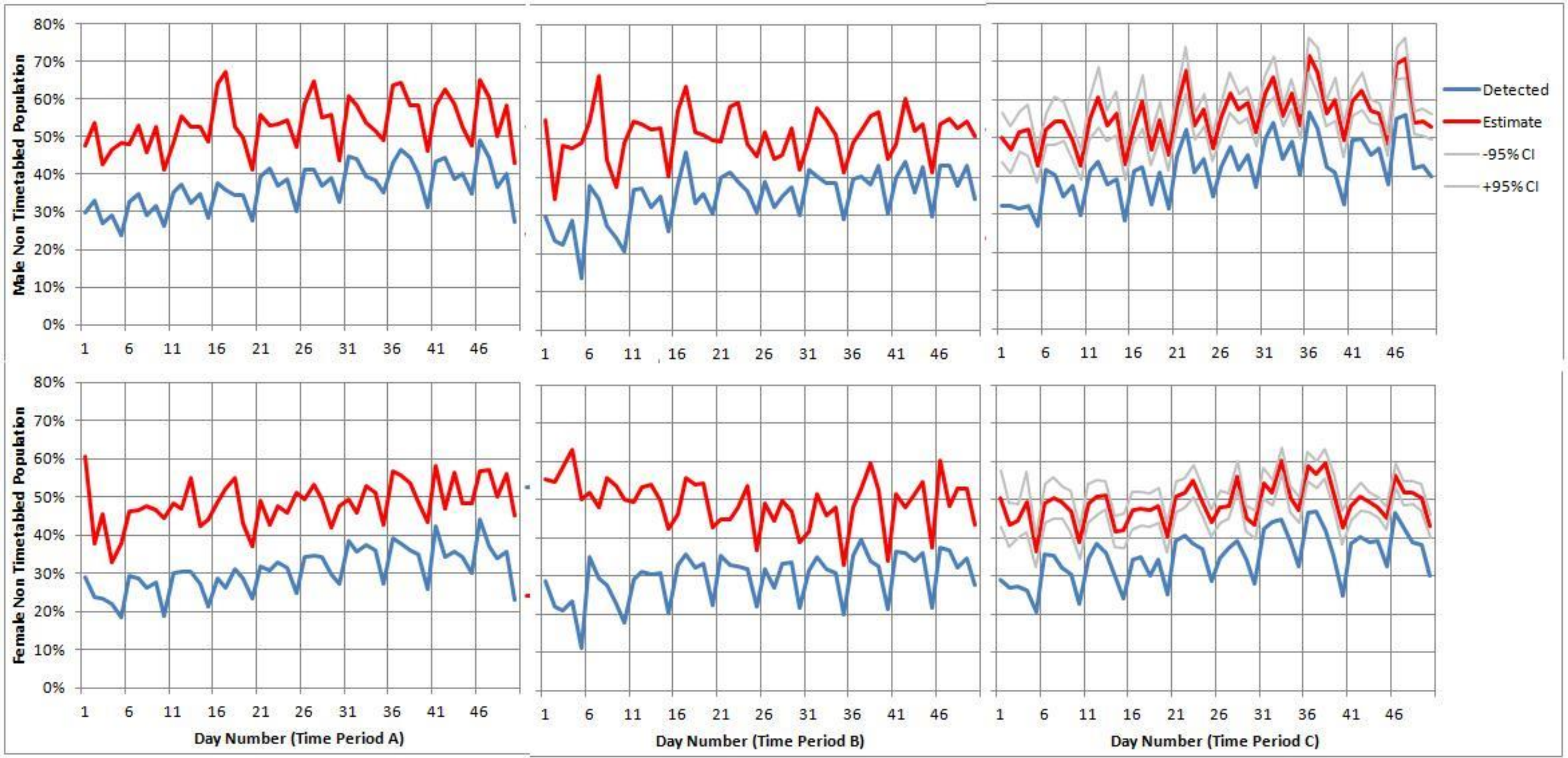


Figure 21 – OSS: Estimated on-campus daily attendance on NTDs

[95% confidence intervals shown around the estimates for the population in period C]

9.4.3 Assigning a trip probability to individual students

The final step in the attendance calculation process is to assign individual trip likelihoods to each cell, t_{ij}, within the trip record matrix so that when the cells are summed for each student i an estimate of their overall attendance on-campus on TTDs and NTDs is obtained (equations 9-1 and 9-2).

To approach this assignment process consider assigning the cells for NTDs in the trip record matrix in the absence of any available information other than the overall attendance figure for the time period as a whole. In this case all applicable cells would receive the same likelihood value, equation 9-23.

$$t_{ij} = \frac{LPntt}{DAYntt} \ \forall\, i,j \ where \ IsnTT(i,j) = 1 \qquad \text{9-23}$$

However, given the daily attendance estimates it is possible to refine the likelihood values so that each student's overall likelihood is dependent upon the attendance figures for just the NTDs in their timetable, equation 9-24. Students with a disproportionately high number of non-timetabled Fridays, for example, would now have a lower overall attendance likelihood compared to those who didn't simply because Fridays are less well attended (Figure 21).

$$t_{ij} = \frac{LPntt_j}{DAYntt_j} \ \forall\, i,j \ where \ IsnTT(i,j) = 1 \qquad \text{9-24}$$

When students are detected on campus, it is known with certainty that they attended on that day and this information can be used to further refine the likelihood estimate for those who weren't detected by assigning a likelihood based on the difference between the attendance estimate and the number actually known to be on campus, equation 9-25.

$$t_{ij} = \left[\begin{array}{l} d_{ij} = 1 : 1 \\ d_{ij} = 0 : \dfrac{LPntt_j - \sum_i IsnTT(i,j) d_{ij}}{DAYntt_j - \sum_i IsnTT(i,j) d_{ij}} \end{array}\right. \ \forall\, i,j \ where \ IsnTT(i,j) = 1 \qquad \text{9-25}$$

In all three cases the total number of non-timetabled student days of on-campus attendance, obtained from summing the cells in the trip record matrix, would be equal to the overall value, *LPntt*. However, whilst the variance of the estimates for each individual within the matrix would be zero in the case of equation 9-23 (since all cells contain the same value), using equation 9-24 would mean that all individuals with the same combination of NTDs would be assigned a unique non-zero value. The variance would increase further through equation 9-25 since the data from those detected on-campus on any given day is used to reduce the scope of the assignment of a likelihood value to only those whose presence on campus could be expected but is not known.

Each refinement to the assignment method increases the possibility of differentiating the behaviour of individual students within the population and the ideal method would improve this level of differentiation by utilising further information regarding each student's on-campus activity available within the matrix d_{ij} and the observational data-set.

Suppose the sub-population of students who always have a non-timetabled day on each Monday within one time period is identified. It is then possible to count the number of Mondays within the time period on which each student was seen entering the library. Some students within this sub-population will have been very conscientious and both attended campus on all 10 occasions and used the library each time, whilst other students may have been on campus on all 10 occasions but never used the library once.

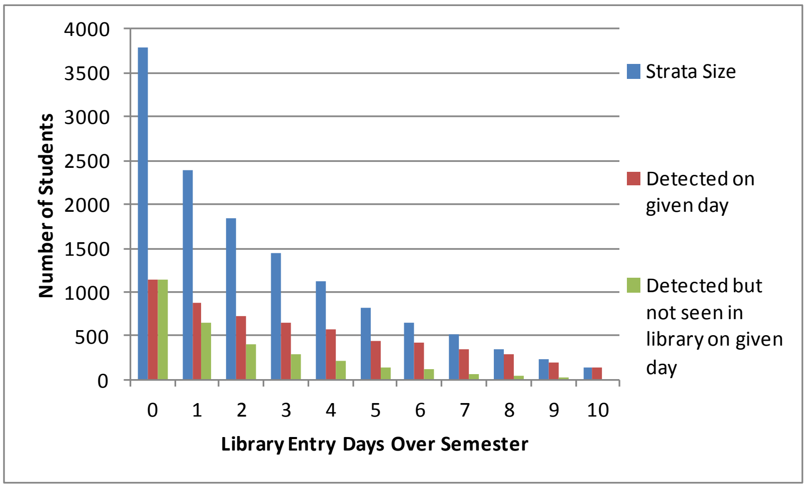


Figure 22 – OSS: Population divided into strata

[Division based on library entries over a 10 day period (1 day per week)]

The students in the sub-population can be divided between 11 strata based on their library attendance on each Monday across the time period (from 0 to 10 times). For any given Monday in the time period it is possible to count the number of students in the strata detected on campus on that day, and the number that were detected on campus but not seen in the library. For the first stratum, containing all students who spent zero days in library across the time period, these two figures will be the same, and when expressed as a proportion of the total this figure will fall in each subsequent stratum, such that in the final stratum, for those students who visited the library on every Monday, there will be zero students who were detected but didn't visit the library, Figure 22.

In each strata there will be an unknown number of students who attended on the given day but were not detected on that day.

Bayes rule provides a mathematically rigorous method for combining prior and conditional probabilities in order to derive the likelihood of a specific conditional outcome, equation 8-1. If the students who were detected and whose attendance is known with certainty are excluded from further consideration then in this context the outcome of interest is the probability of an undetected attendance (UAttend) given that a student is a member of stratum i, equation 9-26.

$$P(UAttend|i) = \frac{P(i|UAttend)P(UAttend)}{P(i)} \qquad 9\text{-}26$$

The prior probability for an undetected attendance can be calculated according to equation 9-25 whilst the prior probability of a student being a member of stratum i can be obtained from the distribution of students across the strata, Figure 22. To solve this equation it necessary to determine the conditional probability that a student is a member of stratum i given that they had an undetected attendance $P(i|UAttend)$.

Within each stratum a number of the undetected students will have used a Wi-Fi enabled mobile phone. Hence the proportion of undetected mobile phone users in each stratum will approximate the conditional probability $P(i|UAttend)$. However, since these proportions will only approximate the true probability and will be subject to a widening confidence interval as the total number of members in the population of each successive stratum reduces, this direct method runs the risk of resulting in probability values for $P(UAttend|i)$ of greater than one and in the sum of undetected attendees in each stratum not being equal to the expected overall total.

The conditional probability curve approximated by the counts of undetected mobile phone users in each stratum needs to be constrained within bounds defining the allowable maximum and minimum number of undetected students within that stratum. Within stratum i the undetected mobile phone users (UMobile) will represent a proportion on the total number of attendees (detected and undetected) within that stratum. The lower bound (LB) for this proportion will occur when all of the population within the stratum attend, equation 9-27, whilst the upper bound (UB) will occur when only detected students within the stratum attend, equation 9-28.

$$LB_i = \frac{UMobile_i}{Population_i} \qquad 9\text{-}27$$

$$UB_i = \frac{UMobile_i}{DetectedInStratum_i} \qquad 9\text{-}28$$

The actual proportion (AP) of undetected mobile phone users compared to the total number of attendees within the stratum will lie somewhere between these two limits. If the actual proportion is approximated using equation 9-29 then the conditional probability for membership of stratum i given undetected attendance can be calculated according to equation 9-30 subject to the constraint that sum of the estimated undetected students over all strata equals the expected total number.

$$AP_i = LB_i + \alpha^{(10-i)}(UB_i - LB_i) \quad 9\text{-}29$$

$$P(i|UAttend) = \frac{(\frac{UMobile_i}{AP_i} - DetectedInStratum_i)}{\sum_i(\frac{UMobile_i}{AP_i} - DetectedInStratum_i)} \quad 9\text{-}30$$

An iterative method (such as Excel Solver) can then be used to find the value of α which gives the required overall level of undetected attendance.

Allocating the undetected population in this way means that the probability of an undetected attendance is highest for the lowest order strata and a greater part of the undetected population is allocated to these lower order strata in comparison with a simple

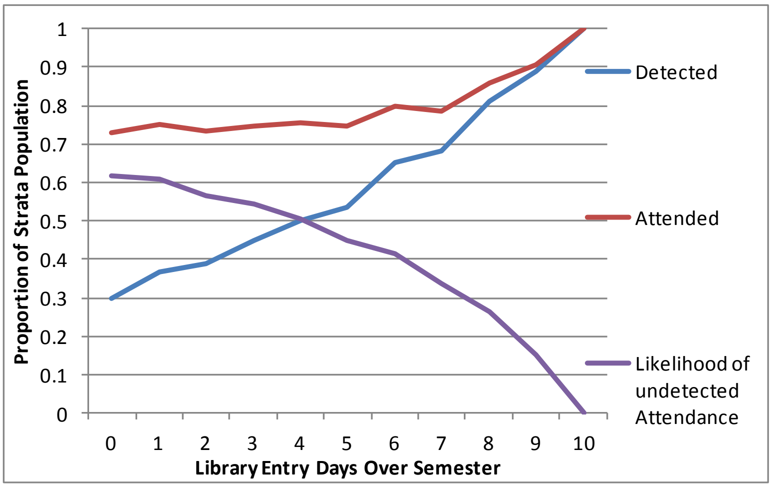


Figure 23 – OSS: Allocation of the undetected population proportion

proportioning method in which the same proportion of members in each stratum would be allocated as being undetected, Figure 23. There may be students in the lower order strata who will have attended on campus regularly but who have used the library infrequently. As has been shown in section 8.4.3, library usage is not universal across the student population and that to a certain extent library usage and fixed computer usage (not in the library) are mutually exclusive. In order to make the best use of the available data, and to ensure a wider dispersion of attendance likelihoods across the population, the attendance allocation method outlined can be applied recursively across the strata based on the on-campus usage of both the library and access to fixed computers. Once the undetected population in a particular library entry stratum has been calculated, the undetected members of this stratum are then divided again into eleven further sub-strata based on their fixed computer access across the time period. The same attendance allocation method is then applied again at this level. This recursive method generates 11x11 unique probabilities of individual attendance for each day across the time period and these are assigned to the population based upon their individual record of use of the library and fixed on-campus computers.

The method was applied to the gender specific timetabled and non-timetabled populations over each weekday in each of the ten weeks across the three time periods. This involved the calculation of sixty distinct population distributions. The method assumes that a student's weekly pattern of TTDs remain constant across the time period, although changing timetables are a common feature the student experience. For example, in time period A 75% of students have a timetabled session on every Monday, whilst a further 11% have no timetabled sessions on any Monday. For the remaining 14% their timetable varies from week to week meaning they have classes on between one and nine of the ten Mondays across the time period.

Students with a variable timetable are allocated to the timetabled population if they have classes on six or more of the ten similar days within the time period, and to the non-timetabled population otherwise. However, this means that on any given day those students who don't have a timetabled class but are allocated to the timetabled population will be assigned an attendance likelihood based on the TTD attendance probability (≈90%) rather than the NTD probability (≈50%). This artificially raises the attendance probability for these students, whilst at the same time lowering it for those students who have timetabled classes but who are allocated to the non-timetabled population. To overcome this problem, the calculation of attendance likelihood is modified so that the non-conforming minority of students in each stratum obtain their attendance likelihood from the same stratum in the parallel population.

The trip likelihood matrix, t_{ij}, is populated according to equation 9-25 with t_{ij} being set to 1 when the corresponding value in d_{ij} is also 1 and with the attendance inference method being used when d_{ij} is 0. An estimate of the overall attendance for a student i across the time period can be obtained by summing the values in the trip likelihood matrix, t_{ij}, whilst the individual probability of attendance on timetabled and NTDs can be calculated according to equations 9-31 and 9-32.

$$P(tt)_i = \frac{\sum_j IsTT(i,j)t_{ij}}{\sum_j IsTT(i,j)}$$

The probability of student i making a trip to campus on a timetabled day (9-31)

$$P(ntt)_i = \frac{\sum_j IsnTT(i,j)t_{ij}}{\sum_j IsnTT(i,j)}$$

The probability of student i making a trip to campus on a non-timetabled day (9-32)

Summing the elements within t_{ij} for timetabled, non-timetabled and weekend days over all students and across each time period produces the total number of students days on which a trip was made to campus, largely matching the figures estimated in section 9.4.1 and on which the individual trip probabilities are based, Table 51.

Gender	Time Period	TTD		NTD	
		Attend (%)	Standard Deviation	Attend (%)	Standard Deviation
Male	A	91.74	3.42	49.82	25.33
	B	91.72	3.67	47.98	23.33
	C	91.81	4.19	51.29	24.22
Female	A	93.62	2.27	46.20	23.28
	B	93.50	2.39	45.98	21.80
	C	93.67	2.86	45.98	23.37

Table 51 – OSS: Mean Individual Attendance Levels

A comparison of these figures with those given in Table 49 shows that the mean level for individual attendance on TTDs and NTDs is below the overall estimated level and this is due to the probability reassignment process. The magnitude of the numerical discrepancy is equivalent to the net difference between the attendance probabilities for TTDs and NTDs multiplied by the net difference in the number of TTDs and NTDs being reassigned. However, in all cases the overall difference is negligible at around 1%

Distributions of the estimated individual probabilities of attendance across the three time periods, for TTDs and NTDs are shown in Figure 24 and Figure 25 respectively. A normal distribution, derived from the mean and standard deviation associated with the population of individual attendance probabilities is superimposed on each plot. The proportion of each attendance probability that is known with certainty is shown in each distribution. This is based on the number of days each student was detected relative to the number when they weren't. The degree of certainty is greatest at the high end of the distribution, and the inference process becomes less certain with reducing attendance probabilities. The distributions for TTDs are compressed into the top fifth of the probability spectrum with no attendance probabilities lower than 0.8 recorded in any of the time periods. These distributions become more positively skewed in the later time periods, due to there being more days where attendance is known with certainty, and meaning that the inference process is applicable to successively smaller subsets of the student days, thereby revealing an estimated distribution that will be closer to the real attendance distribution. These distributions also indicate more homogeneity of behaviour in female students, compared to their male peers.

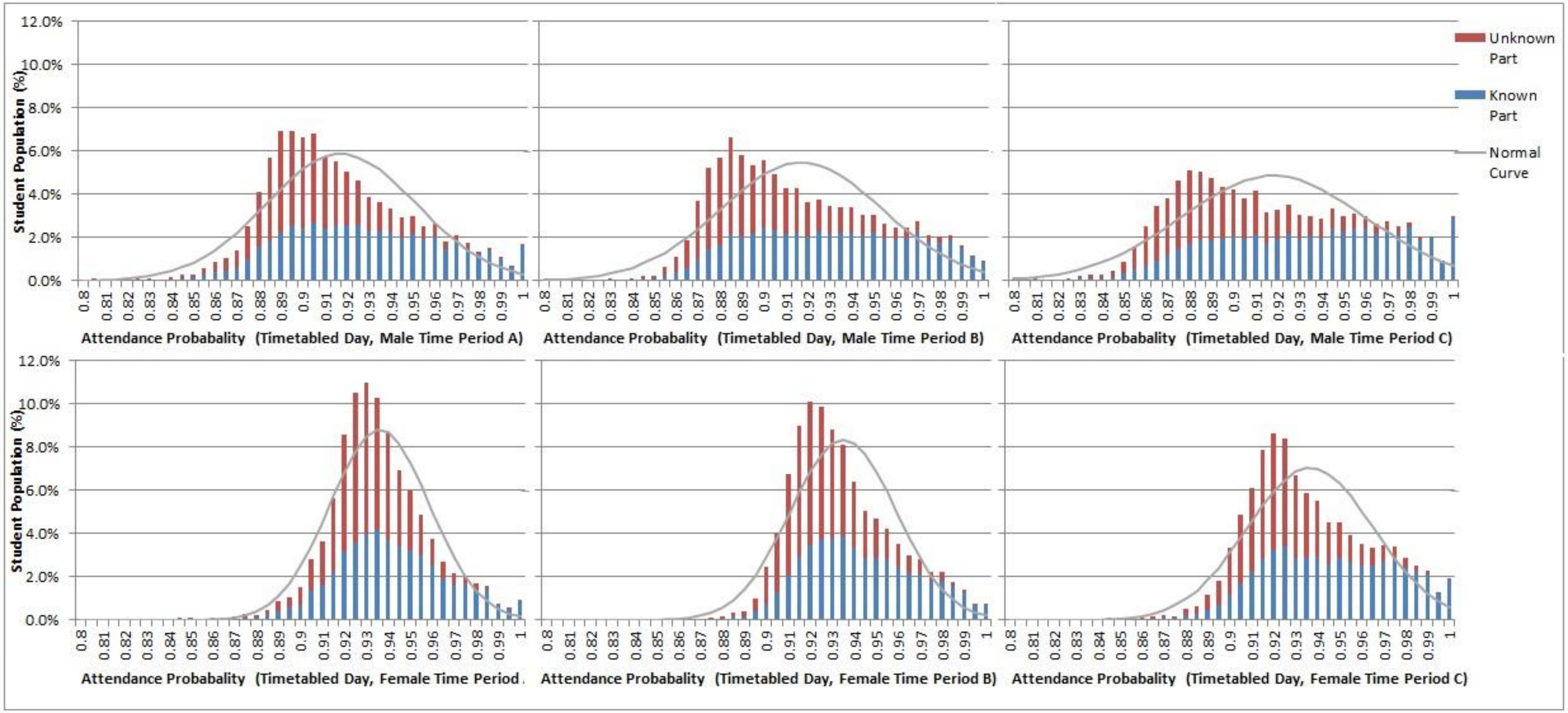


Figure 24 – OSS: Distribution of TTD Individual Attendance Probabilities

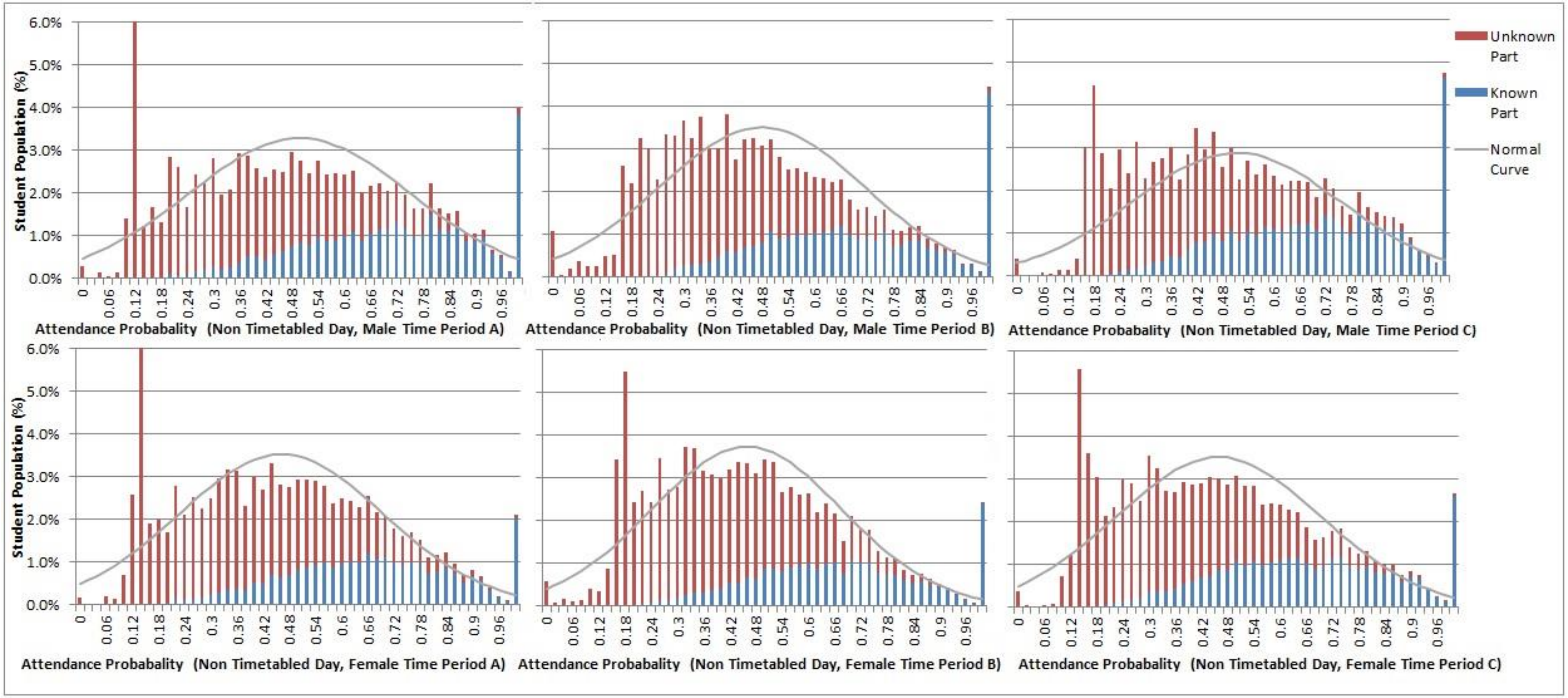


Figure 25 – OSS: Distribution of NTD Individual Attendance Probabilities

[6.8% of male students and 8.0% of female students were estimated to have an attendance probability of 0.12 in time period A]

The plots for NTDs are more interesting, and all follow a predominately normal distribution.

