Assessing the Impact of Recent Fare Policy Changes on Public Transport Demand in London

by

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Abstract

Public transit agencies across the world have been moving towards electronic ticketing technology and to take advantage of the greater flexibility, have made changes in fare structure. Over the last decade, Transport for London has implemented the Oyster smart card based electronic ticketing system (including the Pay-as-you-Go stored credit payment facility) on the major public transport modes: buses, the Underground and National Rail, and there have also been changes in the fare structure on these modes. This thesis explores the impacts that fare structure and technology changes (known here as fare policy changes) have had on user sensitivity to fares (fare elasticities), ticket usage and demand for travel on public transport modes in London.

The first case study uses a log-linear regression model on annual-differenced data to estimate demand on buses and the Underground in London. The findings from this research suggest that London bus and Underground user fare elasticities have not changed significantly since 2000. The implementation of the Oystercard Pay-as-you-Go system increased demand on the Underground, while the effect on buses could not be conclusively estimated.

The second case study uses ticket sales and journey data from before and after the implementation of the Oyster electronic ticketing system on National Rail to assess the impact on ticket use, growth in travel and modal switching. The results show that, within 9 months of the implementation, Oystercard Pay-as-you-Go journeys on National Rail tripled, while single or return journeys on paper tickets halved. Further, after controlling for other changes, the electronic ticketing system increased travel on National Rail by around 3%. This increase resulted from growth in public transport travel and possibly from switching from other public transport modes.

This research is of value to policy makers in public transport agencies since it suggests that electronic ticketing systems, if implemented properly, may increase public transport demand. The findings also suggest that smart card payment systems offering stored credit and multi-journey passes are preferred by users over less convenient ticket media such as limited paper tickets.

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Chapter 1 Introduction

Throughout the world, public transit systems play the role of providing accessibility to the public and these systems are often operated by public agencies. Providing this service requires money and public transport financing generally comes from fares revenue, commercial revenue and public support (UITP, 2003). Fares revenue is the main source of income directly under the control of the transit agency as evidenced by APTA (2010) which indicated that, across public transport agencies in the US in 2008, passenger fares accounted for 21.4% of total funding while other transit agency earnings and government funding came in at 4.4% and 74.2% respectively. Fares revenue is then generally the main source of funding directly under the control of transit agencies and the aim of appropriately managing this source gives rise to fare policy in transit. Agencies formulate fare policy goals to guide them and an example of these goals is found in the MBTA Fare Policy Draft (MBTA, 2007):

- Increase Ridership Utilization and Occupancy
- Establish Equitable Fares
- Enhance Mobility & Access
- Maintain/Increase Fare Revenue Stream
- Maximize Fare Revenue Collection
- Respect Customer Privacy

From these goals it is evident that transit agencies face a constant balance between increasing or maintaining fare revenues while also providing equitable fares and encouraging more users to use their services. Agencies therefore frequently explore implementing changes in their fare structure and technologies (hereafter referred to as fare policy changes) and this will, in general, result in changes in travel behavior. This thesis presents an evaluation of the effects that certain fare-policy changes in the new millennium, such as the implementation of an electronic ticketing system on London buses, London Underground and National Rail, have had on London's public transport demand and travel-media use patterns.

1.1 Motivation

Broadly speaking, the question which lies at the root of this thesis is, "How do fares influence travel behaviour?". The short answer to this simple question is that typically as fares increase, travel decreases. However, this question becomes more and more complicated with the increase in the number of modes available, and with each mode having its own fare structures and policies. Each mode may have different types of tickets, and this adds more layers of complexity to the decision that users have to make to fulfill their travel needs, and further complicates the answer to this basic question.

This basic question, in its increasingly complex form, gives rise to the study of fare policy in transit agencies. Fleishman et al. (1996) mention that fare policy in its broadest sense can be defined as encompassing all aspects related to fares taken by an agency. A stricter definition used by them is that fare policies are the principles, goals and constraints that influence the management of a transit agency in setting and collecting fares. Fare policy is then the precursor to fare structure (defined as a combination of pricing strategy, payment options, transfer policy and pricing levels) and fare payment and collection systems (defined as the existing system and technology for payment and collection of fares) and is also further influenced by both.

In recent times, there have been vast improvements made in the field of fare payment and collection technology, and specifically electronic fare systems. These have benefited from better data processing and communication capabilities and with an increasing number of transit agencies moving in the direction of electronic fare systems, they have become progressively better and cheaper to implement. Fare media form an important component of fare systems, and electronic fare media such as magnetic or smart card tickets enable transit agencies to effectively implement differentiated fares, thereby increasing flexibility to implement a variety of fare structures and enable intermodal and inter-agency travel. Within this integrated and flexible scenario, users may face a simpler fare policy scenario, with increasingly complex decisions assigned to fare technology. However, an opposite effect is also possible, where users are flooded with choices in terms of fare options and have to deal with complex fare structures, and decision making is confounded. User travel patterns, ticket usage and other behavior are therefore increasingly influenced by their interaction with the rapidly changing fare structure and technology they experience and often it is not clear how behavior will change with fare policy implementation. The motivation behind this thesis is to explore and understand these changes, in order to provide evidence regarding what might be the effects of similar future fare policy changes.