The lower than expected frequencies at the bottom end demonstrates a weakness of the inference method. It might be expected that on NTDs some students, perhaps those who live remotely, will never attend on campus, and consequently their electronic record of detection on-campus over all NTDs will be empty. However, the inference method can never assign a probability of attendance of zero because the difference between the estimated daily on-campus population and those actually detected on-campus will be shared between all members who were undetected on that day. When many students have similar detection profiles (i.e. they are never detected) they will all receive identical attendance probabilities. This is why the non-timetabled day distributions exhibit a degree of kurtosis in which a few low probability values occur with high frequency.

The cause of the higher than expected frequency for individuals with a probability of attendance of 1, is as a result of these individuals being detected on campus on all of their NTDs. When students have few NTDs the attendance probabilities assigned to them will be widely distributed at the extreme ends of the distribution and the effect of detection on-campus on any of their (few) NTDs will be more influential than it would be for those students with more NTDs. 4% (7%) of the population have a single non-timetabled day in periods A and C (period B) with 2% (4%) having two NTDs. The high frequency of low numbers of NTDs in student timetables has the potential to explain this feature.

The distribution of attendance on NTDs suggested by the TQS is positively skewed, section 7.3.2, whilst the distribution of inferred probabilities, based on the robust application of conditional probability theory (Bayes rule), is (almost) perfectly normal. The inference method will assign the same attendance probability to all undetected students within one strata on any given day, although the real probabilities of attendance for the students in the group may more closely approximate the distribution described by the TQS results. Obtaining the true distribution would require the inclusion of co-variants in the inference process, meaning that any subsequent analysis of the inferred probabilities by co-variant terms would not be possible. Therefore a normally distributed set of attendance probabilities is a direct consequence of the co-variant free inference method.

Distributions of the number of trips each student is estimated to have made to campus on TTDs, NTDs and over each time period are shown in Figure 26 for male students and in Figure 27 for females.

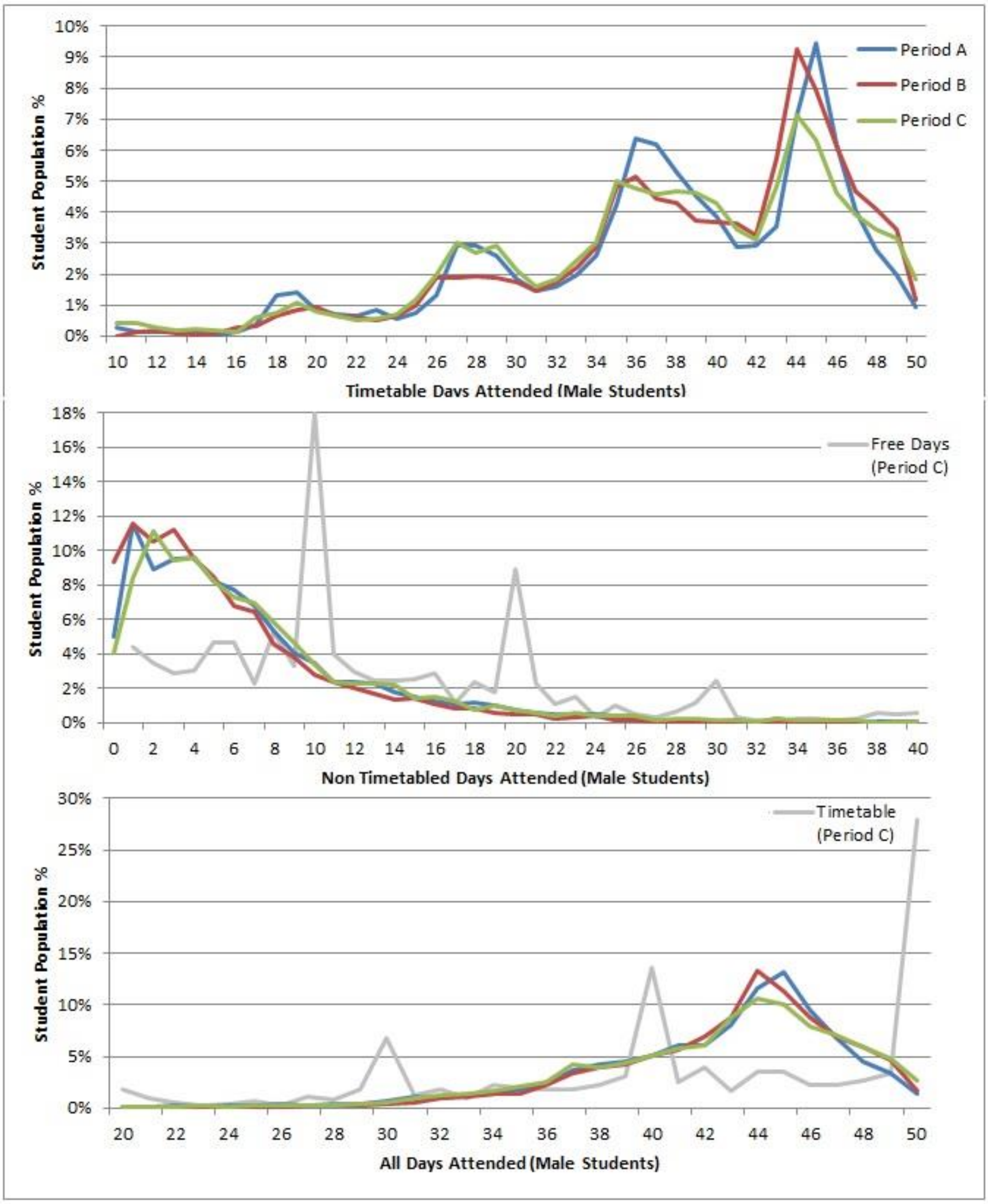


Figure 26 – OSS: Attendance Distributions for Males by Day Type

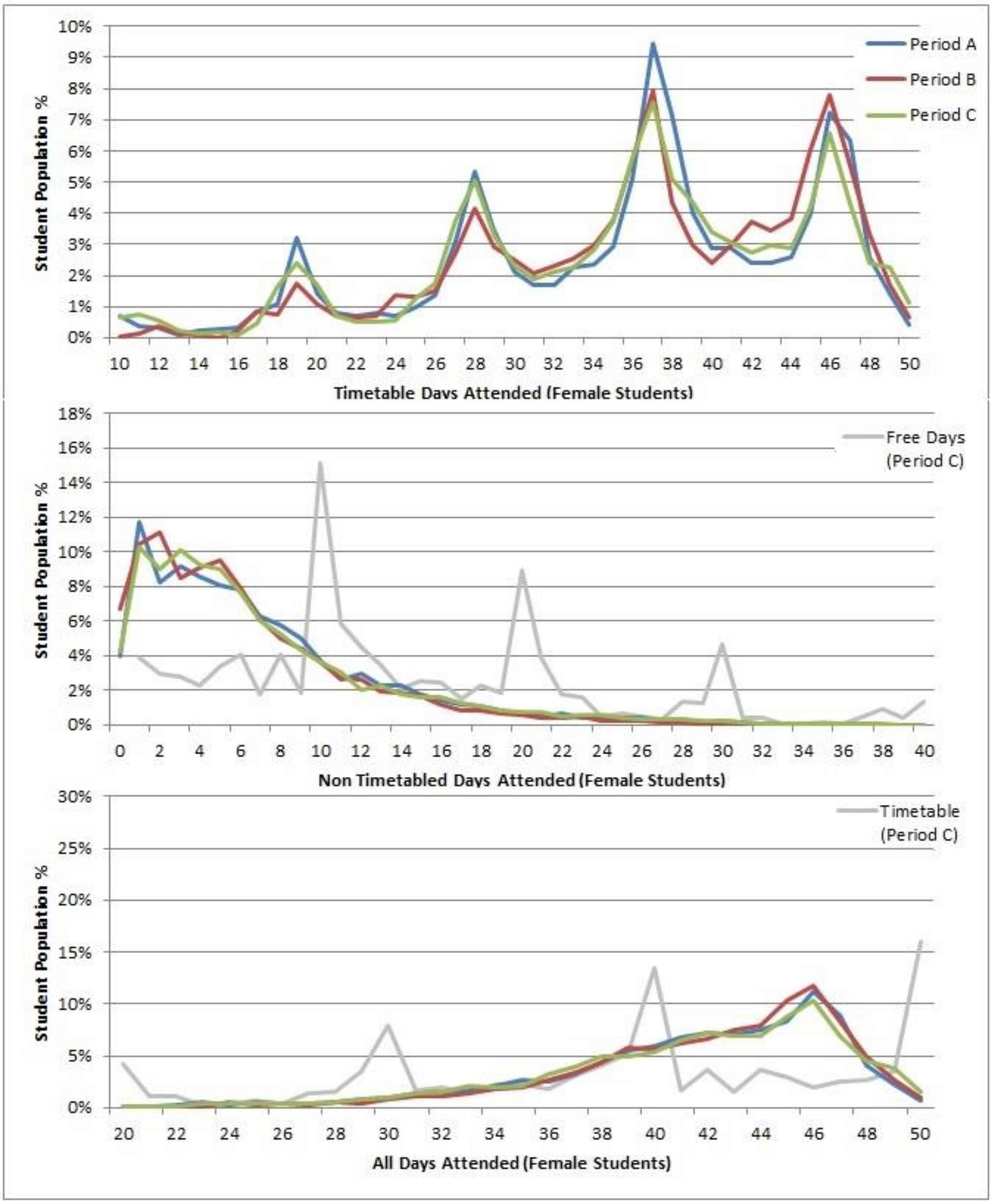


Figure 27 – OSS: Attendance Distributions for Females by Day Type

The distributions for attendance on TTDs have four modal values demonstrating the typical timetabled day attendance for students with between two and five TTDs per week.

On NTDs the modal value is shown as being around 1 or 2 days on-campus, whilst the shape of the distribution suggests that the real modal value is probably zero. This confirms the existence of the issue described earlier around the problem of assigning low non-zero attendance probabilities for students who are rarely detected on-campus.

A distribution showing the frequency of occurrence of NTDs in the population, superimposed over the inferred non-timetabled attendance, shows that unlike TTDs there is no apparent pattern for attendance on these days.

The modal value for overall attendance on-campus for both males and females is around 45 or 46 days, whilst the mean attendance for females is around 42 days (not shown), and for males it is significantly higher at 43 days (independent samples t-test, significant at 1% level). Although females have a higher attendance probability on TTDs, male timetables include more TTDs, and this combined with their higher attendance probability on NTDs results in a higher mean attendance. The distributions for all three time periods appear to be reasonably consistent.

9.5 Analysis of the Trip Probabilities

The previous section described the method used to estimate an overall trip rate on TTDs and NTDs, the number of trips to campus by day, and individual trip probabilities for each student. This section will analyse and discuss these estimates.

9.5.1 Analysis of the Overall Trip Rates

The overall trip rates for TTDs suggested by the LP estimates (period C) correspond to those suggested by the TQS, section 7.3.1, although the difference between the attendance rates for males and females as suggested by the LP estimates are slightly larger than those identified in the TQS.

Overall the TQS and LP estimates suggest that student absence rates for TTDs are approximately twice as large as employee sickness/absence rates.

The estimates for attendance on NTDs show a greater degree of variance with overall LP estimates of attendance at around 52% of days for males and 48% of days for females, compared to TQS figures of 39% and 34% respectively.

However, as shown in Figure 21 non timetabled attendance rises continually over the 10 week time period, whilst the TQS figures are based on a self-reported estimate of attendance during the first 7 weeks of the autumn semester. Therefore the LP estimates will overstate the figure for attendance to the end of week 7, the equivalent overall LP estimate for attendance up to the end of week 7 is 48.5% of NTDs in period B compared to 37% reported by the TQS. This suggests that either the LP estimate is over-reporting the true level of NTD attendance, or that the TQS under-reports trips.

However, over 28% of all the student days in the first 7 weeks of time period B are known with certainty to include a trip to campus, since the students were electronically detected on campus over the course of the day, giving a known lower bound which is almost 80% of the total attendance reported through the TQS. Similarly, as shown in Figure 21, the proportion of students detected exceeds this overall TQS attendance estimate during the latter part of the time period.

Of the students who used a Wi-Fi enabled mobile phone more 50% did not access any other detectable resource whilst on-campus which suggests there will be some non mobile users who likewise weren't detected at all whilst on campus. Whilst there could be some heterogeneity in behaviour between these two groups, the level of non-detected students in the non smart phone group would need to be half that of the group with smart phones for the estimate from the TQS to be correct.

The attendance level suggested by the ratio of Portal logins on timetabled and NTDs, see section 8.4.2, provides independent support for the LP estimates.

Finally, the survey methodology of the TQS itself may have resulted in an underreporting of the true level. In the TQS respondents were asked to state the probability of their likely overall attendance on NTDs using a 5 point scale, with values of 0, 0.25, 0.5, 0.75 and 1. With the exception of the first and last responses, where students might be expected to know their trip frequency with certainty, the intermediate responses are imprecise and suggest that some correction for reporting error might be required. Furthermore studies using GPS to compare travel survey respondents actual travel behaviour with their self-reported travel behaviour show that participants often under-report the number of (particularly short) trips that they have taken (Bonsall, 2006, Bricka et al., 2009).

For these reasons it is reasonable to assume that in the TQS students underreported their presence on-campus on NTDs. If the 5 point scale used in the TQS is recalibrated so that the three intermediate response levels (0.25, 0.5 and 0.75) are increased by 0.125 then the overall trip rate on NTDs, as reported through the TQS increases to 46% and this is then within the confidence intervals calculated for the LP estimate of non-timetabled attendance.

It could be that the underlying LP estimates for NTD attendance are positively biased, and that the actual attendance on NTDs is lower than calculated. However, the individual inference method ensures that the rank order of attendance probabilities between students is independent of the overall attendance level and hence analysis of the individual factors affecting attendance remains valid even if the overall level is incorrect. Similarly if attendance on NTDs is lower than estimated then any findings related to non-attendance on NTDs will be understated, meaning that the real effect will be larger than that reported.

9.5.2 Analysis of the Daily Trip Probabilities

This section examines how the number of students on campus on a given day varies across the weeks and days within each time period. On any given day the population of students can be divided into four sub-populations by both gender and whether the student has a timetabled session on that day.

Highly significant correlations exist between the size of each daily sub-population and the corresponding on-campus attendance (Pearson correlation coefficient > 0.95, significant at 1% level in all cases) suggesting that the overall trip probabilities are the main factor in determining the level of daily attendance, and that weekly and daily factors are less important.

To examine the daily on-campus population further a LRM was built with the dependent variable being the attendance level of each sub-population on any given day, expressed as a percentage of the whole sub-population. Encoding the dependant variable in this way means that the values of the coefficients for each parameter in the fitted model described the percentage change in the population that occurs as result of a unit change in the parameter. Independent variables, were included for time period, week and day. Dummy variables were used to represent the time periods and days of the week, and two continuous variables employed to encode the week number, using the same method as described in section 8.4.2.

The first attempt to build the model resulted in a poor fit, and consequently the population was subdivided by academic term. This is reasonable as student trip-making behaviour may be expected to vary between terms, since students are at different points within the academic year. The fitted models, and the eight sets of coefficients produced, are shown in Figure 28. In each case the constant represents the percentage attendance on the Monday of a notional week zero and the estimated attendance for any day x in week y of time period z can be obtained by multiplying the relevant week coefficient by y and adding the corresponding coefficients from the dummy variables corresponding to x and z.

		Daily On-Campus Attendance							
		Female				Male			
		Autumn Term		Spring Term		Autumn Term		Spring Term	
		Non TT	TT	Non TT	TT	Non TT	TT	Non TT	TT
Adjusted R^2		0.5	0.64	0.5	0.74	0.24	0.74	0.69	0.83
Standard Error		4.577	1.771	3.866	1.267	5.543	1.737	3.878	1.46
Durbin Watson		1.591	1.5	1.912	2.436	2.086	1.48	1.439	1.998
COEFFICIENTS	Constant	54.77	99.23	46.80	97.72	47.04	99.11	50.09	98.29
	Period A			0	0			0	0
	Period B	0	0			0	0		
	Period C			0.46**	-0.04**			2.025*	0.06**
	Weeks 1-5	-1.367	-0.639	0.894	-0.363	1.731	-1.103	1.359	-0.662
	Weeks 6-10	-0.73	-0.728	0.836	-0.509	0.685	-0.936	1.169	-0.775
	Monday	0	0	0	0	0	0	0	0
	Tuesday	0.30**	-0.87**	-2.34**	0.35**	2.37**	-1.19**	2.69*	-0.47**
	Wednesday	3.17**	-3.11	0.09**	-2.33	-0.60**	-4.51	-4.69	-4.88
	Thursday	3.15**	-1.47**	-4.81	-1.14	-1.67**	-1.18**	-3.15*	-1.54
	Friday	-8.92	-2.08*	-8.51	-3.32	-7.05	-2.37	-11.19	-5.33

Figure 28 – OSS: Daily Attendance Variation Model

[All coefficients significant at the 1% level, except *=5%, **=not significant]

The attendance models for TTDs fit well, whilst those for NTDs, particularly males in the autumn term, are a poorer fit.

Inspection of the residuals showed a normal distribution in all models, and examination of scatter plots of the predicted value against the residual showed a random distribution indicating no evidence of heteroscedasticity. The Durbin Watson test statistic is above the threshold value of 1.6 in most models indicating that the error terms are independent and that there is no correlation between pairs of residuals. The lower values for TTDs in the autumn term possibly suggest that the degree of daily variation changes across the weeks to a greater extent than in the spring term.

The model constants correspond to the aggregate attendance figures for TTDs and NTDs, with slightly higher values for females compared to males on TTDs whilst the higher values in the autumn term, compared to the spring term, suggests that the timetabled population on-campus will be at its highest during the first week of the academic year. The pattern of attendance over the two spring term time periods (A+C) are equivalent, although there is a higher overall NTD attendance in period C of 0.5% for females and 2% for males.

The coefficients representing variation due to the days of the week show that on TTDs attendance on Mondays and Tuesdays is similar but from Wednesday onwards trips to campus begin to be made less frequently and that the lowest attendance across the week will occur on each Friday. The daily variation becomes more marked on the spring term. The coefficients for NTDs follow the same pattern but suggest more extreme levels of variation, particularly on Fridays.

The coefficients for the week based parameters show that trips to campus on TTDs for males and females alike reduce by over 0.5% per week through the time period and that the rate of reduction increases the time period progress (with a higher coefficient value in the 2nd half of the period). The pattern of on-campus attendance on TTDs across the days of the week, and the weeks of the time period conforms to that observed in studies of session attendance, which has been shown to fall across the semester (Van Blerkom, 2001) and be lower on Wednesdays and Fridays (Devadoss and Foltz, 1996, Newman-Ford et al., 2008). This indicates that a partial cause of this drop in session attendance, is as a result of students staying away from campus, as opposed to being engaged in other activities on campus.

On NTDs daily attendance rises with each successive week, with the highest rate of increase occurring in the first half of the period. This can perhaps be explained by the coursework demands placed on students with hand-in dates biased towards the end of the semester. However, female non-timetabled attendance in the autumn term does not follow this pattern. In this case the coefficients suggest that the percentage attendance starts high and falls throughout the time period. This pattern is visible in the charts shown in Figure 21 and it is interesting to speculate regarding the causes. It could be that as the more conscientious gender, some, perhaps 1st year, female students start the academic year with the intention of attending on-campus every day, but that as the time period progresses, they learn that it is possible to work as (or more) effectively at home (see section 7.3.3) and reduce their attendance on NTDs.

Another interesting feature of the daily attendance models is that with the exception of females in the Autumn term the attendance on NTDs rises as the attendance on TTDs falls. This suggests, perhaps, that time-pressure from assignments encourages students to stay at home to work on them on TTDs but at the same time also encourages them to attend more frequently on-campus on NTDs in order to get them completed. It is not clear if these trends represent two distinct sub-populations or whether individual students simultaneously attend less frequently on TTDs and more frequently on NTDs. This requires further investigation.

As identified in section 5.2.1, the proportion of the population engaged in timetabled activities across the days of the week is split with more students having sessions on the TTH days: Monday, Tuesday and Thursday. The Pearson correlation coefficients between the size of the population with TTDs and NTDs and the attendance on that day shows a significant positive correlation (at the 1% level) of 0.376 for TTDs, and a similarly significant negative correlation of -0.444 for NTDs. This suggests that timetable planners recognise that attendance will be lower on some days, particularly Friday, and partially adjust the timetable so that fewer sessions are scheduled on these days. Similarly, the negative correlation for NTDs (proportional attendance is lower when more students have a NTD) also suggests that the TTH days are recognised by some non-timetabled students as being reserved for academic study.

9.5.3 Analysis of the Individual Trip Probabilities

The methods used to infer the individual trip probabilities for timetabled and NTDs, as described in section 9.4.3, only use as input each student's gender, the number of days in their timetable containing scheduled sessions and a record of their electronic activity whilst on-campus captured through the observational dataset.

Consequently, provided the assignment method is valid and captures some of the true characteristics of student trip-making behaviour then the co-variants held against each individual within the population should vary systematically and provide some insight into the factors behind student trip-making decisions.

The analysis of the TQS data described in section 07.3 identified factors that affect the student trip-making decision on TTDs and NTDs. Therefore analysing an individual's trip probabilities against their demographic and academic covariants should highlight the same factors, whilst the larger size of the observational dataset, as compared to the TQS sample, might mean that additional factors are also found to be significant.

9.5.3.1 Attendance On-campus on Timetabled Days

For each student their overall probability of making a trip to campus on a timetabled day, $P(tt)_i$, has been estimated.

The attendance data gathered through the TQS, asked each respondent to state the number of TTDs they had missed coming to campus and this figure was used directly in the corresponding analysis as the dependent variable. It is relatively easy to convert a probability of attendance to the number of days missed (and vice versa) and this analysis could also be performed using days missed. However, this approach may bias the analysis since the number of candidate days available to be missed is dependent upon the number of TTDs in each individual timetable, meaning there is the potential for any model to be biased by higher responses from those individuals with more TTDs. The figure for probability of attendance is independent of number of TTDs and for this reason it was decided to use this instead in the analysis.

As has already been discussed in section 9.4.3 the inference process has a compressive effect on the distribution of individual attendance probabilities reducing the magnitude of the deviation around the mean. This reduces the statistical power of any model built to analyse the data since the degree of any differences between groups of individuals within the model will be similarly less pronounced.

An OLR model was chosen to analyse the factors affecting the probability of attendance on TTDs, with the individual probabilities being split into three equally sized categories, each representing one third of the full distribution. Three categories were chosen in preference to four as it was felt that if the model included any coefficients that work in an opposite direction at the either end of the distribution of attendance probabilities it, a model fit was more likely when the extreme category boundaries were closer together (covering 33% of the distribution as opposed to 50% in the four category case). To further improve the fit of the model, the 3.5% of the population with fewer than 20 TTDs within any time period were excluded from the analysis, leaving 46,300 observations spread over the three time periods.

Prior to building the model, the data was split into six groups by gender and time period. Independent variables were then included to represent each student's year of study, and their residential distance from campus encoded in a single dummy variable to represent students living within 0.5 miles of campus, and those living further away. Two variables were included to represent characteristics of the student's timetable. TTDs per week was included using a dummy variable to represent those timetables with less than 40 TTDs in the time period, and a second dummy variable was used to indicate if the student's timetable was one of the third of all timetables in which more than 33% of their TTDs contain a single session.

A further independent variable was added to represent the degree classification category (5 categories from fail to first class) of the student's semester end mean module mark. As discussed in section 2.7.1 attendance at lectures has been shown to be related to academic outcome, and so it is reasonable to assume that given attendance on-campus is prerequisite of attendance at lectures, then the more successful students might also demonstrate a greater desire to attend on campus. Although it could be argued that academic outcome is dependent on attendance (and not the other way around) this variable can also be thought of as a proxy for motivation or ability, and its inclusion gives some indication of the relationship between these factors and attendance, even if no conclusions can be drawn about the causality of any links.

The results of fitting the model to the data are shown in Figure 29. Whilst the model doesn't fit the data well, the model fit for male students is better than for females. For male students the goodness of fit test is passed (non-significant p value) in two out of three cases, whilst the test of parallel lines was passed in one out of three cases. However, in all three cases the coefficients for the fitted model are similar in terms of sign and magnitude suggesting some consistency between the models.

The fit for female students is poorer with both the goodness of fit and parallel lines tests failing in all models. Recasting the models, without the timetable related parameters causes these three models to fit the data, whilst the trend and magnitude of the effects described by the coefficients for the retained parameters remains the same as in the full model. This suggests that the cause of the non-fit is related to either the timetable variables or due to the fourfold increase in cells that occurs when the timetable parameters are added. Since the coefficients in the full models for both male and female students are similar, the full model for females was retained.

			TTDs Attendance Probability, $P(tt)_i$					
			Female			Male		
Test Statistics			A	B	C	A	B	C
% Cells With Zero Expected Value			13.3	11.7	8.9	9.4	12.8	13.5
Model Fit p Value			<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Pearson Goodness of Fit, p Value			<0.001	<0.001	<0.001	0.195	0.235	0.011
Nagelkerke Pseudo R^2			0.026	0.037	0.034	0.05	0.058	0.072
Test of Parallel Lines, p Value			<0.001	<0.001	<0.001	0.027	0.203	0.025
COEFFICIENTS	Threshold	1st Third	-2.806	-2.299	-1.946	-0.772	-0.775	-0.9
		2nd Third	-0.278*	-0.103**	-0.184**	0.296	0.099**	-0.159**
	Academic Year	1st Year	-0.408	-0.67	-0.467	-0.628	-0.871	-0.711
		2nd Year	-0.183	-0.306	-0.121*	-0.3	-0.525	-0.342
		3rd Year	0	0	0	0	0	0
	Academic Outcome	<40	-0.693	-0.929	-1.271	-1.112	-1.045	-1.673
		40-49	-0.477	-0.574	-0.6	-0.851	-0.704	-0.877
		50-59	-0.283	-0.444	-0.364	-0.693	-0.458	-0.597
		60-69	-0.154*	-0.244	-0.246	-0.408	-0.285	-0.356
		>=70	0	0	0	0	0	0
	Residential Distance	>=0.5 miles	-0.545	-0.293	-0.308	-0.236	-0.328	-0.372
		0-0.5 miles	0	0	0	0	0	0
	Single Sessions	<33%	0.094*	0.271	0.252	0.311	0.399	0.463
		>=33%	0	0	0	0	0	0
	Timetabled Days	<40 Days	0.168	0.025**	0.074**	0.098**	-0.199	-0.087**
		>=40 Days	0	0	0	0	0	0

Figure 29 – OSS: Factors Affecting Attendance on TTDs

[All coefficients significant at the 1% level, except *=5%, **=not significant]

Examination of the coefficients assigned to the parameters show that $P(tt)_i$ increases with academic year, and decreases as residential distance increases. These findings partially confirm those found in section 7.3.1 (residential distance) but identify an opposite trend regarding academic year. This discrepancy is discussed further in section 9.6.

Whilst the effect of the number of TTDs on attendance appears to be largely non-significant, those students who have the greatest proportion of single sessions in their timetable are likely to attend less frequently, confirming the qualitative findings outlined in section 6.4.9. The coefficients assigned to the academic outcome parameter, show that attendance probability increases with mean module mark, and that those students achieving the highest marks will have a higher mean attendance probability than all of those in the lower categories.

There is very little variation between the mean attendance probabilities associated with each combination of parameters. Whilst this is due partly to the compression of the overall attendance distribution on which the model is based, it also reinforces the message that for many students trips to campus on TTDs are regarded as being mandatory.

9.5.3.2 Attendance On-campus on Non-Timetabled Days

The estimate of the probability for individual attendance on non-timetabled day, $P(ntt)_i$, was examined in a similar way to that for TTDs, by using an OLR model.

A categorical dependant variable with three levels was computed from the individual attendance probabilities, whilst independent categorical variables were included in the model to represent academic year, outcome, residential distance from campus, and with a dummy variable to indicate whether the student is enrolled in a predominately science based or an arts based faculty. In order to provide a better indication of any link between attendance probability and residential distance, the variable for this parameter was divided into four categories representing a series of concentric rings around the centre of campus. Again the population was grouped by gender and time period producing a series of six models, the results of which are shown in Figure 30.

			NTDs Attendance Probability $P(ntt)_i$					
			Female			Male		
Test Statistics			A	B	C	A	B	C
% Cells With Zero Expected Value			9	9.5	10.1	7.5	7.2	7.8
Model Fit p Value			<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Pearson Goodness of Fit, p Value			<0.001	<0.001	<0.001	<0.001	0.009	0.096
Nagelkerke Pseudo R^2			0.171	0.116	0.172	0.143	0.101	0.165
Test of Parallel Lines, p Value			0.015	<0.001	0.017	0.808	0.072	0.439
COEFFICIENTS	Threshold	1st Third	-0.941	-0.813	-1.062	-1.238	-1.117	-1.349
		2nd Third	0.606	0.868	0.515	0.154*	0.456	0.187**
	Academic Year	1st Year	-1.299	-1.111	-1.237	-0.931	-1.085	-1.233
		2nd Year	-0.414	-0.581	-0.577	-0.438	-0.506	-0.596
		3rd Year	0	0	0	0	0	0
	Academic Outcome	<40	-1.376	-0.864	-1.862	-1.713	-0.934	-1.658
		40-49	-0.8	-0.45	-1.14	-1.01	-0.665	-0.831
		50-59	-0.555	-0.181*	-0.8	-0.831	-0.416	-0.471
		60-69	-0.181**	0.092**	-0.486	-0.333	-0.194*	-0.023**
		>=70	0	0	0	0	0	0
	Residential Distance	0-0.5 miles	0.862	0.988	1.125	0.559	0.655	0.837
		0.05-2 miles	0.634	0.664	0.941	0.533	0.457	0.512
		2-4 miles	0.334	0.21*	0.518	0.277	0.172**	0.119**
		>=4 miles	0	0	0	0	0	0
	Faculty of Study	Science Based	0.745	0.207	0.436	0.633	0.286	0.391
		Arts Based	0	0	0	0	0	0

Figure 30 – OSS: Factors Affecting Attendance on NTDs

[All coefficients significant at the 1% level, except *=5%, **=not significant]

Again the goodness of fit measures fail in five out of six cases, but given the number of empty cells within the model the results of this test should be treated with caution. The result for the parallel lines test is non-significant for all three of the models representing male students, whilst two of the models for female students give values which are significant at the 5% level, suggesting that the relationships in the data are relatively constant across the three dependant variable categories. However, these tests are not significant in a recast model, excluding the dummy variable for faculty of study, whilst the sign and trends indicated by the other coefficients remain the same. Therefore the full models were retained for all six groups.

The models suggest that the probability of a student making discretionary trips to campus on NTDs increases with academic year, that it decreases with residential distance and that those students who achieve a higher attainment level will make more trips and attend more frequently. The model also shows that students in the science based faculties also attend more frequently than their contemporaries in the arts. Since the estimation of the overall trip probabilities has already identified that males attend more frequently on NTDs, section 9.5.1, all these findings are consistent with those found through the TQS and as described in section 7.3.2.

It had been suspected that the gender difference in attendance probabilities might have been skewed by the higher relative proportions of male science students and female arts students. Science students will typically require specialist equipment only available on-campus, whilst arts students may be more able to study remotely using books and online resources. However, if this hypothesis were to be true the coefficients for the arts/science dummy variable would differ between the male and female models. Given that these coefficients are broadly similar it suggests that increased overall levels of male attendance are independent of the subject studied. The largest coefficient responsible for driving down attendance probabilities is related to academic year, with the difference in the attendance probability between a first year and third year student being greater than the difference between that for the most and least able student.

This suggests that whilst the mean non-timetabled day attendance probability is around 0.5, for first years this reduces to around 0.4, and for the weaker students within this cohort (who will attain marks below 50%) this falls further to around 0.33. Variation in residential distance and faculty of study act as modifiers on these attendance probabilities increasing or reducing them slightly, but year of study and attainment level appear to primarily determine $P(ntt)_i$. Across the population it will be the academically weak female first year art students who live remotely who will have the lowest overall attendance probability.

9.5.3.3 Attendance On-Campus Overall

The previous two sections demonstrated that individual attendance probabilities on TTDs and NTDs are both influenced by the same set of factors: academic year, residential distance, and attainment level. Therefore it is not surprising that there is a highly significant Pearson correlation coefficient of 0.318 between $P(tt)_i$ and $P(ntt)_i$. Those students who attend more conscientiously on TTDs are also more likely to visit campus on NTDs.

Whilst the mean ratio for attendance on TTDs compared to NTDs is just under 2:1, the relative differences in the standard deviations associated with $P(tt)_i$ and $P(ntt)_i$ suggest that this ratio will be higher for the less conscientious students, meaning that whilst their attendance will be only slightly below the mean level on TTDs, it may fall way below average on NTDs. As described in section 7.3.4, the differential attendance probabilities between timetabled and NTDs, mean that the most significant influence in terms of determining the overall level of attendance on-campus will be the total number TTDs included in the timetable. When the number of TTDs is higher, students who would otherwise attend less often, due to a low value of $P(ntt)_i$ will be forced to visit campus more frequently because more of their trips will be considered to be mandatory (RQ2, supporting H1a).

A LRM was developed to examine the number of days across the time period in which each student didn't attend on-campus. The dependant variable (the number of days missed) is not an ideal candidate for linear regression modelling as it has a fixed lower bound; zero days missed. However, despite this limitation it was felt that it could provide a degree of insight into overall trip-making behaviour. The model included independent variables for academic year, residential distance, gender and faculty of study encoded using dummy variables, whilst number of TTDs was included as a continuous independent variable. Observations were split into five groups based on the academic outcome of the student (from fail to first class), and the results of fitting the model separately to the data in each group are shown in Figure 31.

			Days Without a Trip to Campus				
			<40 (Fail)	40-49 (3rd)	50-59 (2nd 2)	60-69 (2nd 1)	>=70 (1st)
Days Missed, Descriptive Statistics	Observations		2390	3692	12911	21440	4560
	Mean Days Missed		8.74	7.66	8.14	7.90	5.85
	Standard Deviation		5.429	4.997	4.948	4.804	4.146
Test Statistics	Adjusted R^2		0.747	0.704	0.644	0.525	0.461
	Standard Error		2.73	2.72059	2.95343	3.31179	3.04258
	Durbin Watson		1.826	1.852	1.723	1.615	1.685
COEFFICIENTS	Constant		32.419	29.906	27.951	24.936	21.289
	Timetabled Days in Timetable		-0.554	-0.516	-0.476	-0.405	-0.340
	Academic Year	1st Year	0	0	0	0	0
		2nd Year	-0.676	-0.705	-0.82	-0.796	-0.146**
		3rd Year	-1.763	-1.566	-1.825	-1.964	-1.426
	Gender	Female	0	0	0	0	0
		Male	0.919	0.754	0.618	0.416	0.339
	Residential Distance	0-0.5 miles	-1.623	-1.334	-1.407	-1.731	-1.34
		0.5-2 miles	-0.67	-0.691	-0.781	-1.424	-1.202
		2-4 miles	-0.441**	-0.405**	-0.428	-0.795	-0.475*
		4-8 miles	-0.439**	-0.303**	-0.162**	-0.5	-0.981
		8-16 miles	-0.14**	-0.046**	0.792	0.518*	-0.155**
		>16 miles	0	0	0	0	0
	Faculty of Study	Science Based	0	0	0	0	0
		Arts Based	0.69	0.921	0.896	1.043	0.732

Figure 31 – OSS: LRM of Total Days Absent By Academic Outcome

[All coefficients significant at 1% level, except *=5% and **=not significant]

The fit of the models reduce with academic performance level (falling R^2 values) and this highlights the increasing influence of the fixed lower bound of zero days on the difference between the predicted and actual value, resulting in a greater number of inflated residual values in the higher order models. The systematic reduction in the Durbin Watson test statistic across the models is a further indicator of this problem.

The residuals values in each model were found to be normally distributed, whilst plots of predicted values against the residual display the characteristic funnel shape associated with a heteroscedastic distribution, together with a hard edge representing the fixed lower bound. Heteroscedascity must be expected in this model since the differential probabilities for $P(tt)_i$ and $P(ntt)_i$ indicate that the standard deviations associated with mean levels of attendance across the range of TTDs will increase with the number of NTDs in an individual timetable.

The main interest in these models is around the way the values associated with the constant and the coefficient for the number of TTDs vary by academic outcome. The difference in mean levels of attendance at different levels of outcome a and b can be largely seen to be determined by equation 9-33.

$$\Delta Days\ Missed = (m_a - m_b)TTdays + (c_a - c_b) \quad \text{9-33}$$

Substituting the coefficient values for the two extreme academic outcomes into this equation shows that on average when the time period includes just ten TTDs students who fail will attend more than 10 days fewer than those who will achieve a mark over 70%. However, when all days in the time period are TTDs then the difference in attendance between the highest and lowest performing students falls to less than one day. This supports the attendance model proposed in section 7.3.4 which identifies that it is the number of timetabled days, and the mandatory trips which they entail, that is the main determinant of attendance (RQ6, supporting H1a). It demonstrates that the weaker students are more likely to see NTDs as days off.

9.6 Critical Evaluation of Observational Survey Method

This section critically evaluates elements of the observational survey method.

The LP estimator is a very simple technique which can give reliable results within narrow confidence intervals when the data on which the estimates are based are known to not to contain any bias. However, since the method relies on only two samples sources of bias within the estimator can remain undetected. In this case the OSS dataset can potentially be segmented into more than two samples since wireless mobile usage, library entry, fixed PC logins and sports centre entry all represent different activities and indeed the dataset was initially formatted to identify these sources as distinct. However, analysis of the data found very significant heterogeneity between both individual and combinations of category, whilst further concerns were identified regarding the equal catchability assumption and the need for all students to be present on-campus in all samples for an equivalent length of time. The partitioning the datasets into two samples, representing wireless mobile phone usage and all other types of activity was a pragmatic choice that represented the least worst alternative. This decision necessarily prohibited the use of other closed-population estimation methods and hence meant that with just two samples the LP estimator was the only viable alternative available.

Although the LP estimator has produced reasonable estimates for this problem, it suffers from a weakness in that the sample groups used by it can be unrepresentative when estimating the attendance for TTDs. Since these estimates are solely based on records of activity that occurred during the timetabled sessions themselves, the subset of the population who can be recorded performing on-campus activities (as opposed to mobile phone activity) during a session is limited to those who either have timetabled lab classes that require them to login to an on-campus PC and to the small proportion of students who are missing their classes and participating instead in other activities on-campus. This means that the sample on which the overall estimate is based largely relies on the on-campus activity of the unconscientious minority, rather than the whole on-campus population, as is the case for NTDs. This is a real weakness of the estimation technique and potentially explains why the estimates for TTDs appear to be unstable.

The method used to assign individual trip probabilities also has a weakness in that the probabilities of attendance, $P(tt)_i$ and $P(ntt)_i$ for each student i, will be proportional to the number of times the student has been detected on-campus. The more times the student is detected, the more often they are assumed to have attended. This is a reasonable assumption when considering NTDs since a major student motivation for coming to campus will be to perform one or more of the monitored activity types. However, on TTDs the assumption is less reliable since the TQS quantitative data (section 6.6) suggests that the population includes a subset of students that barely interact with the resources on-campus. These students will be the ones who value time spent on-campus the least and arrive just before their first session, depart immediately their last session is over and since they only spend the timetabled sessions on-campus they are less likely to use a wireless enabled mobile phone. As such, even if they are regular attenders they will be placed in one of the lower order strata in the assignment process and be allocated a probability that will significantly under-represent their true attendance. The evidence for this assessment is that in both models of attendance, for TTDs and NTDs the same coefficients are significant and describe identical trends; later years students, those with higher attainment levels and those who live closer have higher attendance probabilities. For TTDs this is at odds with the finding of the TQS which suggests that early years students have a slightly higher probability of attendance. The assignment method becomes less reliable when student interaction with campus is limited.

However, whilst the OSS method has a number of weaknesses it does provide the basis for a reliable survey technique, as demonstrated by estimates of attendance that generally match those provided through the TQS (section 7.3), whilst the rise in the popularity of smartphones suggests that with each passing semester the reliability of the technique will improve simply because a greater proportion of the population will be holding and using these devices when they are on-campus, thereby answering RQ7 (can an observational student survey technique be developed?).

Chapter 10 – The Campus, Timetable, Attainment and Student Travel Behaviour

10.1 Introduction

The previous two chapters introduced the OSS survey method and demonstrated how this technique could be used to obtain reliable aggregate and disaggregate estimates of attendance over the whole of a time period or on a daily basis.

This chapter continues by introducing a further set of models and techniques for estimating student arrival and departure profiles on TTDs and NTDs, student presence on-campus across the hours of a typical NTD and levels of leave-and-return trips made by students during timetabled breaks.

The chapter then goes on to consider the wider implications of the findings identified through this study and makes recommendations across three areas: changes to the design of the timetable, changes to the way student trip-making is regarded within travel plans, and around the need for more unstructured student space on-campus.

The chapter completes the delivery of research objective O4 (develop an observational student survey method), and introduces and delivers objectives O6 (explore the impact of trip-making behaviour on student engagement/attainment) and O7 (discuss the implications of any findings on the sustainability of the campus-based university). The chapter further answers RQ4 (do students exhibit leave-and-return behaviour?) and RQ6 (do certain timetable designs have a negative impact on student engagement and attainment?) and RQ8 (what are the impacts of timetable design on institutional sustainability?).