Numerous major transit agencies across the world have been implementing electronic ticketing systems and enacting fare policies to incentivize their use. Since 1995, transit agencies in Chicago, Hong Kong, London, Singapore and Washington, D.C. (among others) have implemented a smart card ticketing system and implemented fare initiatives and fare policies to encourage people to use smart cards (Hong, 2006), and these are thought to have caused major changes in travel in these cities. London has been going through significant fare-policy changes over the last decade, with changes in fare structure and an overhaul of the ticketing payment and collection system of the Underground, buses and National Rail. The introduction of the new electronic ticketing system, commonly referred to by the name of its branded "Oyster" smart card, enabled a more seamless integration of fares across modes. The introduction of the stored credit payment system known as Oystercard Pay-as-you-Go, initially on the Underground and Buses and thereafter on other modes such as National Rail, has brought the whole of London together under an integrated and flexible fare system. Changes in the fare structure such as the implementation of free travel for under-16s on buses and bus fare simplification have also occurred. Thus, London provides an ideal location to study the effects of changes in fare policy in light of rapidly evolving technology, further strengthening the motivation behind this thesis.

1.2 Research Objectives

The objectives of this thesis are to understand the impacts that fare structure and technology changes can have on travel within a major urban area served dominantly by public transportation. The questions that are addressed in this thesis are as follows:

1. Have user fare elasticities of travel changed significantly from previous studies?
2. What is the impact of implementing electronic ticketing systems and associated fare initiatives on the demand for public transport travel?
3. How do travel media use patterns change with major changes in the fare systems and technologies?
4. Does implementing an electronic ticketing system across a network lead to more travel?
5. Does the implementation of more flexible fare media encourage changes in travel mode choice?

Though these questions are addressed in the context of London but the answers should also provide insight for similar regions. In the context of London, the questions become more specific and are as follows:

1. Have fare elasticities of travel on the Underground and buses in Greater London changed significantly from previous studies?
2. What was the impact on demand of, the introduction of the Oyster electronic ticketing system on buses and the Underground, and the introduction of free travel for children under 16 on buses?
3. How did ticket media use patterns change with the implementation of the Oyster ticketing system on National Rail?
4. Did the implementation of the Oyster system across National Rail lead to an increase travel along the network?
5. Did the implementation of Oystercard Pay-as-you-Go, a stored credit payment system, encourage changes in travel mode choice?

The first two questions are addressed in Chapter 5 and the remaining three questions are addressed as part of Chapter 6 in the context of the extension of Oyster to National Rail.

1.3 Research Approach and Data

The research approach followed in this thesis is based on an in-depth analysis of fares-related changes in the London region over the past decade including fare structure and technology and how travel behavior has been affected. There are two case studies which depict specific instances of changes and address specific questions within the framework of fare policy, as discussed below.

The first case study analyses how the fare elasticities of demand have changed over time and what has been the impact of specific fare implementations on demand. Demand for travel is affected by numerous factors and demand elasticities represent the percentage change in demand caused by a unit percentage change in a demand factor. The method used is demand elasticity estimation based on a time-series linear regression model on data from 1970 to 2009. This would indicate whether the recent changes have brought about a major change in user behavior. The effect on demand of the introduction of Oyster Pay-as-you-Go and fare structure changes such as free travel for Under-16s on buses have also been estimated using dummy variables.

The second case study focuses on the National Rail system in London, specifically the changes in fare media usage and journey growth resulting from the implementation of Oyster Pay-as-you-Go and Oyster retailing on the National Rail network throughout Greater London, exploring the reasons and the future implications. A before and after study method is used, with journeys in 2009, just before the implementation of Phase 2 of Oyster on National Rail, compared with journeys made in 2010, the period immediately after, at a network-wide level as well as at individual stations. Control factors are estimated and applied to make the analysis more rigorous and to account for changes occurring not associated with Oyster on National Rail. The data used comes from the Association of Train Operating Companies (ATOC) ticket sales, as well as retail sales by Transport for London through its stations and regulated ticket stops. Automatic fare collection data is used to analyse changes in behavior of existing Oystercard users.

1.4 Thesis Organization

This thesis is divided into six chapters. Chapter 2 defines the fare policy framework being used in this thesis, before proceeding to a discussion on regional fare integration and smart card ticketing in transit.

Chapter 3 reviews the key concept of elasticity and some elasticity literature in preparation for the case study on fare elasticity.

Chapter 4 examines travel and fare policy in the London region, with a focus on the London Underground, Buses and National Rail. A chronology of major fare policy changes and other important historical factors impacting the usage of each are explored and an attempt is made to broadly link fare policy changes with travel patterns.