10.2 Hourly Attendance On-Campus on Non-Timetabled Days

As discussed in section 9.5.1 students attend on-campus about half as frequently on NTDs compared to their attendance on TTDs. An analysis of hour-by-hour activity levels allows the changing non-timetabled student population on-campus and their arrival and departure patterns across the day to be estimated. In section 9.4.1 an LP estimator for the overall level of attendance on NTDs was described, and this can be extended to estimate the hourly population through the addition of a further subscript, k, to the student activity matrices introduced in the previous chapter.

m_{ijk} 1 if student i used a mobile phone during hour k of day j and 0 otherwise

c_{ijk} 1 if student i was detected performing some type of on-campus activity during hour k of day j and 0 otherwise

$r_{ijk} = m_{ijk}c_{ijk}$

Using these matrices the LP estimator can be used to calculate the non-timetabled student population on-campus across each hour k on the ‘typical’ NTD created by aggregating the data across all students i and NTDs, j, equation 10-1.

$$LPhntt_k = \frac{(\sum_i \sum_j IsnTT(i,j)m_{ijk} + 1)(\sum_i \sum_j IsnTT(i,j)\, c_{ijk} + 1)}{\sum_i \sum_j IsnTT(i,j)r_{ijk} + 1} - 1 \qquad 10\text{-}1$$

If it is assumed that student arrivals on-campus always occur at the start of each hour-long time period and that any departures occur at the end of each period then the arrival and departure profiles across the typical day can be obtained using the same LP estimator by creating alternate versions of the m, c and r matrices. Equations 10-2 and 10-3 show the derivation of counts for arrival, ma, and departure, md, matrices describing mobile activity.

$$ma_{ijk} = \begin{bmatrix} 0: \sum_{l=1}^{k} m_{ijl} = 0 \\ 1: \sum_{l=1}^{k} m_{ijl} > 0 \end{bmatrix} \qquad 10\text{-}2$$

$$md_{ijk} = \begin{bmatrix} 0: \sum_{l=k}^{n} m_{ijl} = 0 \\ 1: \sum_{l=k}^{n} m_{ijl} > 0 \end{bmatrix} \qquad 10\text{-}3$$

For hour k, each cell in the arrivals matrix will contain a 1 if the student has already been observed on-campus by hour k, whilst each cell in the departures matrix will be 1 if the student was seen between hour k and the end of the day (hour n). The matrices for c and r can be calculated in a similar way.

If the LP estimators are then calculated using these modified matrices they give the cumulative arrivals to hour k, $LPantt_k$, and students still to depart campus at hour k, $LPdntt_k$, with the upper limit in both cases corresponding to the overall estimate of on-campus population, $LPntt$.

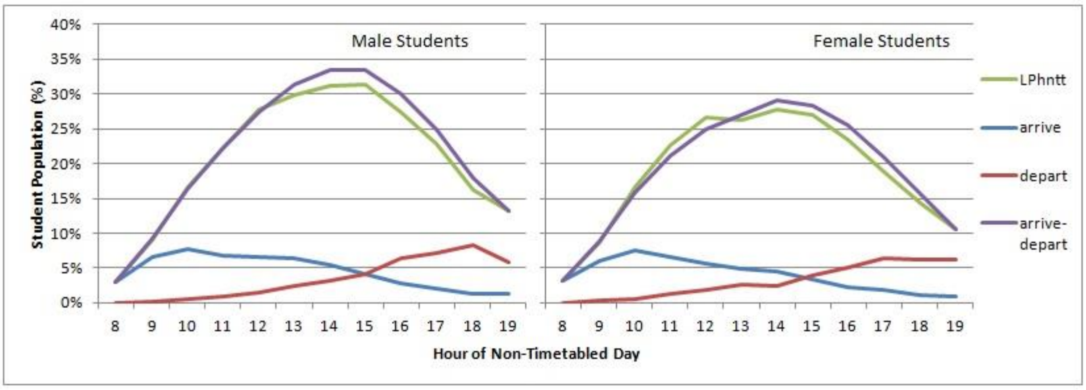
The number of arrivals at the start of hour k and departures at the end of hour k can then be determined, equations 10-4 and 10-5, whilst the on-campus population in any hour will be equal to the cumulative arrivals minus the cumulative departures up to that hour, equation 10-6.

$$arrive_k = LPantt_k - LPantt_{k-1} \quad \text{10-4}$$

$$depart_k = LPdntt_k - LPdntt_{k+1} \quad \text{10-5}$$

$$LPhntt_k \approx \sum_{l=1}^{k} arrive_k - \sum_{l=1}^{k-1} depart_k \quad \text{10-6}$$

These equations were used to calculate the hourly NTD on-campus population for time period C, Graph 20, and each hourly estimate was found to have a 95% confidence interval, (equation 9-9) of +/- 1.5% (maximum).



Graph 20 – OSS: Hourly Attendance on-campus on NTDs

The difference between the estimated hourly attendance for the two calculation methods was also found to be a maximum of 1.5% of the overall student population. This discrepancy is due to the bias caused in the hourly arrival/departure estimates by changes to the ratio of mobile to non-mobile activity throughout the day, whilst the calculation of the direct point estimates are self-contained and not influenced by this bias effect.

The hourly estimates enabled the summary statistics shown in Table 52 to be calculated. These demonstrate that males and females exhibit largely similar behaviour although females arrive and depart slightly earlier.

	Male Students			Female Students		
	Mean	Std Dev	Mode	Mean	Std Dev	Mode
Arrival Time	12:15	2:45	10:00	12:03	2:45	10:00
Departure Time	16:12	2:16	18:00	16:02	2:26	17:00
Visit Duration	4:40 (by LPhntt)			4:45 (by LPhntt)		
	4:53 (by Arrive-Depart)			4:52 (by Arrive-Depart)		
Busiest Hour	15:00 - 62% of Attendees			14:00 - 61% of Attendees		
Remaining on Campus after 19:00	25% of Attendees			22% of Attendees		

Table 52 – OSS: Hourly Attendance on-campus, descriptive statistics

The most popular on-campus arrival time for both genders is 10:00 suggesting that when student choice is unconstrained by the timetable their preferred arrival time is only one hour later than the earliest timetabled start time. Almost 2/3rds of all non-timetabled students who visit campus will be present on campus in the mid-afternoon whilst 25% (22%) of all male (female) visits to campus on NTDs involve a stay that continues to after 19:00.

10.3 The Effect of Timetable on Arrival Times

The analysis of the TQS reported in section 7.3.5 suggested that student arrival times are closely tied to their timetabled start times, although the findings were based on a hypothetical scenario meaning further investigation of the link between timetable and on-campus arrival time is necessary. Unfortunately the method described in section 10.2 for NTDs is not appropriate in this case due to the differential behaviour patterns of mobile phone usage and activity detection between hours during which students have timetabled sessions and those when they don't.

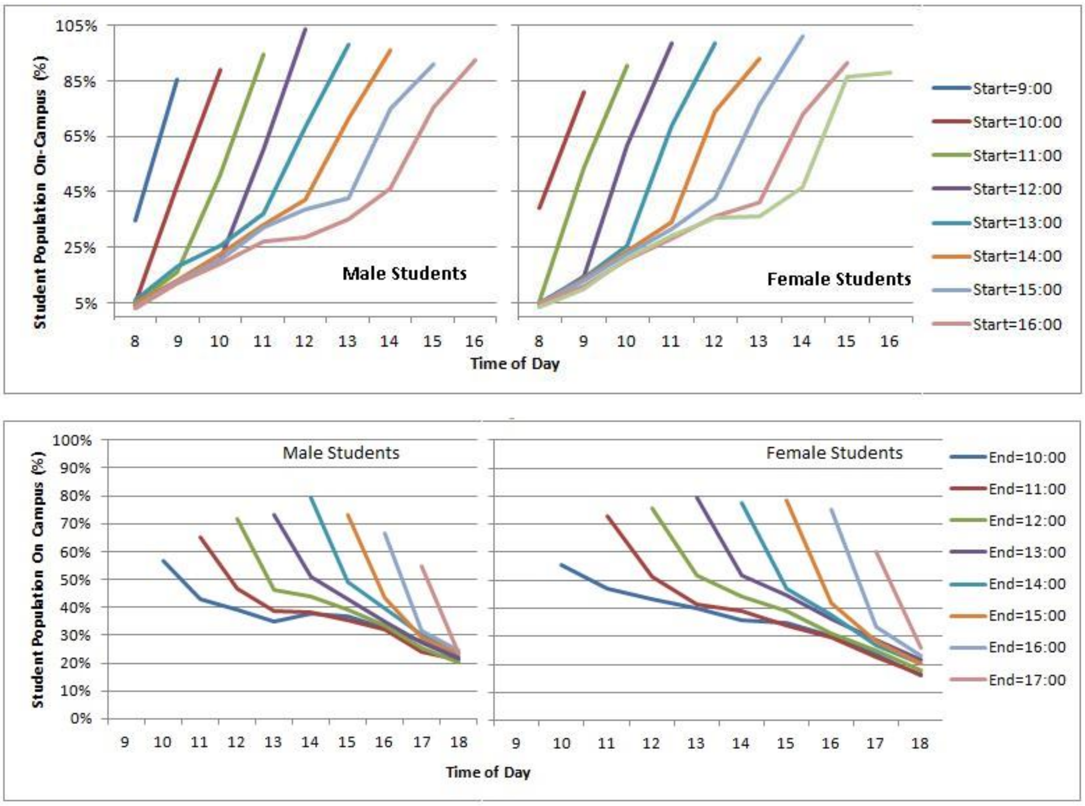
The activity data for all timetabled student days for time period C was grouped by gender and timetable start time. A bias corrected LP population estimator was then applied to the hourly on-campus activity levels for each hour in each group from the first hour of the day (08:00-09:00) to the start time of timetabled sessions in that group. This allowed the arrival rates for different timetable start times to be determined. The bias correction factor, ϒ, as identified in section 9.4.1 for estimating the population in single time slots hour time analysis periods (0.3 for males and 0.29 for females) was adjusted by a factor to compensate for changes to the ratio of mobile devices (m) to other activity types detected across each single hour k within each day, j, and for all students i within the group. Equations 10-7 and 10-8 describe how the ratio for any hour, Υ_k, within a timetabled day from 8:00 to 17:00 is calculated.

$$Ratio_k = \frac{\sum_i \sum_j c_{ijk}}{\sum_i \sum_j m_{ijk}} \qquad \text{10-7}$$

$$\gamma_k = \gamma * \left[2 - \frac{Ratio_k}{(1/(17-8+1)) \sum_{k=8}^{k=17} Ratio_k}\right] \qquad \text{10-8}$$

Each population estimate is based on on-campus activity detected across each hour, and a simplifying assumption is that any students arriving during the hour will all arrive immediately prior to the start of the hour.

The population estimated to be on-campus for all TTDs within time period C for male and female students for each hour up to and including the start of first session and for each hour after the end of the last session and for all timetabled start/end times from 9:00 to 17:00 is shown in Graph 21.



Graph 21 – OSS: On-campus population on Timetabled Days

[Before Timetabled Sessions (top), After Timetabled Sessions (bottom)]

An element of residual bias remains since the estimated population on-campus at the start of some sessions during the middle part of the day exceeds 100%. Therefore the estimate of the daily percentage attendance for each timetabled start time was adjusted, such that the weighted attendance across the whole day equalled the overall timetabled attendance levels calculated in section 9.4.1.

Inspection of Graph 21 shows that the student arrival pattern falls into four broad phases, The first phase describes behaviour up to two hours prior to the start of the timetabled session during which time students seem to arrive at a constant rate, irrespective of the start time of the session. In the second phase, one hour prior to the session the arrival rate accelerates and students continue to arrive at a higher rate in the third phase up until the start time of the session. In the final phase, students who didn’t arrive on time for the start of the session will arrive in the hour after the session start.

The hourly attendance figures for each timetable start time were fit using simple LRMs to describe the arrival of students in each of the four phases, Table 53.

	Male			Female		
	M	c	R^2	m	c	R^2
Phase 1 Arrive up to 2 hours before	0.0792	0.0044	0.9612	0.0776	0.0068	0.9766
Phase 2 Arrive one hour before start of session	0.0372	0.4063	0.92	0.0476	0.4532	0.7123
Phase 3 Arrive at start of session	-0.0305	0.5596	0.8433	-0.04	0.4952	0.5412
Example values using these models for timetabled sessions starting at 11:00	Phase 1: 16%, 8% by 8:00, 8% by 9:00. Of the remaining 84%: Phase 2: 48% (40%) by 10:00 Phase 3: 49% (42%) by 11:00 Phase 4: 3% (2%) late			Phase 1: 16%, 8% by 8:00, 8% by 9:00. Of the remaining 84%: Phase 2: 54% (45%) by 10:00 Phase 3: 41% (35%) by 11:00 Phase 4: 5% (4%) late		

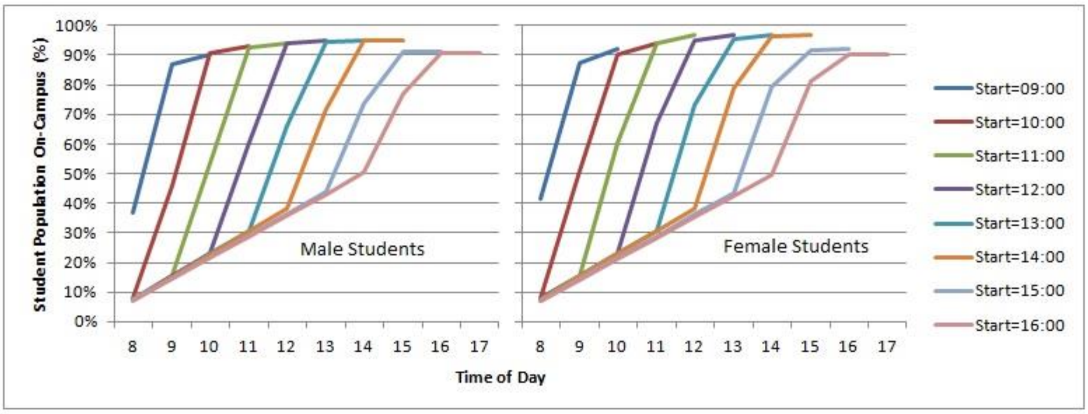
Table 53 – OSS: Arrival Time Regression Models

[Y=mX+c, where Y=Percentage of students arriving in a given hour, X=timetabled start time – 9, i.e. 0=09:00, 1=10:00 etc.]

The models fit reasonably well (high R^2 values) with the exception of the coefficients for females in phase 3, this being caused by the atypical arrival pattern for sessions starting at 16:00.

During the first phase the slope (m) describes the percentage of students who arrive every hour from 08:00 up until two hours prior to the start of the session. The models for phases 2 and 3 describe the arrival profile of the students remaining after phase 1, and the intercept values (c) indicate base arrival levels, suggesting that 40% (50%) of males (females) arrive one hour before, whilst 55% (50%) arrive just before the start of the session. During phases 2 and 3 the balance of those arriving one hour before the start time increases as the day progress at a rate of around 3.7% (4.7%) of students per hour, as indicated by the complementary slope parameters (m). The percentage arriving in phase 4 (late students) is represented by the percentage remaining after summing the phase 2 and 3 values, and the differential slope values for the phase 2 and 3 models results in the percentage of late students tending towards 0 as the day progresses.

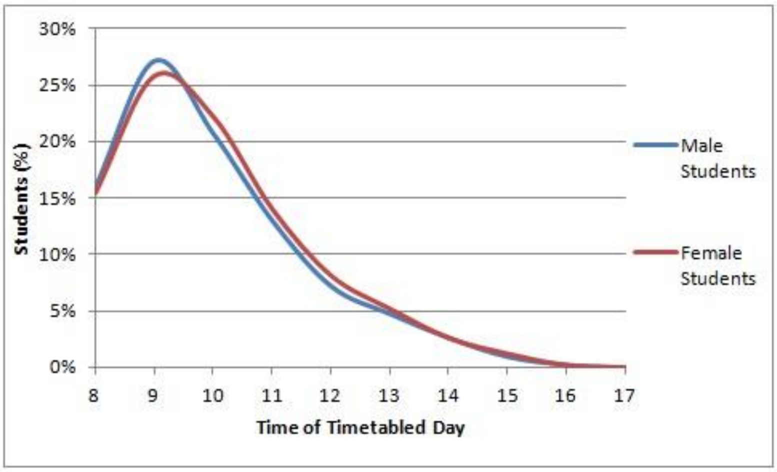
The fitted arrival time models for male and female students are shown in Graph 22.



Graph 22 – OSS: Modelled TTD Arrival Time Distributions

[By Timetable Start Time]

These models demonstrate that whilst student arrival time is related to timetable the degree of correlation between the two reduces for later timetabled start times. The model suggests that the mean arrival time on-campus prior to the start time of the first timetabled session, increases from 22 minutes for sessions scheduled to begin at 9:00 to over 3 hours (184 minutes) for sessions scheduled to start at 16:00. A quadratic equation (Y=x^b2+xB1+b0) describes this relationship, with equivalent coefficients for male and female students of b0=22, b1=11, b2=2.29, and where a 9:00 start time is represented by x=0.



Graph 23 – OSS: Distribution of Student Arrival Times on TTDs

As demonstrated by the arrival time question in the TQS, and by these models, the arrival time distribution for any start time will be negatively skewed. However, when the individual arrival time distributions are weighted by the distribution of timetable start times across the day, the resultant combined arrival distribution is positively skewed, Graph 23 with a mean (median) arrival time of 10:00 (9:10) for males and 10:04 (9:15) for female students. The apparent later arrival of females is due to them having proportionately fewer 9:00 starts. Casual observation of the combined arrival distribution for males and females suggests that many students operate around a fixed arrival time, however this hides the real underlying behaviour that links arrival time to timetable start time.

Modelling student arrival time on-campus is similar to modelling the distribution of patient arrivals for scheduled appointments at a surgery. Typically this is assumed to conform to a normal distribution, although the Johnson distribution has been shown to provide a better fit (Alexopoulos et al., 2008). However, unlike patient arrival at a surgery, early arrival on-campus may generate positive utility for the student. Therefore a negative skew-normal distribution (with 3 parameters: mean, standard deviation and skewness) seems an appropriate choice for modelling arrival phases 2-4. A closed form approximation of the skew-normal distribution, using five functions to represent different sub-sections of the whole distribution was identified (Ashour and Abdel-hameed, 2010) and an attempt was made to fit this to the observed data. However, with only three data points for each timetable start time, the problem proved to be intractable. A revised OSS dataset with a smaller timeslot size (of 15 minutes) could yield a solution to this problem.

10.4 Evidence of Leave And Return Behaviour

As discussed in section 7.3.6 the TQS identified that students frequently consider leaving campus and returning home during breaks between sessions, and that a relationship exists between home-campus travel time and break length suggesting that students begin to consider this behaviour as a option when the time they can spend at home exceeds the time spent travelling to/from campus. However, the TQS was unable to quantify the level of trips taken (as opposed to being considered) by students. The OSS provides information on student activity on-campus, whilst the timetable dataset identifies the presence of breaks during the day, and by combining the evidence leave and return behaviour can be found.

To examine this, each student's activity record was grouped by time period (x3), academic year (x3), module mark category (x5), residential distance category (x4), gender (x2), and faculty of study category (x2) creating 720 distinct strata. The timetables for the students in each stratum were examined and all occurrences of timetabled breaks of between 1 and 5 hours were counted, allowing the proportion of students recorded performing some kind of on-campus activity during the break period to be calculated. A LRM was built, Table 54, with the observed student proportion as the dependant variable and all the strata defining categories encoded as a series of dummy independent variables. The data for the model was restricted to those groups which contained more than 30 observations, to prevent skew caused by unrepresentative groups with small sample sizes. The model fits the data reasonably well with an R^2 value of 0.578. An alternative approach using a weighted least squares model gave a better fit but the trends in the coefficients were similar so the original model was retained. The residuals are normally distributed (visual inspection), homoscedastic (visual inspection of plot of residuals against expected value) and independent (Durbin Watson value>1.6).

Test Statistics	Observations						3295
	Adjusted R Squared						0.578
	Standard Error of Estimate						0.102
	Durbin Watson						1.829
			Unstandardised Coefficients		Standardised Coefficients		Sig. >0.001
			B	Standard Error	Beta	t value	
COEFFICIENTS	Constant		0.261	0.011		23.82	
	Gender	Female	0				
		Male	0.011	0.004	0.037	3.213	0.001
	Faculty of Study	Science Based	0				
		Arts Based	-0.03	0.004	-0.096	-8.404	
	Academic Year	1st Year					
		2nd Year	0.105	0.004	0.315	24.453	
		3rd Year	0.143	0.005	0.412	31.648	
	Time Period	Period A	-0.025	0.004	-0.075	-5.623	
		Period B	0				
		Period C	0.032	0.004	0.095	7.196	
	Module Mark Category	<40 (Fail)	-0.142	0.011	-0.3	-12.771	
		40-49	-0.059	0.011	-0.137	-5.439	
		50-59	-0.01	0.011	-0.027	-0.914	0.361
		60-69	0.062	0.011	0.179	5.9	
		>=70	0.097	0.011	0.223	8.925	
	Residential Distance	0-0.5 miles	-0.092	0.005	-0.229	-17.862	
		0.5-2 miles	0				
		2-4 miles	0.029	0.005	0.077	5.98	
		>4 miles	0.029	0.005	0.076	5.888	
	Break Length	1 hour	0				
		2 Hours	0.075	0.005	0.214	16.203	
		3 hours	0.087	0.005	0.231	17.597	
		4 hours	0.085	0.006	0.19	14.692	
		5 hours	0.08	0.008	0.12	9.709	

Table 54 - OSS: Student Proportion Dectected During Breaks

The dependant value in the model is constrained with a lower bound of zero and this can potentially skew the values given to the coefficients. However, a histogram of the student proportions is normally distributed with negligible zero values at the extreme end of one of the tails. Therefore a linear model was felt to be appropriate and the minimum expected value produced by the model of -0.02 confirms that few values fell below zero, whilst a plot of the standardised residuals against the expected values show little evidence of the hard edge associated with bounded range.

Each distinct group will show a difference in their degree of on-campus activity, but if is assumed that within each group defined by gender, faculty, academic year and academic level that the underlying level of activity in timetabled breaks is constant then any difference identified through this model can be attributed to differential on-campus attendance rates for part or all of the break period, and this in turn will be influenced by both the length of the break and the student's residential distance (travel time). The model suggests activity levels rise with residential distance (suggesting that those who live further away may leave less frequently) but also with break length, and this seems counter-intuitive. However, since the dependant variable describes the proportion detected across the whole break period, then if all students remained on-campus for the duration of the break then as shown by the binomial equation 9-3 the proportion observed will increase with break length. However, the level of increase suggested by the model is below the level suggested by the hourly probability of being detected indicated by the model (if break length and residential distance as excluded). This suggests that some students leave campus for some or all of the break period.

To investigate this further it is necessary to fit the proportion of students detected in breaks of between 1 and 5 hours suggested by the LRM against a second model that represents a possible distribution of student's stay or leave-and-return behaviour across the break (the stay/leave model). If the function *present(i,j)* returns the proportion of students who have a break of i hours and who are on-campus for j of those hours (0≤j≤i) then the overall proportion of students who can be expected, ed_i, to be detected across all i hours of the whole break can be defined as equation 10-9.

$$ed_i = \sum_{j=0}^{i} present(i,j)\left[1 - (1 - dg)^j\right] \qquad 10\text{-}9$$

where:

dg — The group probability that a student will be detected during any hour they are on-campus. This will be equivalent to the probability suggested by the model after taking into account: time period, year of study, mark category, gender, faculty of study and at a residential distance of greater than 4 miles (as this group of students are least likely to leave during a single one hour break).

The proportion of students expected to be seen, ed_i, should be equivalent to the proportion suggested for the equivalent group by the LRM model for i hours, od_i.

The function *present* accepts two parameters and is defined through two components, equation 10-10. The first is built from a normalised Poisson distribution of the values between 0 and the break length j with the parameter λ constrained between 0 and 5. This provides a distribution that varies between two extremes; of all students leaving campus for the duration of the break (λ low) to one in which most students remain on campus for the duration of the break (λ high). This distribution is modified by a second parameter, α, in the range 0 to 1 that splits the population into two partitions: those students who will never leave campus during the break and those who are subject to the Poisson stay and leave distribution. This second parameter is required as the Poisson distribution alone gives a poor fit to the output from the LRM.

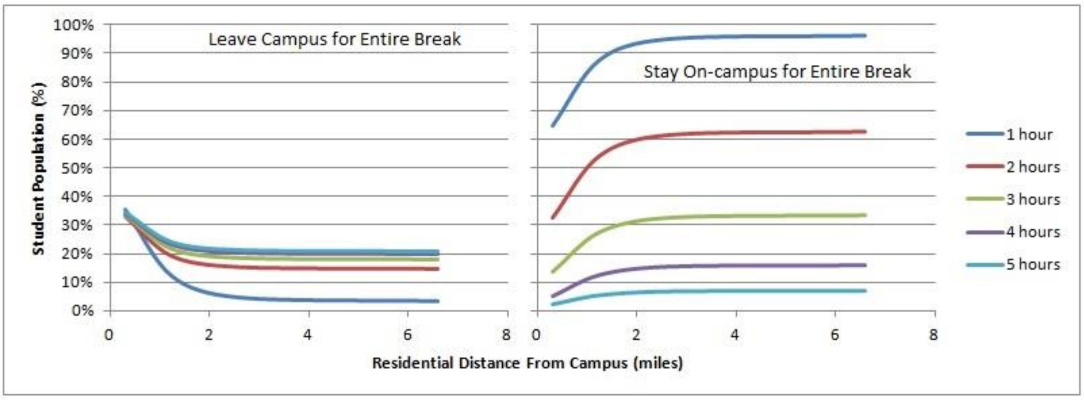
$$present(i,j) = \left[1 - \frac{\alpha}{2^{(i-1)}}\right]\left[\frac{\frac{\lambda^j e^{-\lambda}}{j!}}{\sum_{l=0}^{i} \frac{\lambda^l e^{-\lambda}}{l!}}\right] + \begin{cases} j = i: & \frac{\alpha}{2^{(i-1)}} \\ j < i: & 0 \end{cases} \qquad (10\text{-}10)$$

The stay/leave model assumes that the parameter λ is constant across all break lengths, whilst the significance of α is halved for each unit increase in break hours. The two models were fit using a hill-climbing algorithm to identify the values of λ and α for each distinct group that gave the smallest sum of squared error between the ed_i and od_i terms across the range of break lengths. For each fitted model the estimate of the proportion of students who leave campus for the entire duration of a break of length i: *leave=present(i,0)* and the proportion who don't leave campus at all during the break: *stay=present(i,i)* were calculated, with the remainder being assumed to leave campus for some part of the time. An example of the output from the stay/leave model for four student groups is shown in Table 55.

	1st Year, Mark <40, 0-0.5 Miles		1st Year, Mark ≥70, 0-0.5 Miles		1st Year, Mark <40, >4 Miles		1st Year, Mark ≥70, >4 Miles	
α	0		0.325		1		0.9	
λ	0.8125		1.0687		1.5500		1.5000	
Error	0.0013		0.0002		0.0001		0.0009	
Break	Leave	Stay	Leave	Stay	Leave	Stay	Leave	Stay
1 hour	55%	45%	33%	67%	0%	100%	4%	96%
2 hours	47%	15%	32%	34%	13%	66%	15%	62%
3 hours	45%	4%	32%	15%	17%	36%	19%	33%
4 hours	44%	1%	33%	6%	19%	17%	20%	16%
5 hours	44%	0%	34%	2%	20%	8%	21%	7%

Table 55 – OSS: Leave-And-Return, Sample Leave and Stay Proportions

The fitted models show that the leave-and-return behaviour of students who live closest to campus, <0.5 miles, is both more frequent and subject to a greater degree of variation across the academic years and between the best and worst performing students. Those who live further away exhibit a more homogenous behaviour in which the greater home to campus travel times limit the ability to undertake a leave-and-return trip more uniformly across all students living at this distance. Graph 24 shows how the mean leave and stay percentages across all student groups vary with distance and break length and demonstrates that residential distance becomes less important in determining both leave and stay behaviour above around 2 miles.



Graph 24 – OSS: Leave And Return, By Residential Distance

The results from the leave and return model, combined with the frequency of occurrence of breaks identified through the stratified timetable for each group suggest that in each of the three time periods in around 17% of breaks students will leave campus for the duration of the break, whilst in another 20% of breaks students will leave campus for some part of the break, and may include a trip home. Across all lengths of break the overall proportion of ‘leave’ trips in each distance category is 38% for those students who live within 0.5 miles of campus, 16% for those living up to 2 miles away and around 10% for those at further distances. This suggests that many of these will be walking trips, and that students living on-campus or very close to it are much more likely to absent themselves during breaks, compared to those who live slight further away (answering RQ4, supporting H1b).

If 22% (17% + ¼ *20%) of breaks are assumed to include a full leave-and-return trip then given the representative mode emissions figures and approximate mode split figures for students living in each of the four distance categories (see section Chapter 5) this suggests that an additional 105 tonnes of carbon will be produced as a result of these trips. As these leave-and-return trips are invisible within current travel survey methodologies this represents an additional 3% emissions on top of the level calculated in section Chapter 5. This is below the 6% addition previously estimated in section 5.3.5, but does show that these invisible trips potentially cancel out most of the 4% emissions savings that can be achieved through mode change alone at UoL (see section 5.3.2).

10.5 The Effect of (Non)Attendance on (Dis)Engagement

The discussion in section 8.4.4 reiterated the findings of earlier studies showing that on-campus activity can be used as a partial proxy for student engagement and proposed that the lack of on-campus activity might be a reasonable indicator of student disengagement with their studies. Given that the analysis discussed in sections 9.5.3.1 and 9.5.3.2 highlighted a relationship between academic outcome and attendance on campus, it could be reasonable to assume that (non)attendance may also have some effect on student (dis)engagement. At the same time since student trip probabilities across the ability/outcome spectrum are largely homogeneous for TTDs, the differential in attendance probabilities on NTDs is of most interest. To examine the relationship between attendance and (dis)engagement the population was split by gender and faculty of study (arts or science) and then by their whether their attendance probability $P(ntt)_i$ fell into bottom third of the distribution of all similar probabilities (equivalent to $P(ntt)_i$ being ≤ 0.35). Contingency tables were constructed to examine the effect of attendance probability on the relative proportion of the population who were members of three of the groups identified in section 8.4.4; students who borrow very few library books, those who are identified by the NEG indicator (low use across 5 different measures of resource usage), and those who are identified by the POS indicator (no low use in any of the 5 different measures), see Figure 32.

Gender	Faculty of Study	$P(ntt)_i$	<3 library books borrowed			NEG Indicator Present			POS Indicator Present		
			Yes	No	Odds Ratio	Yes	No	Odds Ratio	Yes	No	Odds Ratio
Female	Science	<=0.35	56.7%	43.3%	1.99	2.8%	97.2%	14.37	8.9%	91.1%	0.43
		>0.35	39.7%	60.3%		0.2%	99.8%		18.6%	81.4%	
	Arts	<=0.35	39.0%	61.0%	2.89	5.2%	94.8%	13.66	3.4%	96.6%	0.20
		>0.35	18.1%	81.9%		0.4%	99.6%		14.7%	85.3%	
Male	Science	<=0.35	74.0%	26.0%	2.12	6.4%	93.6%	11.33	4.0%	96.0%	0.31
		>0.35	57.3%	42.7%		0.6%	99.4%		11.7%	88.3%	
	Arts	<=0.35	52.4%	47.6%	3.05	6.6%	93.4%	10.02	3.0%	97.0%	0.24
		>0.35	26.5%	73.5%		0.7%	99.3%		11.6%	88.4%	

Figure 32 – OSS: Link between attendance and (Dis)Engagement

For each 2x2 contingency table the Chi squared test statistic was calculated and these were all shown to be significant at the 1% level. Similarly the odds ratio of being identified by the each indicator given an non-timetabled attendance probability of ≤ 0.35, relative to a higher attendance probability were also calculated. The odds ratios demonstrate that students with lower attendance are more likely to be disengaged (as represented through these indicators). The figures for the NEG indicator are particularly stark and demonstrate that students with lower discretionary attendance probabilities are at least 10 times as likely to be a member of the NEG group, whilst section 8.4.4 demonstrated that those in this group were more likely to attain a failing mark (RQ6). The figures for a low level of library books borrowed, are also interesting. The library lending data was not used in the estimation of individual student attendance probabilities, and as such provides some independent verification of this relationship.

The leave and return model discussed in section 10.4 and these figures raise questions around the optimal siting of student residential accommodation. When this is on-campus, the leave and return model shows that students will return to it more than twice as frequently, than if it were located slightly further away (>0.5 miles). Given that those who spend most time on-campus appear to be less disengaged this suggests that placing residential accommodation too close may have negative consequences. To some extent this resonates with the work of Redmond who suggests that a non-excessive workplace commute has positive time utility in that it brackets the work activities and provides a period for adjustment (Redmond and Mokhtarian, 2001).

10.6 The Effect of Timetable on Attainment

Comparison of academic marks across faculties and between academic years within a faculty is problematic since the assessment process must include an element of subjectivity on the part of the assessors. It is unlikely that even if the same assessment criteria are used across the University that staff in different departments will then apply them consistently. Therefore any analysis that compares raw marks between groups must be treated with caution. However, since the main purpose on an academic mark is to rank a student relative to their peers, creating a ranked order from the raw marks allows students in different percentiles of the attainment spectrum to be directly comparable between faculties and year of study. Separate orders of rank were determined for the students within each academic year of each faculty and within each time period. Since the size of the cohort varies between faculties/tears the ranks were standardised in the range 0 to 1 and students with a standardised rank of ≤0.1 (or ≥0.9) can be considered as being in the bottom (top) 10% of their cohort.

The students were subdivided by time period, gender and academic year and then by the number of TTDs, with students split into two groups based on whether their timetable contained more or less than 35 contact days (equivalent to 3 contact days per week). Although these groups were not of equal size, if the number of TTDs does not have an impact on attainment then the proportion of each group within three attainment bands, representing the bottom 10%, middle 80% and top 10% of students would be expected to be the same. Contingency tables showing how attainment for male and female students in each academic year is affected by the number of contact days in their timetable are listed in Table 56.

	Faculty and Year Adjusted Rank	Female			Male		
		Trend Odds Ratio	20-35 TT Days	36-50 TT Days	Trend Odds Ratio	20-35 TT Days	36-50 TT Days
Period A 1st Year	Bottom 10%		14.50%	85.50%		6.00%	94.00%
	Middle 80%		13.60%	86.40%		5.70%	94.30%
	Top 10%		15.50%	84.50%		7.70%	92.30%
Period A 2nd Year	Bottom 10%	↓	15.70%	84.30%	↑	12.70%	87.30%
	Middle 80%		18.00%	82.00%		10.70%	89.30%
	Top 10%		20.30%	79.70%		8.50%	91.50%
Period A 3rd Year	Bottom 10%	↓ x1.27	33.10%	66.90%		27.10%	72.90%
	Middle 80%		38.50%	61.50%		32.30%	67.70%
	Top 10%		44.90%	55.10%		31.50%	68.50%
Period B 1st Year	Bottom 10%	↑** x1.81	16.30%	83.70%	↑** x2.07	6.30%	93.70%
	Middle 80%		9.70%	90.30%		3.00%	97.00%
	Top 10%		4.60%	95.40%			100.00%
Period B 2nd Year	Bottom 10%	↑* x1.07	16.50%	83.50%		6.50%	93.50%
	Middle 80%		15.90%	84.10%		11.80%	88.20%
	Top 10%		12.40%	87.60%		7.50%	92.50%
Period B 3rd Year	Bottom 10%		35.50%	64.50%		26.00%	74.00%
	Middle 80%		34.80%	65.20%		22.80%	77.20%
	Top 10%		44.70%	55.30%		31.10%	68.90%
Period C 1st Year	Bottom 10%	↑ x1.20	18.60%	81.40%		7.10%	92.90%
	Middle 80%		15.90%	84.10%		5.90%	94.10%
	Top 10%		14.40%	85.60%		6.40%	93.60%
Period C 2nd Year	Bottom 10%		14.80%	85.20%		10.20%	89.80%
	Middle 80%		16.60%	83.40%		11.80%	88.20%
	Top 10%		14.70%	85.30%		10.80%	89.20%
Period C 3rd Year	Bottom 10%	↓ x1.02	43.40%	56.60%	↓** x1.64	24.80%	75.20%
	Middle 80%		43.90%	56.10%		36.00%	64.00%
	Top 10%		45.60%	54.40%		41.30%	58.70%

Table 56 – The Effect of Timetable on Attainment

[**(*): difference significant at the 1% (5%) level using Chi square tests (section 6.5.2)]

Trends across the three attainment levels are highlighted and shown together with the odds ratio of a student with <35 TT days being in the most extreme attainment group. The results are interesting and tentatively suggest that the effect of the TTDs works differently at the beginning and end of a student's time at university. During the first semester (period B) of the first year, students who have fewer TTDs are at least 1.8 times as likely of being ranked in the lowest 10% of students, whilst final (3rd) year students appear to do better if they have fewer TTDs. Male and female students appear to be equally susceptible to these effects (RQ6).

The effect of timetable on a student's level of engagement and on the other constraints imposed on their lives may possibly provide explanations for these two opposing trends. Since students with fewer TTDs in their timetable will make fewer trips to campus overall, this suggests that first year students with fewer TTDs are at an increased risk that their academic experience is marginalised and that they become disengaged. Disengagement is known to be particular issue for first year students (Krause et al., 2005), and as a student progresses through their course their level of engagement with it is likely to increase as they develop intellectually, become an independent leaner and invest time and energy into their studies. Therefore by the third year engagement is less of a critical factor, and instead it becomes more important that the student is able to plan their own time, and to fit their academic studies around other activities such as part-time or voluntary work. Completely free days allows them to be more effective in this regard.

The total number of contact hours in a student's timetable may also be affecting these trends. When contact hours are high, whilst fewer timetabled days may discourage engagement, the effect of squeezing more hours into fewer days may also cause the student to become overloaded, adversely affecting performance. Therefore the effect of TTDs on engagement must be separated from the effect the number of timetabled hours per day has on attainment. Whilst the student attainment data is approximately normally distributed (although slightly negatively skewed) the standardised rank data is evenly distributed across the range of possible values. This means that independent samples t-test which assumes a normal distribution can-not be used and the non-parametric equivalent , the Wilcoxon rank sum test can be selected instead (Field, 2013, p. 219).

The test ranks the observations from two groups into one combined ascending sequence, and exploits the closed form equation 10-11 which describes the cumulative sum of all integers (ranks) in the range from 1 to N.

$$CSum(N) = \frac{N(N+1)}{2} \qquad \text{10-11}$$

Assuming there are *N/2* observations in each group then if the grouped observations are from the same population they should be equally spread throughout the ascending sequence, and two sums of the ranked position of each observation from each group should be approximately equal to *CSum(N)/2*. If however, the groups come from different populations then their members will each be over represented at opposite ends of the ranked sequence and the two sums will show a difference, up to a maximum of *CSum(N)-2*CSum(N/2)* when the grouped observations aren't overlapped at all.

The Wilcoxon ranked sum, W_s, is taken as the smallest of the two cumulative sums with an expected rank sum and associated standard error, assuming the observations are from the same population, calculated according to equations 10-12 and 10-13, (Field, 2013, p. 220).

$$\overline{W_s} = \frac{n_1(n_1 + n_2 + 1)}{2} \qquad 10\text{-}12$$

$$SE_{\overline{W_s}} = \sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}} \qquad 10\text{-}13$$

where

n_1, n_2 Number of observations in groups 1 and 2

The distribution of the differences between the expected mean score and all possible observed scores is assumed to be normal and a z-score, and hence a p value, can be calculated by subtracting the expected rank sum from W_s and dividing by the standard error.

In section 6.6.10 the TQS identified that students with fewer than nine contact hours per week would prefer their sessions spread over between 1 and 3 days per week, whilst the table above shows that students with few sparsely filled TTDs will be most at risk from disengagement. Around 37% (40%) of the total student population have a timetable with fewer than 85 contact hours in the 10 weeks of period B (A and C), and although only 30% of first years have a timetable with this number of hours, this figure rises to over 60% in the third year. The results of performing a Wilcoxon ranked sum test on the ranked mean module marks for these students only are shown in Table 57.

		1-3 Timetabled Days/week		4-5 Timetabled Days/week		Wilcoxon ranked sum test results	
		n	Median	N	Median	z	p
1st Year	A	485	0.54	1209	0.49	-2.318	0.02
	B	312	0.39	995	0.53	5.605	<0.001**
	C	520	0.46	1251	0.52	1.410	0.159
2nd Year	A	679	0.54	1326	0.48	-3.162	0.002**
	B	545	0.50	1209	0.52	1.406	0.295
	C	616	0.53	1295	0.53	-0.410	0.682
3rd Year	A	1297	0.56	1128	0.47	-4.734	<0.001**
	B	1061	0.54	1190	0.46	-4.151	<0.001**
	C	1348	0.54	1044	0.47	-3.641	0.001**

Table 57 - The Effect of Timetable on Attainment (Low Contact Hours)

[Results significant at the 1% level marked **]

These results show the same effect as identified in Table 56 and confirm the hypothesis that fewer TTDs discourage engagement for first year students in their first semester at university. The results also strongly support the argument that students in later (their last) year achieve a higher level of attainment when their timetables contain fewer days. The results for first year students in period A appear to be inconsistent.

Curriculum designers recognise the developmental path that students embark upon when entering university by front-loading more contact hours into the first year of the course, and reducing the contact hours in each successive year. Contact days are broadly correlated to contact hours and therefore many students will receive an advantageous timetable simply because of this relationship. These results demonstrate that university planners should consider the number of contact days in a timetable, especially for students enrolled on low contact hours courses, to ensure that these follow a similar pattern with more contact days in the first year and fewer in the later years (answering RQ6, partially supporting H4).

This is particularly important in the first semester of the first year since as Tinto observes *“Universities have a very small window to establish strong connections with students”* (Soria et al., 2013, quoting Tinto) and that *“Institutions should front-load their actions on behalf of student retention”* (Tinto, 1993, p. 152)

10.7 Timetable Design and Student Development

The TQS identified a series of student preferences towards the attributes of their timetable that they value, whilst the OSS showed that it is the number of TTDs in the timetable that is the main determinant of on-campus attendance. This section discusses how the timetable could be modified to improve the student experience in the light of the findings of the TQS and OSS, and is divided into two sections examining within-day and between-day timetabling improvements.

10.7.1 Within-Day Timetable Improvements

The TQS demonstrated a general consensus amongst respondents with regards to the ideal structure of the within-day timetable. This consisted of a slightly delayed start to the day (perhaps at 10:00 rather than 9:00), no fewer than two sessions (hours) of contact per day, fewer longer breaks (but more shorter ones) and with daily sessions arranged within a school-day type of arrangement with two blocks of sessions around midday break.

To create a more usable student timetable, the session framework within which it is built requires modification. The current timetable day is defined by a series of one hour slots that all start and end at the same time, creating problems for students as they move around campus and preventing them taking of short comfort breaks.

An alternative framework for the daily timetable is shown in Figure 33 in which five separate session patterns, F1-F5 are defined within the day, and in which the resolution of the timetable grid is 15 minutes and not 1 hour. The framework relies on students being split into 5 cliques[1], C1-C5, built around year of study or faculty. Students can share modules with other students within each clique but modules will not (in the main) be shared between cliques making the timetabling of each clique largely independent and easier to construct.

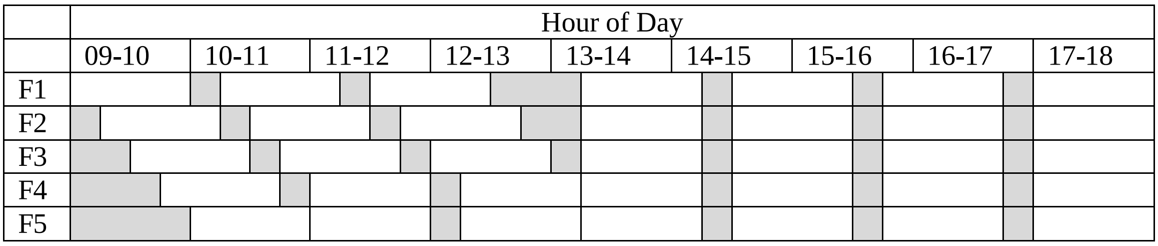


Figure 33 – Alternative Daily Timetable Layout

[Fixed break periods shown in grey, whilst the start time of first session for each framework is: F1=09:00, F2=09:15, F3=09:30, F4=09:45, F5=10:00]

Each clique C1-C5 will be allocated to a different pattern, F1-F5, across each day of the week meaning that students will have at most one 09:00 AM start per week whilst also creating a more dispersed peak arrival time distribution and meaning that the staggered arrangement of session start times removes the most intensive

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[1] A clique is a timetabling term which refers to a subset of the population that can be scheduled independently of the rest of the population, without the generation any clashes.

resource demand peaks seen with the current arrangement (section 8.4.1, Figure 15). All but three of the hour long sessions within the framework is delimited by a short 15 minute break, allowing students to arrive promptly for their next session irrespective of where it is located on campus (section 6.6.5). Two of the frameworks F1, F2 guarantee a lunch break of at least 30 minutes, whilst the later starts in F4 and F5 compensate for the potential lack of a lunch break in these two patterns (section 6.4.11). The commonality between session timings in the afternoon retains compatibility with the existing timetabling arrangement and allows some modules to be shared between cliques. Overall the revised framework provides almost 80% of the session slots available within the current timetable, but at the same time delivering a full one hour session length to each lecturer (instead of the current nominal 50 minutes), and replacing longer timetabled breaks (which are unpopular) with shorter timetabled gaps. Within this framework back-to-back session scheduling will have fewer negative effects on the students.