Chapter 5 is the first case study which explores how demand for travel changes with major fare policy changes on the London Underground and London Buses network. The underlying basis for this work is previous work on fare elasticity modeling conducted by TfL and its predecessor

London Transport, and results for these are presented and discussed with the emphasis on linking fare policy changes and demand.

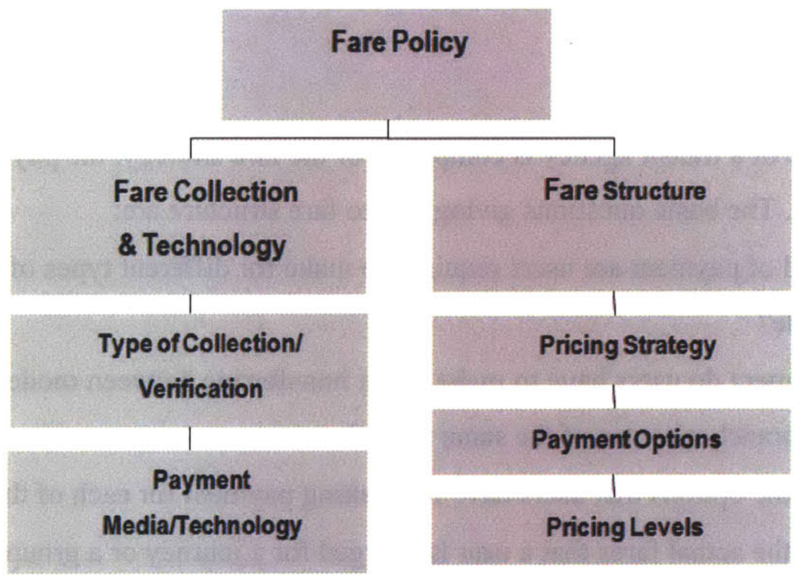
Chapter 6 is the second case study which examines changes in travel and fare media use due to the implementation of the Oystercard Pay-as-you-Go across the National Rail network in London. This is done through a network-wide analysis of journeys for the whole of London supplemented with an in-depth look at specific stations and corridors.

Chapter 7 concludes the thesis by summarizing the major findings and conclusions as well as the limitations of the research and suggestions for future research on related topics.

Chapter 2 Fare Policy Framework

Fare policy was defined in Chapter 1 based on Fleishman et al (1996) as follows: "the principles, goals and constraints that influence the management of a transit agency in setting and collecting fares". Components of fare policy are shown in Figure 2-1.

Figure 2-1 : Fare Policy and its Components
(Fleishman, Fare policy and technology lecture in MIT, 2010)



Fare policy is therefore the theoretical basis which guides changes in the fare structure, fare payment technology and fare collection system, and is also constrained by these (and other) elements. In order to fully understand what sort of impacts fare policy changes can have, we need to understand each of these terms better.

Section 2.1 looks at the existing literature on fare policy, presents the questions which give rise to the components shown in figure 2-1 and then defines each of the individual components and how they come together. Sections 2.2 presents a brief review on literature of the emerging trends of regional fare integration and section 2.3 discusses smart card ticketing systems in transit in preparation for the second case study.

2.1 Fare Policy and its Components

In the literature, fare policy is divided into the elements identified above, each having its own questions and issues. The elements relevant to this thesis are briefly discussed in this section, as their knowledge is needed to understand the components of London's fare policy. The definitions used here are based on Fleishman et al. (1996) and Multisystems Inc. (2003), and these can be consulted for a more detailed discussion.

2.1.1 Fare Structure

The fare structure of a transit agency is comprised of the fare strategy, the payment options and the pricing levels. The basic questions giving rise to fare structure are:

- What kind of payment are users required to make for different types of journeys on the same mode?
- What payment do users have to make when transferring between modes or even between different branches/routes of the same mode?
- What are the options that users have for making payment for each of their journeys?
- What are the actual fares that a user is charged for a journey or a group of journeys?

Each of these questions and their potential answers are next discussed briefly.

The first two questions above comprise the fare strategy. The first question has two possible answers, flat fares and differentiated fares:

1. Flat Fares: Users are charged the same amount for any trip, regardless of any other factors in travel. Few agencies use a purely flat fare approach, as there is generally some amount of differentiation even within a broadly flat fare strategy.
2. Differentiated Fares: Users are charged different fares for different trips. The differentiation can be based on factors such as
    a. Length of trip: Distance based pricing is commonly used to charge each user an amount based on the distance travelled.

b. Area of origin and destination: Zonal fares are a combination of flat fares within a zone (origin and destination both in same zone) combined with differentiated fares between zones (origin and destination are in different zones).
c. Time of day: The time of travel can determine the fare and is commonly used to differentiate between peak (higher use) vs non-peak period fares.
d. Service of travel: The fare can depend on the type of service provided, generally with higher fares charged for better service.
e. Market or consumer based: The fare varies by customer being served, where the differentiation may be based on age, ability, willingness to pay or some other factor.

The second question addresses the transfer pricing policy. The answer to this question specifies the level of discount in fare for consecutive journeys within a linked trip and indeed what constitutes a linked trip. The discount can vary from 100%, where the user pays no extra charge for using the new route or mode, known as a free transfer, to 0% where the user pays the full fare for each segment of their linked trip. Transfers can be inter-branch, inter-modal or inter-operator and these add other dimensions to the strategy.

The third question is that of payment options and the answer to this is strongly influenced by the available payment media and technology, which will be discussed later in this chapter. The typical payment options are:

- Single-ride payment, where payment is made for each journey separately.
- Multi-ride payment, where payment for a set of journeys is made together.
- Period pass, where a single payment covers all journeys made during a given period.
- Stored value, where money can be stored on the fare media and an appropriate amount deducted when a journey is made.
- Post payment, where payment for a journey is made after the journey is completed.

The fourth question is that of setting fare levels. Once the fare strategy and payment options are defined, the fare level can be set. In reality, the decided fare levels can also play a role in what type of fare strategy or payment options should be implemented and no dominant sequence is evident.

All of these elements together comprise the fare structure of a transit agency. The fare structure is also strongly influenced by other factors, such as those relating to the fare technology. The fare technology refers to the fare collection system and the fare media as discussed in the next section.

2.1.2 Fare Payment and Collection Technology

Fare technology applies to the technological options available or feasible for the transit fare collection and distribution system. The major questions that relate technology to fare policy can be stated as follows-

- What technology is available to implement the fare payment, collection, verification and administration systems of a transit agency?
- What fare policy capabilities does each technology support?
- Which technology is most appropriate for the transit system of interest?

The technology can then be divided into categories for the user, the operator and their interface. The consumer side of the equation is the fare or ticket media technology. The operator side is the fare administration and the interface between the two is the fare payment and verification technology. This interaction and some common technology options are shown in Fig 2-2.

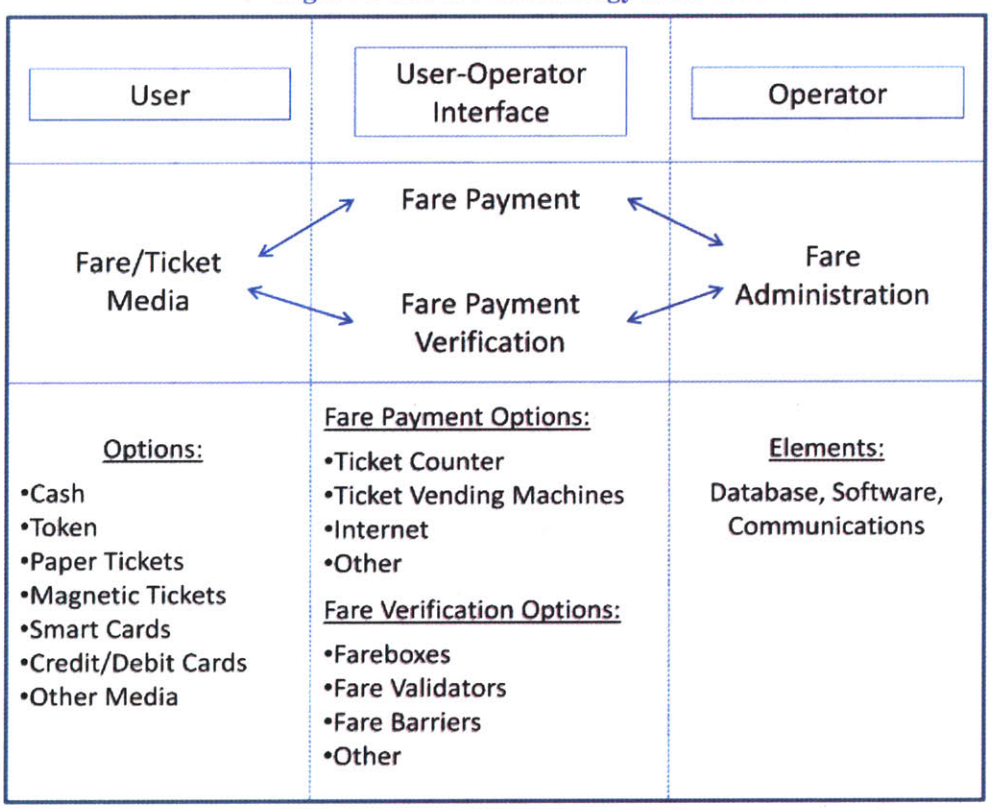
Each technology has different capabilities which will influence fare policy options. Fare media is an important component of the technology and discussion of this is necessary for this thesis.

- Cash: Cash is the simplest possible fare media. It directly pays for the journey being made.
- Paper Ticket: Paper tickets are typically used for single rides or passes, while multi-ride paper tickets are often sold in booklet forms. They have only read or read-print capabilities at validators, and must otherwise be inspected visually. These issues limit their effective use for complex fare structures.
- Electronic Fare Media/Tickets: Electronic fare media offers multiple advantages to users, in comparison with paper tickets or tokens including convenience and ease of use. They

offer greater flexibility to an agency in establishing fare options and levels and can also facilitate regional integration across operators because of better revenue control and generation of better ridership data. There are two main types of electronic fare media in use.