10.7.2 Between-Day Timetable Improvements

The TQS indicated that there was less of a consensus amongst students with regards to preferences for between-day timetable attributes. Although students would almost universally prefer a balanced timetable, individual preference, rather than a shared group preference, appears to driving the choice of the number of TTDs per week, and towards the scheduling of sessions on Wednesdays and Fridays.

The results from the OSS suggest that the number of TTDs should be a function of both contact hours and year of study, with students in the lower years receiving the same number of contact hours over more days, whilst the TQS demonstrates that student preference for TTDs is influenced by their current experience, section 6.6.10, and that when a change to TTDs is made students would prefer them to be reduced rather than increased. These results are important in terms of timetable planning/policy as they appear to suggest that continuity in timetable design/layout across semesters (and also perhaps within the weeks of a semester) will be as valued as attempting to give students more free days. Where changes to the number of TTDs are required students will be less dissatisfied when these changes are incremental and result in a decrease the number of TTDs.
Section 6.6.10 (Figure 9) demonstrates how the distribution of contact hours across the week can be classified into one of three bands: relaxed, ideal and intense by the number of TTDs over which the hours are delivered. The results from the OSS, section 10.6, suggest that an optimal timetable would see first year's receiving their contact hours in a relaxed manner, second year's according to the ideal preferences suggested by the TQS and third year's in an intense manner, Table 58.

This shows that whilst a 1^{st} year student with up to 9.5 contact hours per week should receive their sessions over 4 days, this falls to 3 days for 2^{nd} years, and 2 days for 3^{rd} years.

		Timetabled Contact Hours per Week			
		4-9.5	9.5-14.5	14.5-20	>20
Year of Study	1^{st} Year (Relaxed)	4	5	5	5
	2^{nd} Year (Ideal)	3	4	5	5
	3^{rd} Year (Intense)	2	3	4	5

Table 58 – Suggested Timetabled Days Per Week By Contact Hour

A timetable based on this suggested distribution of TTDs would produce 8% fewer TTDs in semester 1 and 5% fewer in semester 2 compared to the current timetable, although the absolute number of TTD's for first years would increase relative to current levels (+8%), matched by a small reduction in TTD's for 2^{nd} years (-5%) and a big reduction for 3^{rd} years (-25%). This approach would produce a timetable that more closely matched student perceptions of their ideal timetable, whilst at the same time encouraging engagement for the reasons discussed in section 10.5.

Student preference for timetable balance can be achieved across each of the TTDs within the week, by setting the target number of hours to be delivered within each day to be equal to contact hours per day divided by the number of TTDs. The TQS highlighted that some students suffer from receiving a disproportionately high number of their total contact hours on a single day, section 6.4.6. In some cases sessions are deliberately organised in this way to allow part-time students, who represent 10% of the cohort, to receive the core of their course over a single day. However, this policy risks reducing the level of engagement felt by the 90% of the population who are full-time.

Whilst a majority of students indicated that they would prefer more sessions earlier in the week, including Wednesday, (section 6.6.9) a minority indicated that they valued a free Wednesday (afternoon) to allow them to play sports (section 6.4.10). Whilst any long-term resolution of these opposing positions is simultaneously unlikely and potentially politically unacceptable, a measure that may mitigate it is described below. When large modules are delivered through multiple groups, the scheduling of the sessions could always been split between the traditional TTL days of Wednesday and Friday. The students would then be invited to self-select the session that best matches their individual preference. Priority could be given to those registered with university sports clubs (who would probably choose the Friday alternatives anyway), whilst those who didn't value free time on Wednesday would be able to select sessions scheduled on this day.

The clear within-day preference for two or more contact hours per day (section 6.6.7), combined with the student desire for a balanced timetabled (section 6.6.8), and the TTD allocation mechanism described above suggests that there is an absolute minimum number of timetabled contact hours which should be delivered per week, and that 1st years require a minimum of 8 hours over 4 days, 2nd years 6 hours over 3 days and 3rd years 4 hours over 2 days.

This supports the argument proposed in section 7.4 which suggested that the timetable itself constrains the minimum number of contact hours students should receive. A university curriculum can be designed that favours self-directed study over direct staff-student contact but without a minimum number of contact hours it is simply not possible to create a meaningful timetable for full-time study, and without this students can become disengaged.

10.7.3 Implementation of Changes to the Timetable

The TQS allowed students to describe the look and feel of their ideal timetable without being constrained by the need to consider how their preferences might fit with those of others.

The design of an organisational entity as complex as the institutional timetable for a university with more than 20,000 students is always going to involve compromises and it will never be possible to provide a timetable that matches every student's requirements. However, as demonstrated by the literature review (section 2.2.4) and the analysis of the NSS survey data (section 6.7) institutional focus appears to be on optimising the timetable to meet space management targets. This approach assumes that the effect of the design of the timetable on students is neutral and that all timetables are equivalent. The TQS demonstrates that this assumption is incorrect and that students are concerned about how their timetabled sessions are organised within the week. Design of the timetable has been appropriated by the institution to help meet internal goals, and the possible use of the timetable to influence student trip-making is another example of this kind of institutional appropriation.

If the campus-based university is to remain economically sustainable in the long-term more attention needs to be given to incorporating student preferences into timetable design. In the customer focused and highly competitive environment in which the higher education sector now operates a student-centred timetable design is evidence of an institution that is focused on the needs of the student.

> *"Student-centred institutions are in their everyday life tangibly different from those institutions which place student welfare second to other goals"*
>
> (Tinto, 1993, p. 146)

10.8 Timetable Design and Trip-Making

The TQS and the OSS have shown that students use different probabilities of attendance on TTDs and NTDs and that overall students will attend half as frequently on NTDs compared to TTDs. In parallel to this, the OSS has shown that students benefit from being on-campus and that the higher achievers on average spend more time on-campus, and that compressed timetables can reduce observable levels of engagement and absolute levels of attainment for first years, whilst encouraging higher levels of attainment for third year students.

Collectively these results suggest that whilst intelligent timetable design could be used as a soft travel measure to control and reduce the number of study-place commuting trips thereby increasing institutional environmental sustainability, the indiscriminate use of such a policy would only serve to reduce institutional economic and social sustainability through a reduction in the levels of engagement and attainment (answering RQ8, partially supporting H4).

The transfer of knowledge and the awarding of degrees are two of the core functions of a university, and by implication policies which restrict the effectiveness of the institution in achieving these goals should be discouraged. Therefore whilst timetable design could be seen as an effective measure for achieving a reduction in commuting emissions levels, as it can potentially limit the ability of students to study it should be discounted.

Indeed this study raises questions about the presence of any student-focused measures that promote alternatives to travel within a university's travel plan. VLEs and blending-learning approaches may have a place within the modern university curricula since they encourage the development of self-directed study skills and offer students flexibility in terms of how they receive their material. However, this study shows that it is incorrect to include such measures within a travel plan since this implies an institutional mind-set that views student time spent on-campus negatively. The findings of the study suggest that perhaps the travel plan should assume that all students attend on-campus every day and include measures to promote the facilitation of this.

Attention to aspects of timetable design can reduce the impact of student trips without harming the social and economic sustainability of the institution. On-campus arrival and departure times are linked to timetable start and end times (sections 7.3.5 and 10.3) and therefore the student timetabled day could be repositioned so that the modal start and finish times no longer coincided with the commuting peaks. Similarly, leave-and-return trips have been shown to be a significant student behaviour (sections 7.3.6 and 10.4) and removing breaks from the timetable removes the demand for these trips. Both of these changes would broadly support student timetable preferences for fewer earlier starts (section 6.6.4) and fewer breaks of one hour or longer (section 6.6.2). The manipulation of the provision of TTDs to support student engagement objectives may also provide a small reduction in trip frequency. The changes suggested in section 10.7.2 would probably reduce student days that included a trip to campus by between 2-3%, with the model introduced in section Chapter 5 suggesting a corresponding reduction in emissions levels by around 4%.

The travel plan review (section 4.3.4) revealed that the standard university travel survey methodology is based on the assumption of workplace commuting behaviour, whilst the results of the TQS and OSS demonstrate that this approach is not appropriate for capturing study-place behaviour, and an alternative method that captures travel behaviour relative to the timetable is required. The survey format used in the TQS is one example of such a timetable-relative survey methodology, whilst the questions used by The University of York (section 4.3.4) offers another example. The TQS and the OSS have established that leave-and-return behaviour is a regular feature of student trip-making and the degree to which this is undertaken also needs to be captured by the survey methodology. At the same time a revised methodology can provide an insight into the institutional health of the university and the degree to which students are engaged with it, based around the number of discretionary trips taken and the amount of discretionary time spent on campus.

10.9 Students And Campus Space

The TQS qualitative analysis identified that students dislike spending time on-campus (section 6.4.15) whilst a further TQS question related to trip-making behaviour suggested that students find it easier to work away from campus (section 7.3.3) suggesting that the campus is in some way unsuited to this activity.

Table 59 shows the hourly student attendance on-campus across a typical day during time period C. The timetabled session attendance is based on the number of sessions multiplied by the mean timetabled day attendance figure of 93% (section 7.3.1), the proportion of students present on-campus before and after their sessions is taken from the arrivals and departures models (section 10.3). During timetabled breaks 80% of the attending timetabled population is assumed to remain on-campus (section 10.4), whilst a profile of the attendance on NTDs is taken from the OSS data analysed in section 10.2.

Hour	Timetabled Day				Non TT Day	On-campus		
	Before TT	TT Session	TT Break	After TT		Total	In session	Out of Session
8-9	12.2%	0.0%	0.0%	0.0%	0.7%	12.9%	0.0%	12.9%
9-10	15.4%	18.3%	0.0%	0.0%	2.0%	35.7%	18.3%	17.4%
10-11	13.4%	29.0%	4.3%	1.3%	3.8%	51.9%	29.0%	22.9%
11-12	10.2%	30.4%	9.8%	4.9%	5.1%	**60.4%**	30.4%	30.0%
12-13	7.5%	26.0%	13.6%	10.5%	6.1%	**63.7%**	26.0%	37.7%
13-14	5.8%	20.4%	14.7%	16.0%	6.3%	**63.2%**	20.4%	42.8%
14-15	2.6%	23.8%	9.5%	20.0%	6.6%	**62.5%**	23.8%	38.7%
15-16	1.3%	21.8%	6.4%	22.8%	6.5%	58.8%	21.8%	37.0%
16-17	0.0%	16.6%	2.0%	26.8%	5.6%	51.0%	16.6%	34.4%
17-18	0.0%	5.2%	0.1%	20.0%	4.6%	29.9%	5.2%	24.7%

Table 59 – Hourly On-campus Attendance during a typical day

[All figures taken from Period C and given as percentages of the total student population]

A maximum of just over 60% of the student population is on-campus at any time (between 11:00 and 15:00) and after 12:00 there are more students on-campus who are out of sessions, than there are attending timetabled sessions. To meet this demand, the university needs to provide a significant amount of non-teaching space to cater for the students not in sessions. The UoL library provides over 3,000 study places, and there are a further 1,550 on-campus workstations available to students (Salter, 2013). Whilst this provides places for 29% of the OSS population, these facilities must be shared with a further 8,000 medical, and Masters students meaning that the provision is not as generous as it first seems[2]. Furthermore in any given hour the available provision will be distributed across the campus meaning, and it will often be difficult for students to locate a suitable study place (section 6.4.1).

The level of space available on-campus combined with the low overall level of maximum attendance (64%) suggests that there is a supressed demand for study areas within the student population and that one of the reasons why students don't come to campus on NTDs and exhibit leave-and-return behaviour on TTDs is simply due to there not being enough of the right kind of space available on-campus (RQ4).

The built environment that is the university campus has undergone a dramatic transformation over the last twenty five years. Universities are businesses where the need to deliver a profit (or at least avoid a loss) is as important as producing

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[2] The UoL is building a new undergraduate library, ready in 2016, to provide an additional 1,000 study places to meet this need

educated and well-rounded graduates. Opportunities to maximise the revenue earning potential of the estate must be exploited. This has led to an explosion of on-campus commercial businesses that would have been unimaginable a generation ago. The expansion in student numbers has generated the critical mass necessary to make these businesses viable, and to an extent university campus will remain vibrant commercial micro-economies irrespective of the national financial situation, funded as they are through student debt. The commercial imperative to maximise the capture of this never ending revenue stream is difficult to resist. This is good from a sustainability angle, as it minimises the need for the student to make trips away from campus. It could be argued that the breaks in the timetable encourage students to spend money at campus based facilities, particularly when the breaks are short or frequent. Students on-campus are a captive market to be exploited. The emphasis on generating revenue means that the unstructured public space on-campus where students can spend time without spending money is limited. The majority of the provision of study-space is within the library, but the need to remain (largely) silent whilst using this space means they are not ideal for certain types of study. There are few shared spaces, breakout spaces (the common rooms of old) where students can relax and interact with their peers.

More unstructured space on-campus appears to be required, whilst at the same time universities are being encouraged to maximise the utilisation of their estate (section 2.2.4). One potential solution would be to use the timetable to identify unused teaching rooms and to allocate these on a hour-by-hour basis as ‘pop-up’ common rooms. Although some students currently unofficially use unallocated rooms for this purpose, formalising the arrangement would allow the university to claim that the space was being used (thereby improving utilisation rates) whilst if the space was assigned on a course or subject basis they might also act as social forums allowing students with similar interests to interact informally.

The OSS demonstrates that the use of Wi-Fi enabled devices is increasing rapidly within the student population (section 8.4.1, Figure 14) and it could be that the presence of free Wi-Fi connectivity on-campus will encourage students to attend on-campus more frequently in future specifically to take advantage of this free facility. The availability of areas to allow students to browse the Internet using their own devices is therefore also important.

The higher education landscape is changing rapidly with the emerging threat of competition from MOOCs. This suggests that universities with a physical presence (and a campus) must do more to ensure that these assets differentiate them from the competition. A campus that offers insufficient space may lead some potential students to question the benefit such a university offers over cheaper alternatives.

Chapter 11 – Summary And Conclusions

11.1 Introduction

The three aims of this study were to explore current understanding of the relationship between the timetable and trip-making behaviour, to investigate the features present in a high quality academic timetable and to examine the impact of timetable design policy on institutional sustainability. This chapter reviews how successful this study was in addressing these aims, in achieving the associated objectives, in answering the research questions and testing the hypothesises identified in chapter 1. It then continues with a short review of the limitations of the study, and how the results can be disseminated and developed through further work. The chapter concludes with a some thoughts about the study as a whole.

11.2 Review of Research Conducted

The research questions and objectives for this study are collectively reviewed in Table 60 and Table 61 respectively, and provide references back to the relevant sections within the thesis. Table 62 provides a brief recap of the hypotheses that were introduced in Chapter 1 and tested through this thesis. This table demonstrates that all the hypotheses can be accepted, although the final one, H4, that timetable design can be used as a travel planning soft measure has the caveat that although this is possible it is not sensible (section 10.8).

Table 63 contains a review of the outcomes of the study by area, demonstrating the relevance of the findings and suggesting how they can be taken forward and disseminated. It also identifies how the work conducted within the thesis can be developed into practical applications and used to generate further research questions.

Research Question	Answer to Research Question	Supporting Evidence
RQ1: Do students hold a traditional or a contemporary view of their timetable? (section 1.1.2)	Students tend towards a contemporary view of their timetable and time their trips around their sessions. However, evidence shows that some students do value discretionary time on-campus and attend on NTDs, and arrive before their sessions and stay after them.	TQS qualitative analysis: section 6.4, TQS quantitative analysis: section 7.3, OSS: section 9.5.3 and section 10.3.
RQ2: Are students less likely to come to campus on non-timetabled days? (section 1.1.2)	Students are on average just over half as likely to attend on NTDs as they are on TTDs, although individual behaviour is diverse, with some students never attending, and others attending on every NTD	TQS: section 7.3.4 and OSS: section 9.5.3.3
RQ3: What constitutes a high quality timetable from a student point of view? (section 1.1.4)	Students prefer balanced timetables with few breaks, no single session days and slightly later starts. There is no big desire for many more free days and student preference in this regard is determined by their current timetable.	TQS: quantitative analysis: section 6.6
RQ4: Do students exhibit leave-and-return behaviour? (section 1.1.4)	Students regularly consider leave and return behaviour and will make a trip if break length and residential distance means that the time spent at home exceeds travel time. Consequently students who live on-campus are most likely to exhibit this behaviour. It may be being caused by a supressed demand for space on-campus	TQS qualitative analysis: section 6.4.1, TQS trip making: section 7.3.6, OSS: section 10.4, section 10.9
RQ5: How do university travel plans represent student trip-making behaviour? (section 1.1.5)	Travel plans generally assume a commuting workplace model for student trip-making behaviour, with the effect of timetable either being ignored or interpreted ambiguously	UTR section 4.4.2
RQ6: Do certain timetable designs have a negative impact on engagement and attainment? (section 1.1.7)	The number of timetabled days is the main determinant of the total time students spend on-campus. Timetables with fewer timetabled days mean discretionary attendance of weaker students is lower and this is reflected in lower attainment levels for 1st years.	TQS trip making: section 7.3.4, OSS: section9.5.3.3, OSS: sections 10.5 and 10.6
RQ7: Can an method to observe student trip-making behaviour be devised? (section 1.1.9)	An observational survey method was developed that provides estimates of aggregate attendance that are similar to those found through an independent survey and a consistent disaggregate picture of attendance	OSS: section 9.6
RQ8: What are the impacts of timetable design on university sustainability? (section 1.2.2)	This study shows that compact timetables could be used to influence trip-making and reduce trips to campus. However, this would result in a negative impact of levels student engagement, and it is suggested that instead timetable should be used to improve student engagement which means encouraging more trips to campus.	TQS: section 6.7, UTR: section 5.3.4, OSS: section 10.7

Table 60 - Review of Research Questions

Research Objective	Initial Research Problem	Research Solution/Outcome	Evidence of Completion and Success
O1: Identify previous work into student trip-making and which links the areas of academic timetable to trip-making, engagement, attendance and attainment	Concerns around the sustainability of campus-based universities motivated a study to investigate how timetable design could be used to help address these concerns	Very little research was identified linking student trip-making to the timetable, although some research had been conducted into the links between timetable and session attendance	Chapter 2, student trip making: section 2.6, timetable and attendance: section 2.7.1, timetable and travel behaviour: section 2.7.2
O2: To conduct a review of UK University travel plans	University travel plans represent responses to the travel behaviour described through travel surveys and therefore provide an understanding of student trip-making behaviour at an operational level	Review Conducted. Universities tend to regard student study-place trips as being synonymous with staff workplace commuting behaviour, generally adopting similar methodologies to survey, report and influence this behaviour. Recognition of timetable is limited	Chapter 4 and Chapter 5, Survey Methodologies: section 4.3.4 Study-place vs workplace: section 4.4.2 Timetable related measures: section 4.3.3
O3: To conduct a survey of student timetable preferences	Limited and contradictory evidence was found in the literature in terms of what constitutes a high quality student timetable	Survey Conducted. Students are dissatisfied with their current timetables, and desire a balanced timetable with significantly fewer breaks, less single session days and later starts. These preferences seem to be driven by a desire to minimise the time spent on-campus	Chapter 6, Qualitative assessment: section 6.4.15, Quantitative assessment: section 6.8 Institutional dissatisfaction: section 6.7
O4: To develop an observational student survey method utilising secondary data sources	Student behaviour is constantly variable, snapshot surveys risk being non representative, whilst longitudinal surveys present a high burden on respondents	Survey Method Developed. LP estimation technique used to provide estimates of the population on-campus on TTDs and NTDs, whilst Bayesian method developed to infer individual student attendance levels	Chapter 8, Chapter 9, LP estimation: sections 9.3, 9.4 Inference Method: section9.4.3

Table 61 - Review of Study Objectives

Research Objective	Initial Research Problem	Research Solution/Outcome	Evidence of Completion and Success
O5: To explore the trip-making behaviour of students at an aggregate and disaggregate level	Travel surveys typically ask about trips in isolation and don't consider the effect of timetable on trip-making	TQS and OSS used to study behaviour. Similar results found in both cases, suggesting that students have differential trip rates for TTDs and NTDs, that they time their arrivals and departure to match session times and leave campus in breaks if time/distance allow. OSS provides a less pessimistic picture and suggests students may make more trips to campus and stay for longer.	Chapter 7 (TQS), Chapter 9 (OSS), TTD trip-making, sections 7.3.1 and 9.5.3.1, NTD trip-making: sections 7.3.2 and 9.5.3.2, Arrival and departure: sections 7.3.5 and 10.2, 10.3, leave-and-return behaviour: sections 7.3.6 and 10.4
O6: To explore the impact of student trip-making behaviour on academic outcome and indicators of student engagement	Levels of student engagement depend to a certain extent on time on-task and including time on-campus (Tinto and Astin)	OSS used to study behaviour. Weaker students spend less discretionary time on-campus, and since timetable is the main determinant of on-campus attendance first year students with fewer TTDs perform significantly poorer.	Chapter 8: section 8.4.4, Chapter 9: section 9.5.3.3, Chapter 10: sections 10.5 and 10.6.
O7: To discuss the implications of any findings on the sustainability of the campus based university	Universities operate within a competitive environment, and traditional campus-based universities must ensure that they do not inadvertently discourage student engagement through institutional policies	The TQS showed that nationally timetable dissatisfaction is related to the availability of teaching space available. Institution are using the timetable to meet internal objectives resulting in timetables that are unfriendly to students. Similar policies to reduce TTDs to meet institutional environmental objectives risk marginalising the campus within the student experience	Chapter 6 (TQS), section 6.7 Chapter 10, sections 10.7, 10.8 and 10.9.

Table 61 - Review of Study Objectives (Continued)

Hypothesis	Status (Accepted/ Rejected)
H1: That student trip-making behaviour tends towards the contemporary view of the timetable, rather than the traditional view	ACCEPTED, (RQ1)
H1a: That students are less likely to attend campus on non-timetabled days and that as a consequence it is the number of timetabled days in the timetable, which is the main determinant of trip-making behaviour.	ACCEPTED, (RQ2)
H1b: That students exhibit leave-and-return behaviour.	ACCEPTED, (RQ4)
H2: That that there is little recognition of the contemporary view of the academic timetable in the operational documents (travel plans) used by universities to describe and mitigate student trip-making behaviour.	ACCEPTED, (RQ5)
H2a: That current university travel planning practice, does not represent an optimal response to the challenges by institutional carbon reduction targets.	ACCEPTED, (RQ8)
H3: That student preferences for a quality timetable differ fundamentally from the timetable that they currently receive.	ACCEPTED, (RQ3)
H4: If H1 is correct then that this new understanding of the relationship between timetable and trip-making can be used to improve the environmental sustainability of the institution by controlling and perhaps reducing the level of student trip-making.	ACCEPTED (with caveat), (RQ6, RQ8)

Table 62 – Study Hypotheses and Outcomes

11.3 Limitations of the Study

The methodology used by this study means that there are some limitations to the applicability of its findings. Firstly, the TQS and OSS investigations were performed using data obtained from UoL and the findings may be more or less applicable to other institutions depending upon their similarity to Leeds. Students at new universities, those with out-of-town campus and perhaps those located in central London may exhibit different trip-making behaviour or adopt non travel related responses to their local conditions. Timetabling design practice varies by institution and the approaches adopted by other universities (for example using a fixed weekly timetable or scheduling all lectures in the AM) may change the relationship exposed in this study between timetable and trip-making. However, the analysis of the results taken from the NSS (section 6.7) suggests that timetable design is a concern in many institutions and the UTR hints at trip-making patterns similar to those observed at Leeds giving some confidence to the applicability of the findings.

The study has been careful to restrict any discussions to a broadly UK context and avoided suggesting that the findings are applicable to universities within other countries. The trip-making behaviour of students attending university will be influenced to some extent by the culture of the host society and it could be that in other countries constant presence on-campus is regarded as the cultural norm. The review of how timetabling factors affect attendance, section 2.7.1, does contain evidence which suggests student behaviour in other countries is similar to the UK, as does a commentary on student disengagement in Australia (McInnis, 2001).

11.4 Future Areas and Further Work

The research conducted in this study has been based largely on data obtained from a single university, UoL. For the findings of the research to be applicable to a wider audience, the research needs to be validated using data collected on other campus. Given that the TQS is online it could be easily administered for other institutions, and candidates might include a ‘new’ university and perhaps one with an out-of-town campus.

Some of the evidence in the UTR and the timetable quality literature suggests that Leeds’ student behaviour is typical, but how much of this behaviour is a response to combination of institutional conditions and those of the containing transport network, and how much of it describes a more universal student behaviour?

The population estimation method needs to be improved to provide more stable estimates of the hourly on-campus population on TTDs. It can then be used, combined with the data for arrivals, departures and leave-and-return behaviour to create an integrated activity based model of student behaviour which is responsive to both the student demographic attributes and within-day timetable variation. To achieve this would also require a method for synthesising representative academic timetables from a set of attribute values that describe the timetable features investigated in the TQS.

The three-way relationship between on-campus space, timetable breaks and demand for leave-and-return trips is worthy of further investigation since it would allow predictions to be made about the impact of institutional investment in increased space. It appears that this might be very similar to the wider and more general relationship between land-use and the demand for transport.

A series of timetable metrics could be developed which describe the quality of a timetable in a succinct manner. Some potential candidates: Convenience, Clumping, Balance and Position were developed as part of this study (not reported). These could be used by students to measure their timetables against institutional benchmarks (service level agreement type approach), and be used as an institutional performance measure to encourage year-on-year improvement in timetable quality.

Area	Practical Application	Dissemination (Planned)	Practical Development	New Research Questions Areas
University Travel Plans	Use revised Travel Survey Method, Consideration of leave-and-return behaviour and differential trip rates for TTDs and NTDs in university travel models	Research talks to university travel planners Paper in the Journal Transport Policy? (this journal contains most papers around university transport issues)	Further develop the Car-equivalent study-mile as a metric for comparing institutional environmental performance.	What is the ideal residential distance for student accommodation?
Student Timetable Preferences	Consider findings from TQS Reduce single session days and breaks within timetables Consider a revised timetable framework (section 10.7.1)	Research talks to university administrators Work with UoL timetabling team (ongoing) Meeting with UoL Pro-Deans, April 2013 (Completed) Develop analysis of NSS statistics and publish results (support available from HEFCE)	Development of a set of metrics to measure timetable quality using the findings from TQS. To be used at student, faculty and institutional level, and trialled/assessed using a focus group approach	Why do students dislike spending time on-campus? What can be done to encourage students to spending more time on-campus?

Table 63 - Review of Study Outcomes by Area

Area	Practical Application	Dissemination (Planned)	Practical Development	New Research Questions Areas
Student trip-making behaviour	Continue to monitor student trip making on a semester by semester basis, to identify trends in trip-making behaviour.	Paper on trip-making behaviour of students, the effect of timetable and the differential trip-rates on TTDs and NTDs	Extend the analysis into the non-teaching weeks of the semester, and weekends Make use of the locational information in OSS dataset to examine on-campus spatial reach of students relative to their timetable	Is student trip-making behaviour, and the differential trip-rates for TTDs and NTDs institution specific, like travel mode shares? Do these trip-rates describe a response to local conditions or do they reflect a more universal student approach to study?
Observational Survey Technique	Use real-time versions of the OSS datasets to identify individual students at risk from disengagement (NEG group) and proactively target these students?	Pitch the techniques to library administration (tentative interest shown: Bo Middleton – Head of Library Digital Services)	Develop a more advanced method for estimating on-campus attendance on TTDs before/during/after and in gaps between timetabled sessions Develop full student trip model, using an activity based approach, responsive to student demographic characteristics and within-day timetable variation	How does the availability of campus space affect the demand for leave-and-return trips?

Table 63 - Review of Study Outcomes by Area (continued)

11.5 Conclusions

This study has demonstrated that students hold a contemporary view of their timetable and plan their trips to and from campus around it. It has shown that students have largely consistent views about how their timetable should be organised and these views demonstrate that to some extent they wish to minimise the time they spend on-campus.

The study was motivated by the simple idea that timetable design could be used to influence and reduce student trips to campus in order to meet institutional environmental sustainability objectives. However, the research has shown that such a policy would be counter-productive and result in reduced levels of engagement between the student and their university. The study as originally envisaged (at the time of the upgrade report) was as a transport modelling exercise, examining the impact of timetable on student trip-rates, but it evolved into something broader and more multi-disciplinary.

The study has answered the research questions it was designed to investigate and the findings are potentially very useful to campus-based universities, both in terms of the development of student travel plans and the design of the academic timetable

The development of the OSS population estimation method provides the means through which student behavioural data can continue to be collected, whilst the increasing prevalence of smart-phones within the student population combined with free on-campus wireless access means that accuracy and coverage of the method will only improve in future. The method could generate a plentiful supply of raw data for use in further analysis of the complex relationship between the student, their timetable and the campus.

The multi-tasking nature of both modern life and the contemporary student experience means that the issues discussed within this thesis will continue to remain relevant, and that an institutional focus on timetable quality as a mechanism for improving the overall student experience (both academic and social) is overdue.

This thesis concludes with a quote of my own that summarises my feelings about the relationship between students, their campus and their trip-making behaviour.

> *"Students appear to regard a trip to campus in the same way they would a visit to the hospital; they know that going to campus can do them some good, they just don't want to go there that often."*

(Andrew Tomlinson, February 2014)

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List of Abbreviations

BANNER	The University of Leeds Student Information System
HESA	Higher Education Statistics Agency – This is the official agency for the collection, analysis and dissemination of quantitative information about higher education [in the UK]
LRM	Linear Regression Model
NSS	National Student Survey – Annual UK survey of final year undergraduate satisfaction with their course/institution
NTD	Non-timetabled Day
OLR	Ordered Logistic Regression Model
OSS	Observational Student Survey (Thesis Analysis Stream 3)
SMART (target)	Specific, Measurable, Attainable, Realistic and Time-bound.
SOV	Single Occupancy Vehicle – Refers to what is regarded as the least sustainable mode of transport: a vehicle, typically a car, containing a single person.
TTD	Timetabled Day
TTH	Timetable High Day: Monday, Tuesday, Thursday
TTL	Timetable Low Day: Wednesday, Friday
TQS	Timetable Quality Survey (Thesis Analysis Stream 2)
UoL	The University of Leeds
UTS	University Travel Survey
UTR	UK University Travel Plan Review (Thesis Analysis Stream 1)
UoL-TS	University of Leeds Travel Survey 2010
VLE	Virtual Learning Environment

Appendix A. University Travel Plan Survey

List of Institutions

[Institutions that are struck out were initially excluded from the analysis. No document, travel plan or otherwise, could be found for those which are shaded].

England	Document
Anglia Ruskin University	Travel Management Plan
Aston University	
Bath Spa University	Travel Plan (2007)
The University of Bath	Travel Plan (2011)
University of Bedfordshire	Travel Plan (2008)
Birkbeck College	Statement of Objectives Only
Birmingham City University	In Development
The University of Birmingham	Smartmover Travel Guide Only
~~University College Birmingham~~	
~~Bishop Grosseteste University College Lincoln~~	
The University of Bolton	
~~The Arts Institute at Bournemouth~~	
Bournemouth University	Travel Plan (2008)
The University of Bradford	
The University of Brighton	Travel Plan (2010)
The University of Bristol	Student Travel Plan (2008)
Brunel University	
Buckinghamshire New University	
The University of Buckingham	
The University of Cambridge	Travel Plan (2011)
~~The Institute of Cancer Research~~	
~~Canterbury Christ Church University~~	
The University of Central Lancashire	Travel Plan (2011)
~~Central School of Speech and Drama~~	
University of Chester	Travel Plan (2005)
The University of Chichester	Green Travel Plan (2011)
The City University	Workplace Travel Plan (2010)
~~Conservatoire for Dance and Drama~~	
~~Courtauld Institute of Art~~	
Coventry University	Sustainable Travel Plan (2010)
Cranfield University	
~~University for the Creative Arts~~	
University of Cumbria	Travel Plan (2009)
~~Dartington College of Arts~~	
De Montfort University	Travel Plan (2011)
University of Derby	Travel Plan (2009)
University of Durham	Travel Plan (2011)
The University of East Anglia	Transport Policy (2010)
The University of East London	In Development
Edge Hill University	
The University of Essex	Smart Targets Document
The University of Exeter	Sustainable Travel Plan (2010)

~~University College Falmouth~~	
University of Gloucestershire	Draft Sustainable Travel Plan (2011)
~~Goldsmiths College~~	
The University of Greenwich	Travel Plan (2011)
~~Guildhall School of Music and Drama~~	
Harper Adams University College	Travel Plan (2009)
University of Hertfordshire	Travel Plan (2011)
~~Heythrop College~~	
The University of Huddersfield	Travel Plan (2009)
The University of Hull	Travel Plan (2007)
Imperial College of Science, Technology and Medicine	
~~Institute of Education~~	
The University of Keele	
The University of Kent	Travel Plan (2011)
King's College London	
Kingston University	Travel Plan (2008)
The University of Lancaster	Travel Plan (2010)
Leeds College of Music	
Leeds Metropolitan University	Transport Strategy Progress Report (2006)
The University of Leeds	Travel Plan (2009)
~~Leeds Trinity and All Saints~~	
The University of Leicester	Travel Plan (2010)
The University of Lincoln	Draft Travel Plan (2010)
Liverpool Hope University	In Development
Liverpool John Moores University	Travel Plan (2010)
~~The Liverpool Institute for Performing Arts~~	
The University of Liverpool	Travel Plan (2009)
~~University of the Arts, London~~	
~~London Business School~~	
~~University of London (Institutes and activities)~~	
London Metropolitan University	
London South Bank University	Sustainable Travel Plan (2010)
London School of Economics and Political Science	Travel Plan (2010)
~~London School of Hygiene and Tropical Medicine~~	
Loughborough University	Travel Plan (2010)
The Manchester Metropolitan University	Travel Plan (2001)
The University of Manchester	Travel Plan (2006)
Middlesex University	Green Travel Plan (2011)
The University of Newcastle-upon-Tyne	Travel Plan Update (2009)
~~Newman University College~~	
The University of Northampton	Green Travel Plan (2008)
The University of Northumbria at Newcastle	
~~Norwich University College of the Arts~~	
The University of Nottingham	
The Nottingham Trent University	Travel Plan - Statement of Objectives Only (2012)
The Open University	Travel Plan (2006)
Oxford Brookes University	Travel Plan (2010)
The University of Oxford	Sustainable Travel Plan (2008)
~~University College Plymouth St Mark and St John~~	
The University of Plymouth	Workplace Travel Plan (2012)
The University of Portsmouth	Travel Plan (2009)
~~Queen Mary and Westfield College~~	
~~Ravensbourne College of Design and Communication~~	

The University of Reading	Travel Plan (2012)
Roehampton University	Staff Travel Plan (2010)
~~Rose Bruford College~~	
~~Royal Academy of Music~~	
Royal Agricultural College	
~~Royal College of Art~~	
~~Royal College of Music~~	
~~Royal Holloway and Bedford New College~~	
Royal Northern College of Music	
~~The Royal Veterinary College~~	
~~St George's Hospital Medical School~~	
~~St Mary's University College, Twickenham~~	
The University of Salford	
~~The School of Oriental and African Studies~~	
~~The School of Pharmacy~~	
Sheffield Hallam University	
The University of Sheffield	
Southampton Solent University	Travel Plan (2011)
The University of Southampton	Travel Plan (2011)
Staffordshire University	Sustainable Travel Plan (2009)
~~University Campus Suffolk~~	
The University of Sunderland	Travel Plan (2010)
The University of Surrey	Transport Consultation (2012)
The University of Sussex	Travel Plan (2009)
The University of Teesside	
Thames Valley University	Travel Plan (2009)
~~Trinity Laban~~	
University College London	Travel Plan (2010)
The University of Warwick	Travel Plan (2007)
University of the West of England, Bristol	
The University of Westminster	
The University of Winchester	
The University of Wolverhampton	Sustainability and Environmental Policy (2012)
~~The University of Worcester~~	
~~Writtle College~~	
~~York St John University~~	
The University of York	Travel Plan (2012)

Wales	**Document**
Aberystwyth University	Green Paper On Travel Plan Development (2009)
Bangor University	Sustainable Travel and Transport Policy - Statement of Objectives Only (2009)
Cardiff University	Travel Plan (2010)
~~University of Wales Institute, Cardiff~~	
~~University of Glamorgan~~	
~~Glyndŵr University~~	
The University of Wales, Lampeter	
The University of Wales, Newport	
Swansea Metropolitan University	Sustainable Travel Plan (2008)

Scotland	Document
The University of Aberdeen	Sustainable Travel Plan (2008)
~~University of Abertay Dundee~~	
The University of Dundee	Travel Plan (2009)
~~Edinburgh College of Art~~	
The University of Edinburgh	Transport and Travel Planning Policy - Statement of Objectives Only (2010)
Glasgow Caledonian University	Presentation - Understanding Main Forms of Travel (2012)
Glasgow School of Art	Green Travel Plan (2010)
The University of Glasgow	Strategic Travel Plan (2010)
Heriot-Watt University	In Development
Napier University	Strategic Transport Policy (2007)
Queen Margaret University, Edinburgh	Travel Plan (2011)
The Robert Gordon University	
The Royal Scottish Academy of Music and Drama	
The University of St Andrews	Travel Plan (2010)
~~Scottish Agricultural College~~	
The University of Stirling	
The University of Strathclyde	
UHI Millennium Institute	Travel Plan (2010)
The University of the West of Scotland	Travel Guide Only

Northern Ireland	Document
The Queen's University of Belfast	Travel Plan (2010)
~~St Mary's University College~~	
~~Stranmillis University College~~	
University of Ulster	Travel Plan - Statement of Objectives Only

Appendix B. Timetable Quality Survey

Timetable Quality Survey – Screenshots

The images below are screenshots taken from the TQS, demonstrating the format and layout of each question asked within the survey.

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University of Leeds Timetable Quality Survey (Student) V4

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Leeds University Timetable Quality Survey 2012 (Student Questionnaire)

Welcome to the University of Leeds Timetable Quality Survey. This survey aims to find out what you like and dislike about the timing and layout of the sessions in your academic timetable and how you would like to improve it.

The survey is open to all students and teaching staff at the University and is completed anonymously, can be saved part way through and takes a maximum of 15 minutes to complete.

As a gesture of thanks for completing the survey you can be entered into a **prize draw**, with **3 top prizes of £50 each**, and 5 prizes of £20 each up for grabs.

This version of the questionnaire is designed for *students*. If you are a member of staff, please refer to the email/web page from which you launched the survey and choose the alternative web link.

All data collected in this survey will be held anonymously and securely. No personal data is asked for or retained.

Cookies, personal data stored by your Web browser, are not used in this survey.

The survey has been approved by the University ESSL, Environment and LUBS (AREA) Faculty Research Ethics Committee under reference *AREA 12-022*

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Your Timetable

We are interested in finding out about the times and days that are most suitable for timetabled sessions.

On the next page you will be asked to complete three empty timetable grids representing:

1 - Your *current timetable*,
2 - The *best (ideal) timeable* that the University could offer you,
3 - The *worst* days and times on which sessions can be scheduled.

IMPORTANT: When completing these grids please focus on your general preferences for particular arrangements of sessions, rather than thinking about any specific time constraints which may be affecting you at the moment.

Note that once you have clicked on the CONTINUE button at the bottom of each page you can not return to review or amend that page

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Your Timetable (continued)

Your Actual Timetable

1. Thinking about your timetable for the current week, use the grid below put a tick in all timeslots in which you have scheduled sessions.

If your timetable changes from week to week just concentrate on those sessions that you are scheduled to take during the current week.

	Session Time									
	09:00-10:00	10:00-11:00	11:00-12:00	12:00-13:00	13:00-14:00	14:00-15:00	15:00-16:00	16:00-17:00	17:00-18:00	18:00-19:00
a. Monday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
b. Tuesday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
c. Wednesday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
d. Thursday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
e. Friday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Your Ideal Timetable

2. If you could redesign your timetable for the current week how would you rearrange the scheduled sessions within it to suit yourself? Please enter your **ideal timetable** for the current week into the grid below.

You should aim to put the same number of ticks into this grid, as you put in the previous one. You may move sessions to different days, or place them at different times on the same day.

You may feel that some or all of your existing timetable is already ideal as far as you are concerned in which case just tick the *already ideal* box for each day for which this is the case

	Session Time										Timetable
	09:00 - 10:00	10:00 - 11:00	11:00 - 12:00	12:00 - 13:00	13:00 - 14:00	14:00 - 15:00	15:00 - 16:00	16:00 - 17:00	17:00 - 18:00	18:00 - 19:00	Already Ideal
a. Monday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
b. Tuesday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
c. Wednesday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
d. Thursday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
e. Friday	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Your Worst Timetable

3. Which times and days of the week are **least preferable** to you in terms of timetabled sessions?

On the grid below please select the times/half-days/full-days that would cause you the most problems if your timetable had sessions scheduled on them.

For each day select the response that best describes your **least preferable** times for that day.

	Session Time (or period)								
	All Day	All Morning	All Afternoon	09:00-10:00	09:00-11:00	16:00-18:00	17:00-18:00	09:00-10:00 & 17:00-18:00	All times are acceptable
a. Monday	○	○	○	○	○	○	○	○	○
b. Tuesday	○	○	○	○	○	○	○	○	○
c. Wednesday	○	○	○	○	○	○	○	○	○
d. Thursday	○	○	○	○	○	○	○	○	○
e. Friday	○	○	○	○	○	○	○	○	○

4. Do you have any *general* comments that you would like to make about the design of your timetable and the layout of the sessions within it?

If so please add them into the box below. *(Optional)*

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How you value the free time in your timetable

5. In your ideal timetable you may have indicated that you would like one or more completely free days or free half days (morning or afternoon).

How would you compare the value to you of two completely free half days in your timetable to the value of one completely free day?

In comparison with one free full day, two free half days are.....

◯ Much more valuable ◯ More valuable ◯ The same value ◯ Less valuable ◯ Much less valuable ◯ No Opinion

6. If you have specified that you would like to have free days or free half days in your timetable please indicate the reasons why this free time is valuable to you.

	Yes	Main Reason
a. I have a part-time job (<=16 hours per week)	☐	☐
b. I have a full-time job (>16 hours per week)	☐	☐
c. I have childcare commitments	☐	☐
d. I have family commitments	☐	☐
e. I have other commitments on my time	☐	☐
f. I find I can work better away from the University campus	☐	☐
g. I like to go out at socialising at night and need time to recover	☐	☐
h. I want time during the week for leisure activities	☐	☐
i. I want some time for myself	☐	☐
j. I need some time for domestic tasks such as shopping, washing, cleaning	☐	☐
k. Travelling to University takes time and/or costs money that I would rather use in other ways	☐	☐

7. On a scale of 1-5, where 1 is not important and 5 is very important, how important is it to you to have a break from timetabled sessions for lunch some time between 11:30 and 14:00?

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University of Leeds Timetable Quality Survey (Student) V4

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Your Experience this Semester

8. Thinking about the whole of this semester up to and including this week, on the days when you **have had timetabled sessions**, on how many of them have you missed coming to campus at all?

- None, I have attended campus on every day I've had a timetabled session
- 1-2 days
- 3-4 days
- 5-6 days
- 7-8 days
- 9-10 days
- More than 10 days

9. Thinking about the whole of this semester up to and including this week, on days when you **don't have any timetabled sessions**, how often have you come to campus anyway?

- Never
- About 25% of the time
- About 50% of the time
- About 75% of the time
- All the time
- I have timetabled sessions on each day of the week

10. Thinking about the whole of this semester up to and including this week, and just about those days when you **have come to campus**, how many timetabled sessions have you missed attending even though you were on campus on that day?

- None, I have attended all of my timetabled sessions
- I have missed 1-2 sessions
- I have missed 3-4 sessions
- I have missed 5-6 sessions
- I have missed 7-8 sessions
- I have missed 9-10 sessions
- I have missed more than 10 timetabled sessions

11. Thinking about the whole of this semester upto and including this week, and about **all of your timetabled sessions**, how many of these sessions been cancelled and/or rearranged?