- Magnetic Ticket: Magnetic tickets have the capability to store single-ride, multi-ride, period pass or stored value options. They can be used with a variety of readers including read-write, read-only read-write-print.
- Smart Card: Smart cards contain a microprocessor chip with built-in logic. They have all the capabilities of magnetic tickets but are more secure. Their internal logic and higher memory capacity than magnetic tickets also make them more flexible.

Figure 2-2: Fare Technology Interaction

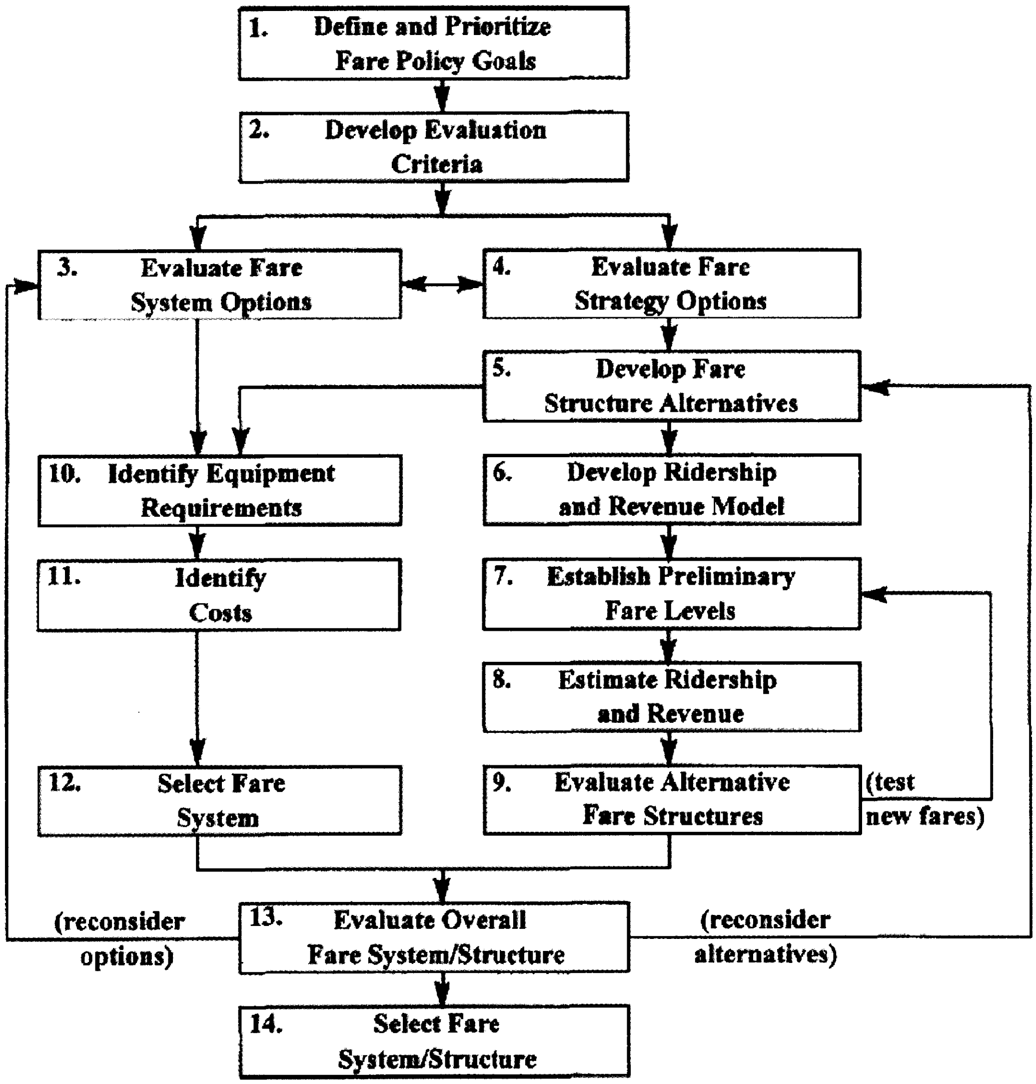


In recent times, the emergence of smart cards along with the improved computing and communication capability of validators and smart card readers has greatly influenced fare policy. Smartcard ticketing is particularly relevant to this thesis and is therefore discussed further in Section 2.3.

2.1.3 Fare Policy Decision Making

The combination of all of these issues together lead to any decision-making process. Fleishman et al. (1996) very succinctly presents the fare policy decision framework shown in Fig 2-3.

Figure 2-3: Fare policy, structure and technology decision-making process (Fleishman et al, 1996)



As is evident from the diagram, the first step in the decision making process is to formulate clear fare policy goals, evaluation criteria for fare policy options defined, and each option judged against these criteria. At each step of the process, there is interaction between the components of fare policy, and this interaction produces an initial fare system and structure. The evaluation of different such systems and structures eventually produces a final fare system and structure.

This whole decision making process is complex and even when the major issues regarding fare policy are clear, the interaction of different goals can lead to different outcomes. As an example, a focus on the customer's ease of use of the system can mean that a transit agency might attempt to simplify its fare structure by moving from a zonal fare structure to a flat fare structure. But this policy might be in direct conflict with the aim of increasing equity, in which every individual would pay according to the distance traveled.

2.2 Regional Fare Integration

In an urban public transport context, the needs, concerns and ideologies of users, operators and policymakers are stimuli which affect the existing fare policy. The current state of the fare policy system is a product of previous needs, concerns and ideologies, and similarly future evolution is a function of the current concerns. Thus, it is important to understand both the present and changing system and concerns. One way of looking at the concerns in a public transportation system is to consider the source of concern or need. We can define two sources, users and the transit system managers/administrators. Users and administrators may have concerns regarding the transportation system and these concerns may or may not affect transit system fare policy. User concerns are typically geared towards their own individual user experience, while those of the agency are focused on the system finances and performance as well as for the aggregate group of users, but both lead to the formulation of, or change in, certain fare policy goals.

Multisystems, Inc. et al. (2003) reviewed the experiences of transit agencies in the US and identified the following emerging priorities:

- Equity and environmental concerns – Provision of pricing and fares such that effects are distributed across all segments of society.
- New programs and partnership opportunities – Increasing development of fare partnerships between transit agencies with other entities
- Focus on providing seamless travel – An increasing focus on allowing users to travel across regions without paying during each segment through means of regional payment agreements.

The issues and developments affect each city and operator differently and can have different implications for emerging fare structures and technologies. The issue most pertinent to our second case study is providing seamless travel. The first case study, which analyses the change in travel behavior due to the introduction of Oyster on National Rail, analyses the impact of a regional fare integration policy with a focus on electronic ticketing.

Regional fare integration increases the level of convenience to users, can improve their service and provide greater flexibility in travel (Miller et al, 2005). It can also encourage travel and decrease fare collection costs in the long run. This issue has come to the fore with the development of smart card technology. The use of smart card as the fare media of choice allows multiple operators and modes to either come under the same fare structure or retain their individual fare structures in a more integrated regional fare structure. There are challenges that must be overcome such as the creation of effective agreements between the agencies involved to implement comprehensive revenue management policies and systems.

Miller et al (2005) reviewed the practices and impacts of integration of transit service using a survey of transit agencies in the US. While they discuss integration in terms of infrastructure, fare payment, schedule, information and special events, it is pertinent to discuss a case study referring to the experience from integration in Washington. In 1999, Washington Metro Area Transit Authority (WMATA) implemented regional bus transfer agreements allowing riders to transfer from the WMATA-run Metrobus to other regional bus services for a discount.This was followed by a steady increase in Metrobus ridership though it was not clear whether this was due to the fare integration or due to general service increases. Significant ridership increases also occurred on the regional agencies with the consistent timing of these increases suggesting that fare integration played an important role.

2.3 Smart Card Ticketing Systems in Transit

Smartcard ticketing systems have been gaining in popularity worldwide. Multisystems Inc. et al (2003) found in their case studies for the Metropolitan Transportation Commission (San Fransisco), Ventura County (California) and Washington Metro that smart cards provided greater flexibility regarding fare options, presented opportunities for regional integration, and also provided other benefits. They suggest that major customer benefits are:

- Availability of features such as registration/balance protection.
- Ability to use same card with multiple operators.
- Improved convenience of contactless interface.

Further potential benefits suggested by the same authors are:

- Multiapplication capabilities – use for non-transit purposes
- Innovative fare options