- None of them
- 1-2 sessions
- 3-4 sessions
- 5-6 sessions
- 7-8 sessions
- 9-10 sessions
- More than 10 sessions

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University of Leeds Timetable Quality Survey (Student) V4

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Your Arrival and Departure From Campus

12. Thinking about days when you have a timetabled session, if your first timetabled session started at 11:00 in the morning, at what time would you arrive on campus?

- Before 9:00
- Between 9:00 and 10:00
- Between 10:00 and 10:30
- Between 10:30 and 10:45
- Between 10:45 and 11:00
- Between 11:00 and 11:15
- After 11:15

(Optional)
- My arrival time is not linked to the time of my first timetabled session

13. Thinking about days when you have a timetabled session, if your last timetabled session ended at 15:00 in the afternoon, at what time would you leave campus?

- Before 15:00
- Immediately the session finished
- Between 15:00-15:15
- Between 15:15-15:30
- Between 15:30-16:00
- Between 16:00-17:00
- After 17:00

(Optional)
- My departure time is not linked to the time my last session ends

14. If you had a break from 12:00 to 15:00 between two sessions in your timetable, which of the following activities would you consider doing:
(select all that apply)

- Go to the library
- Go to somewhere quiet to study
- Go to a computer cluster
- Go to the refectory/students union
- Go for lunch somewhere other than the refectory/students union
- Go to the sports centre
- Leave campus and return to home/hall of residence
- Leave campus and go into the city
- Leave campus and do something else
- I don't have any breaks in my timetable
- Other *(please specify)*:

Continue >

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University of Leeds Timetable Quality Survey (Student) V4

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About You

15. What is your age?

◯ Less than 22 ◯ Between 22 and 30 ◯ Greater than 30

16. What is your gender?

◯ Male ◯ Female

17. Which of the following best describes your country of orgin?

◯ Britain ◯ European Union ◯ Elsewhere

18. What is your Degree programme?

◯ Undergraduate ◯ Masters ◯ Postgraduate

a.
◯ Full-time ◯ Part-time

b.
◯ 1st Year ◯ 2nd Year ◯ 3rd Year ◯ 4th Year

c. In the Faculty of
Select an answer

If you selected Other, please specify:

19. What is your normal mode of transport when travelling to campus? (tick all that you use regularly)
(select all that apply)

☐ Walk
☐ Cycle
☐ Motorcycle
☐ Bus
☐ Train
☐ Car (as passenger)
☐ Car (as driver)
☐ Other *(please specify)*:

20. What is your normal travel time to campus in minutes?

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Prize Draw and Further Surveys

If you wish to be entered into the prize draw or would like to participate in further timetable quality related surveys or research please enter a contact email address below.

21. *(Optional)*
(select all that apply)

- ☐ I wish to be entered into the prize draw
- ☐ I would like to take part in further timetable related surveys or research

Contact email address. *(Optional)*

22. If you have any further comments on the quality of your timetable, or on the design of this questionnaire, please make them now. *(Optional)*

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University of Leeds Timetable Quality Survey (Student) V4

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Thank You

Thanks for completing the Leeds University Timetable Quality Survey.

We will use the results of this survey to try to find ways of improving the overall quality of timetables issued to students and staff at the University.

Timetable Quality Survey – Student Email

The following email was distributed to all undergraduate and all Masters students registered at UoL at the start of the TQS survey week.

Dear Student,

This week (19th - 25th November) we are conducting the first Timetable Quality survey at the University of Leeds. This survey is open to ALL students and teaching staff at The University.

This is your opportunity to provide some feedback to the University on how you feel about your timetable, and how well it works for you. The results from the survey are of value to the University and may be used to inform future timetabling policy.

The aim of the survey is to determine what timetable design attributes characterise a good quality timetable, with particular attention on:

- The timing of sessions in the day, and across the days of the week
- The minimum/maximum and ideal number of sessions that should be scheduled on any day
- The maximum number of back-to-back sessions that are acceptable
- The maximum length of break between sessions that is acceptable
- The importance of a lunch-break
- The value of free full days or half days without any timetabled sessions.

The survey only takes between 10-15 minutes to complete, and individuals who take part can be entered into a prize draw, with three top prizes of £50 each, and five runners up prizes of £20 each.

To participate in the STUDENT survey, please click on the link below:

www.survey.leeds.ac.uk/studentttqualityv4

Thanks for your help.

Andrew Tomlinson,
PhD Research Student,
The Institute for Transport Studies (ITS),
University of Leeds.

This survey is being conducted as part of a PhD research programme examining the influence of the academic timetable on student/staff trip making behaviour and has been approved by the University's ESSL, Environment and LUBS (AREA) Faculty Research Ethics Committee, reference AREA 12-022.

National Student Survey: Selected Institutions

Pre-1992 (traditional) universities	Post-1992 (new) universities
Brunel University	Anglia Ruskin University
Cardiff University	Birmingham City University
Lancaster University	Bournemouth University
Loughborough University	Coventry University
Queen's University Belfast	De Montfort University
Swansea University	Edge Hill University
University of Aberdeen	Edinburgh Napier University
University of Bath	Glasgow Caledonian University
University of Birmingham	Kingston University
University of Bradford	Leeds Metropolitan University
University of Bristol	Liverpool John Moores University
University of Dundee	London Metropolitan University
University of Durham	Manchester Metropolitan University
University of East Anglia	Middlesex University
University of Edinburgh	Nottingham Trent University
University of Exeter	Oxford Brookes University
University of Glasgow	Sheffield Hallam University
University of Hertfordshire	Southampton Solent University
University of Hull	Staffordshire University
University of Kent	Teesside University
University of Leeds	University of Bedfordshire
University of Leicester	University of Brighton
University of Liverpool	University of Central Lancashire
University of Manchester	University of Derby
University of Newcastle upon Tyne	University of Glamorgan
University of Nottingham	University of Greenwich
University of Reading	University of Huddersfield
University of Salford	University of Lincoln
University of Sheffield	University of Northumbria at Newcastle
University of Southampton	University of Plymouth
University of Strathclyde	University of Sunderland
University of Surrey	University of the West of England
University of Sussex	University of Ulster
University of Warwick	University of Westminster
University of York	University of Wolverhampton

Appendix C. Observational Student Survey (OSS)

Data Set Samples

StudyId	Gender	Age	Nationality	Fee Type	Offer	Conditions	Entry Tariff	Clearing	First Choice	Affluence
1904135	M	22	UK	H	U		530	N	Y	3
1904389	F	22	UK	H	U		480	N	Y	5
1904391	M	22	UK	H	U		0	N	Y	
1969414	F	21	UK	H	C	340	420	N	Y	5
1969430	M	21	UK	H	U		0	N	Y	1

Individual student dataset

StudyId	Time Period	YearNo	ParentFaculty	Distance	Residence
1052420	A	3	BU	9.213774	Home
1052433	A	2	AR	1.437966	Other
1052434	A	1	EN	1.493603	Other
1052434	B	2	EN	0.5126246	Other
1052434	C	2	EN	0.5126246	Other

Time Period specific individual student dataset

StudyId	Time Period	Total Modules	Total Credits	Total Exams	Mean Module Mark	Module Mark SD
1052420	A	6	120	6	66.33334	5.46504
1052433	A	3	60	4	58.88	23.85971
1052434	A	3	60	2	38.66667	2.309401
1052434	B	6	120	4		
1052434	C	6	120	4	50.5	15.05656

Student academic performance dataset

StudyId	Time Period	Week No	Day No	Start	End	Zone Code
988177	A	1	4	12:00:00	14:00:00	BAINS
988177	A	1	2	09:00:00	11:00:00	RS
988177	A	1	2	12:00:00	14:00:00	RS
988177	A	1	3	09:00:00	17:00:00	BAINS
988177	A	2	4	12:00:00	14:00:00	BAINS
988177	A	2	2	09:00:00	11:00:00	RS
988177	A	2	2	12:00:00	14:00:00	RS
988177	A	2	3	09:00:00	17:00:00	BAINS

Timetable dataset

StudyId	Entry Date Time	Site
596505	07/03/2012 11:09:00	EBL
596505	19/03/2012 12:26:00	EBL
596505	25/04/2012 09:17:00	BL
596505	04/05/2012 10:43:00	BL
596505	18/05/2012 18:29:00	BL
596505	18/05/2012 18:54:00	EBL

Library entry turnstile dataset

StudyId	Time Period	Borrowed Total
1049104	B	48
1049105	B	26
1049106	B	1
1049107	B	43
1049112	B	5
1049114	B	0

Library books borrowed dataset

StudyId	Location	Login Date Time	Logout Date Time
462866	Woolhouse	07/03/2012 19:17:00	07/03/2012 20:35:00
462866	Brotherton Library	07/03/2012 20:48:00	07/03/2012 21:41:00
462866	Woolhouse	13/03/2012 16:12:00	13/03/2012 17:45:00
462866	Brotherton Library	14/03/2012 14:18:00	14/03/2012 15:05:00
462866	Woolhouse	15/03/2012 10:42:00	15/03/2012 11:05:00
462866	Brotherton Library	20/03/2012 17:13:00	20/03/2012 17:41:00

On-campus fixed-PC login/logout dataset

StudyId	Association Time	Disassociation Time	Location Id	MAC Address Part1	MAC Address Part2
169348608	08/04/2012 22:16:13	08/04/2012 22:21:13	94	8131006	8566101
152243983	08/04/2012 23:16:24	08/04/2012 23:21:24	94	283731	1534842
152243983	08/04/2012 00:37:16	08/04/2012 00:42:16	94	8176951	2224229
152243983	08/04/2012 17:05:44	08/04/2012 17:10:44	94	8176951	2224229
118489881	08/04/2012 13:18:02	08/04/2012 13:23:02	97	3985656	10865087
236847888	08/04/2012 22:36:15	08/04/2012 22:41:15	100	8176545	1419559
253298193	08/04/2012 11:27:52	08/04/2012 11:32:52	100	15774841	11651730
253036311	08/04/2012 19:40:59	08/04/2012 19:45:59	102	13688730	4862954

Wireless device usage dataset

The Location Id refers to the wireless router through which the wireless association and disassociation events were performed. Since all routers are geo-coded it is possible to associate each event with a location. The 48 bit MAC address identifying the device making the connection was split into two 24 bit elements since Microsoft Access does not include a primitive data type for storing integers with more than 32 bits.

StudyId	Login Date Time
67871	14/02/2012 09:24:00
67871	14/02/2012 10:20:00
67871	14/02/2012 11:19:00
67871	14/02/2012 16:44:00
67871	15/02/2012 08:39:00
67871	15/02/2012 11:50:00

Portal dataset

StudyId	Login Date Time
101191701	22/02/2012 15:12:34
101191701	22/02/2012 15:18:43
101192727	02/02/2012 15:55:40
101192727	02/02/2012 16:44:07
101192727	02/02/2012 16:51:58

Desktop Anywhere dataset

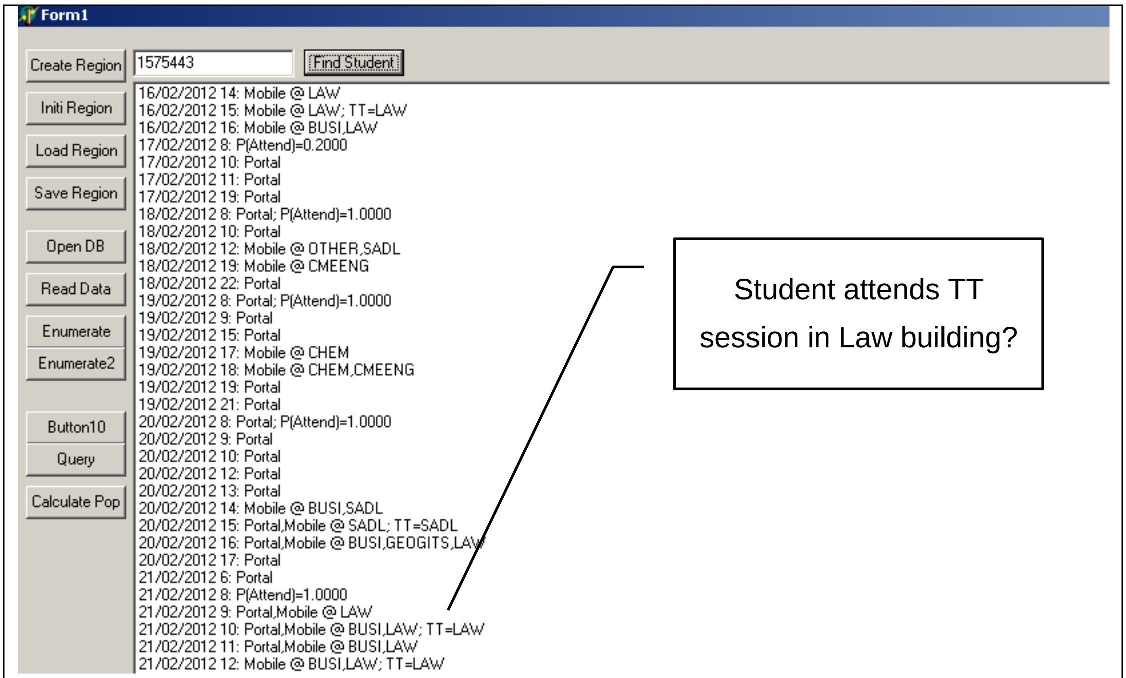
StudyId	Event Date Time	Acc Entry Success	Acc Door Name
1770513	24/01/2011 06:51:00	Y	Main Rec T2
34932249	24/01/2011 06:52:00	Y	Main Rec T2
119014431	24/01/2011 06:59:00	Y	Climb Wall T2
169477382	24/01/2011 07:00:00	Y	Main Rec T2
169477382	24/01/2011 07:00:00	Y	Poolside T1
51449605	24/01/2011 07:01:00	Y	Main Rec T3
203227145	24/01/2011 07:01:00	Y	Main Rec T2
51449605	24/01/2011 07:02:00	Y	Poolside T1

Sports centre entry turnstile dataset

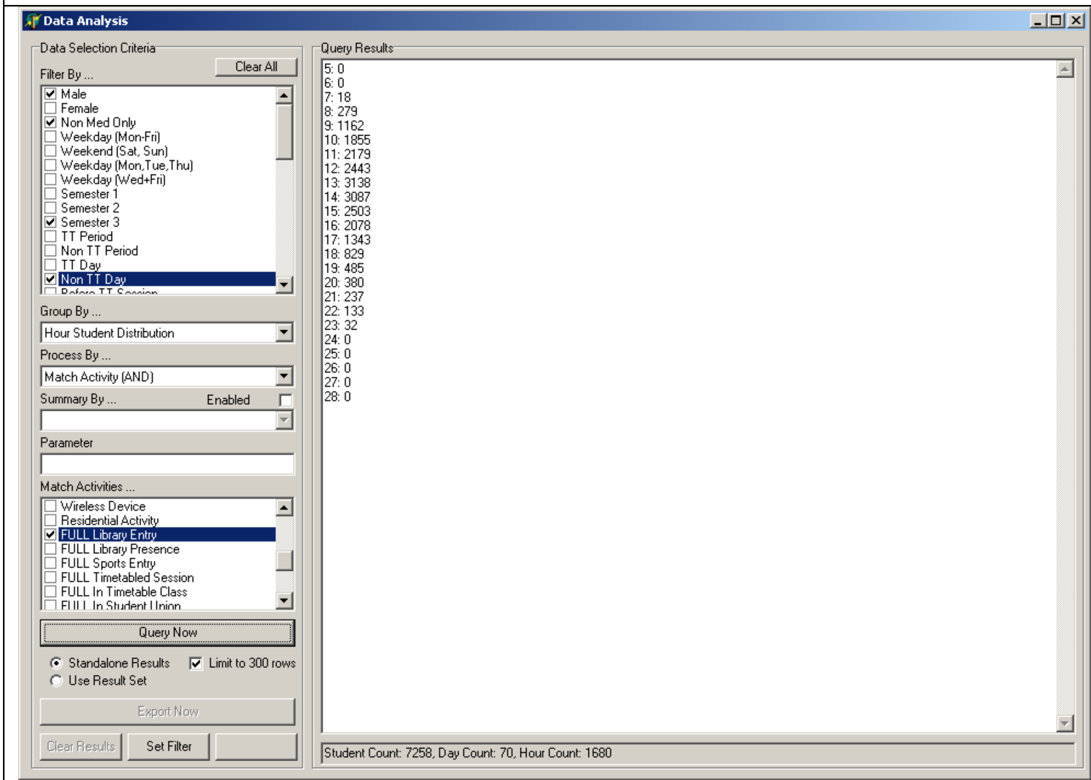
StudyId	Transaction Date Time	Machine Name
169476884	25/01/2012 18:21:00	Refectory Till 4
169476884	25/01/2012 18:24:00	Refectory Till 3
169476884	25/01/2012 18:25:00	Refectory Till 3
169476884	26/01/2012 17:30:00	Refectory Till 2
169476884	26/01/2012 17:33:00	Refectory Till 2
169476884	27/01/2012 17:44:00	Refectory Till 3
169476884	27/01/2012 17:46:00	Refectory Till 2
169476884	28/01/2012 11:54:00	Refectory Till 1

Meal card usage dataset

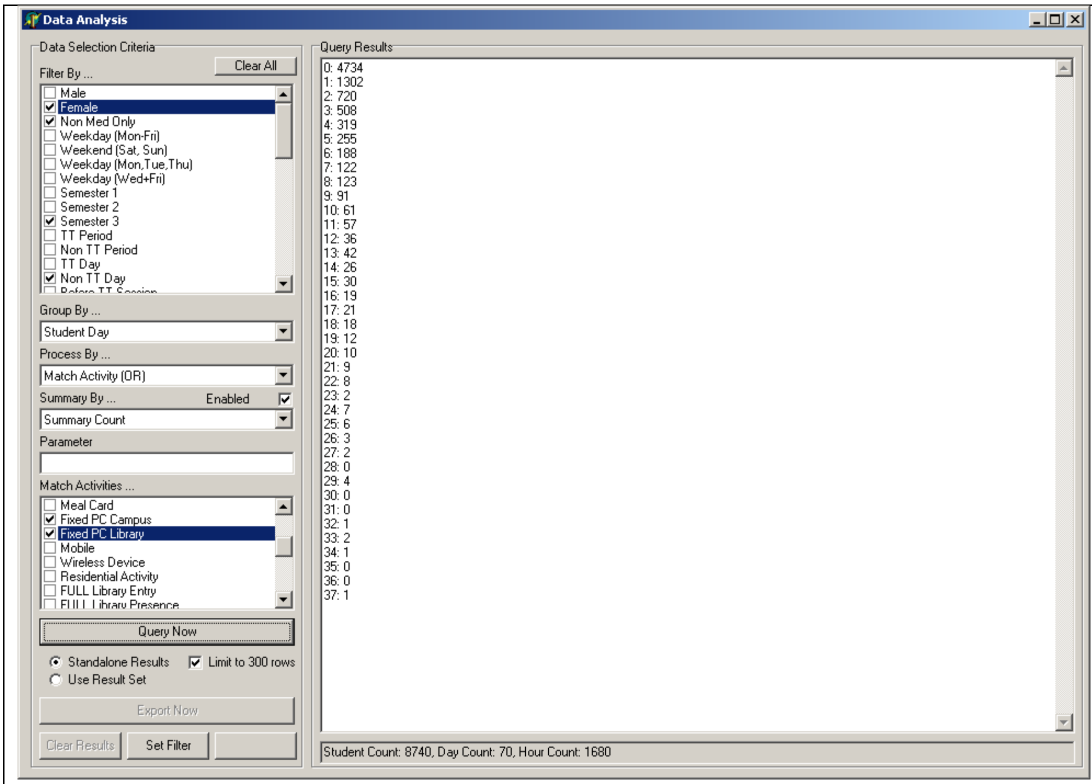
Screenshots from Analysis Application



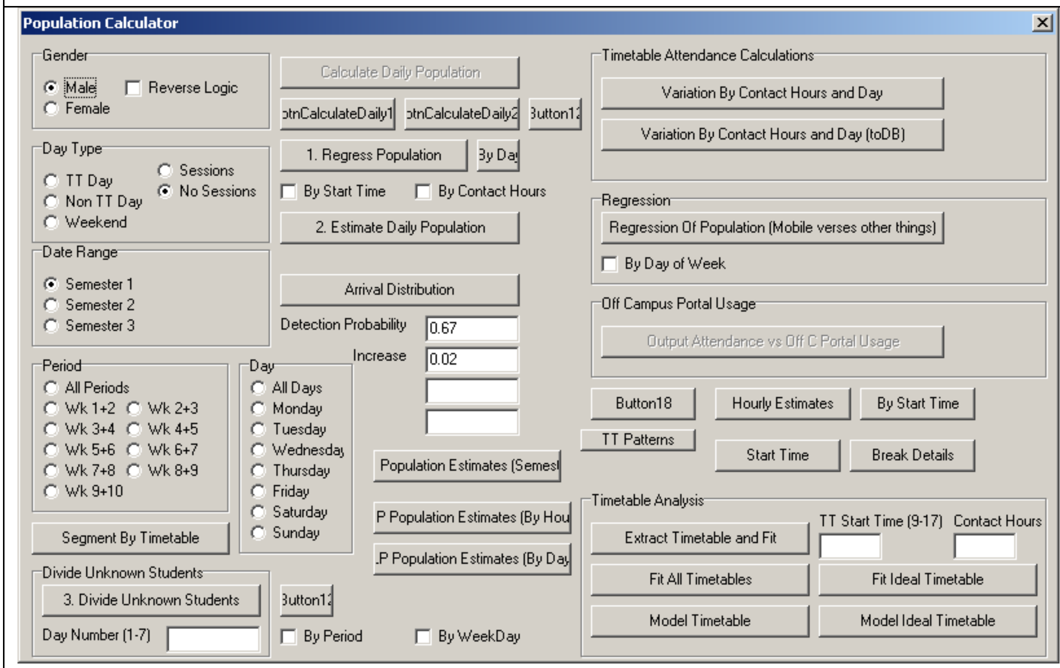
Combined record of electronic activity (and timetabled classes) for student 1575443



Standard query window, showing the distribution of all non-medical males who entered one of the libraries in time period C by hour of the day



Standard query window showing distribution of the number of NTDs on which each non-medical female student logged into a fixed PC on campus in time period C. Out of the total of 8740 students, 4734 didn't login once.



Bespoke analysis launch screen. Each button represents a different method or technique that was used or attempted.