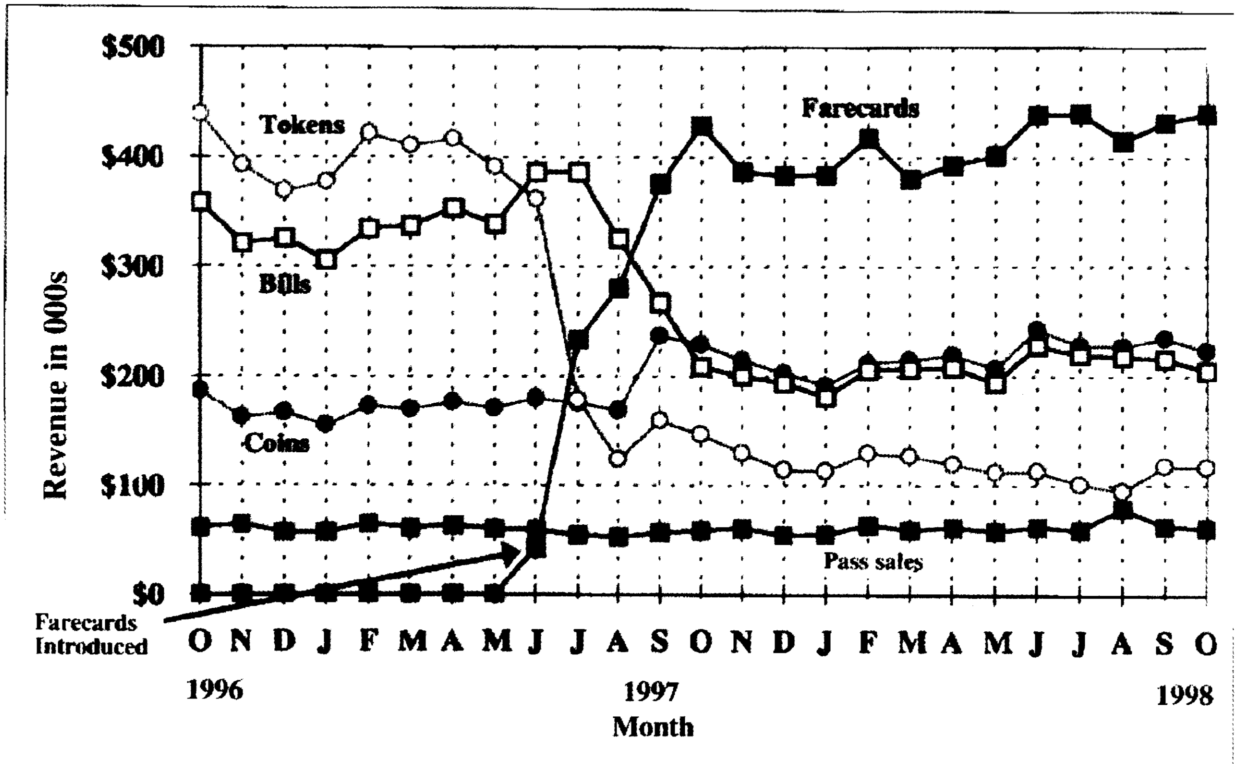
There are also agency benefits noted, specifically:

- Contactless cards allowing faster boarding or throughput than swipe fare media
- Higher data capacity and processing capability

Hong (2006) presented a review of smart cards and how they influence fare policy and also how fare policies can impact customer's transitioning to smart cards. She presented strategies to encourage the take-up of smartcards under the category of fare policy incentives, maintaining a balance between restriction and provision of smart card alternatives. The most effective fare policy incentives were found to be price differentials (travel on smart cards should cost less than equivalent travel with other fare media), bonuses (added values such as frequent use bonuses or daily capping) and implementation of refundable deposits rather than requiring purchase of smart cards.

There are few studies in the literature which have estimated the impact of smart card ticketing systems on ticket media use or travel, though there are a few case studies on user acceptance of such systems. One study is by Foote et al. (1999), who analysed the impact of the introduction of Automatic Fare Collection (AFC) systems by the Chicago Transit Authority in Chicago. This study uses descriptive statistics on ridership, ticket use and ticket share over time as its main methodology, supplemented by user satisfaction surveys. The study showed how electronic farecards using the AFC systems gained immediate popularity and within 3 months accounted for a third of all boardings, at the expense of tokens, cash and transfer journeys. Figure 2-4 has been reproduced from the study and shows the farebox revenue by ticket type.

Figure 2-4: CT average daily farebox revenue, by month and faretype (Foote et al, 1999)



The figure shows how electronic farecards immediately replaced tokens while a shift from coins occurred after a period of 3-4 months. There are said to be many factors contributing to this, such as the elimination of discounts on token multipacks, reduced availability of turnstiles for using tokens and coins, extensive availability of Automatic Vending Machines. Another interesting fact noted in this study is that the vast majority of users shifting to farecards used the single day farecard rather than the discounted multi-day versions, indicating that users might tend to shift only towards ticket types similar to those they were previously using. It becomes evident that smart card ticketing systems have a major influence on ticket use and travel and these will be tested in the following chapters.

While this chapter focused on elements of fare policy, fare elasticity modeling and fare integration, the next chapter discussed fare policy and travel on public transport in London.

Chapter 3 Fare Elasticity Literature

A significant amount of research on fare policy is focused on the estimation of fare elasticities of demand for travel. Elasticity is defined as the percentage change in one variable in response to a one percentage change in another and depends on the shape of the demand curve (Pindcyk & Rubinfeld, 2005). The basic equation is:

$$Price\ Elasticity\ of\ Demand = \frac{\%\ Change\ in\ Quantity\ Demanded}{\%\ Change\ in\ Price} = \frac{\frac{\Delta Quantity}{Quantity}}{\frac{\Delta Price}{Price}}$$

This measure of elasticity refers to the point elasticity estimate and is valid only for very small changes at a given point on the demand curve. When larger changes in the explanatory variable are considered a preferred measure is arc elasticity (TRL, 2004) since it considers the elasticity over a portion of the demand curve, by taking an average of initial and final prices and quantities demanded as in the following equation:

$$Arc\ Price\ Elasticity\ of\ Demand = \frac{\frac{\Delta Quantity}{Q'}}{\frac{\Delta Price}{P'}}$$

Where

$$P' = \frac{Initial\ Price +\ Final\ Price}{2}$$

$$Q' = \frac{Initial\ Quantity\ +\ Final\ Quantity}{2}$$

Fare elasticity of demand is a specific example of elasticity as are other measures such as service elasticity, income elasticity. For demand elasticities, there are further categorizations possible and one such categorization is whether changes in demand on a given mode are due to changes in variables associated with that mode itself (own elasticities) or other competing or complementary modes(cross elasticities) (TRL, 2004). As an example, bus fare own-elasticity would be the change in travel on buses due to change in bus fares, while bus cross-elasticity with underground fares would be the change in travel on buses due to a change in underground fares. Another possible categorization is based on the time over which the demand response occurs and the time horizon may be specified according to the data available and model used. Other categorizations are also possible, by distance travelled, by time of travel, location of travel etc. and further details on these can be obtained in TRL (2004).

Knowledge of fare elasticities helps quantify the effect of previous fare changes and these values can be used by transit agencies to forecast the future impacts of fare changes they are considering (Colin Buchanan Ltd., 2006). The emphasis throughout most of the literature is to isolate the effect of fares from the other possible factors that might influence travel so as to calculate the influence of changes in fare. Section 3.1 reviews the main elasticity estimation methodologies, while Section 3.2 reviews the use of elasticity values as part of a fare model.

3.1 Elasticity Estimation

The most common methodologies for elasticity estimation are cross-sectional choice models using SP and RP data and time-series regression models. A third methodology is a composite of these two and all of these have been briefly reviewed in this section.

3.1.1 Cross-sectional choice models

Taplin et al (1997), Hensher (1998), Hensher and King (1998) calculated joint mode and ticket usage cross elasticities based on stated and revealed preference data, using choice modeling methodologies including nested multinomial logit and heteroscedastic extreme value (HEV) functions. This work recognized that transit operators are not only interested in the average fare in predicting demand but are highly interested in the usage of each ticket type and mode type based on the cost of the ticket choice alternatives. The HEV formulation is more attractive than MNL models since it allows meaningful estimation of cross elasticities between fare classes within each mode type, resulting in accurate values of combined mode and ticket choice elasticities. Hensher and King (1998) applied this methodology to a sample of bus and car users in Newcastle whose choice set consisted of car, bus with current ticket, bus with 1 hour ticket, bus with 4 hour ticket, bus with day ticket and bus with weekly ticket, where three ranges (low fare, base fare and high fare) of prices were presented for the new ticket types on bus. Attributes such as trip cost, trip time and dummies for recreation, shopping and student trips were tested as part of this choice model. The result was a matrix of elasticities and cross elasticities between all the ticket and mode choice combinations at different fare levels. While this methodology is particularly interesting in the case of a relatively simple fare structure, it is less clear how it would perform in a highly complex zonal and time based fare structure such as the London Underground. Further it requires the use of extensive surveys prior to any fare policy change.

3.1.2 Time Series Regression Models

Time series models have commonly been used to estimate fare elasticities for urban travel and there is extensive literature on this. An example can be found it Tegner et al. (1998), who use a two-stage aggregate non-linear time series model to estimate a demand for ticket choice as well as total public transport demand based on the ticket choice. The explanatory variables utilized include fares, employment indices, and dummy variables to account for introduction of certain faretypes. The elasticity estimates are represented as changes in share of the three main ticket types used in Sweden. This model works well with simple structures but could run into complications with the introduction of more complex fare structures. Detailed data is required on disaggregate ticket sales and journeys over a long time period along with other aggregate data. This category of models will be discussed further in Chapter 4 and 5 since a linear regression model is used to estimate elasticity factors in London.

3.1.3 Composite Choice and Regression Models

Zureiqat et al (2008) developed a discrete-continuous methodology for analyzing the impact of fare changes on ticket choice and public transport demand. This method combines a discrete choice model for ticket choice with a continuous linear regression model for the frequency of use of ticket type to estimate a set of demands for different ticket types, and applies it to public transport in London. The model was shown to work well in predicting ticket type shares based on different fare levels within the existing fare structure. While this method is extremely useful for providing disaggregate demand elasticities using automatic fare collection data, it has limitations preventing its use for the purposes of this thesis. Specifically, his method relies on longitudinal smartcard panel data and this means that unless the network has a high smart card penetration rate the estimates will be biased and scaling up to network-wide effects will be challenging. Further, the demand depends only on inertia (i.e. prior use) and cost, and while seasonal effects are implicitly controlled for by a dynamic estimation process, there is no explicit treatment of other factors which may have an influence on demand. This complicates the comparison of results with previous studies and also complicates an assessment of aggregate changes over the network.

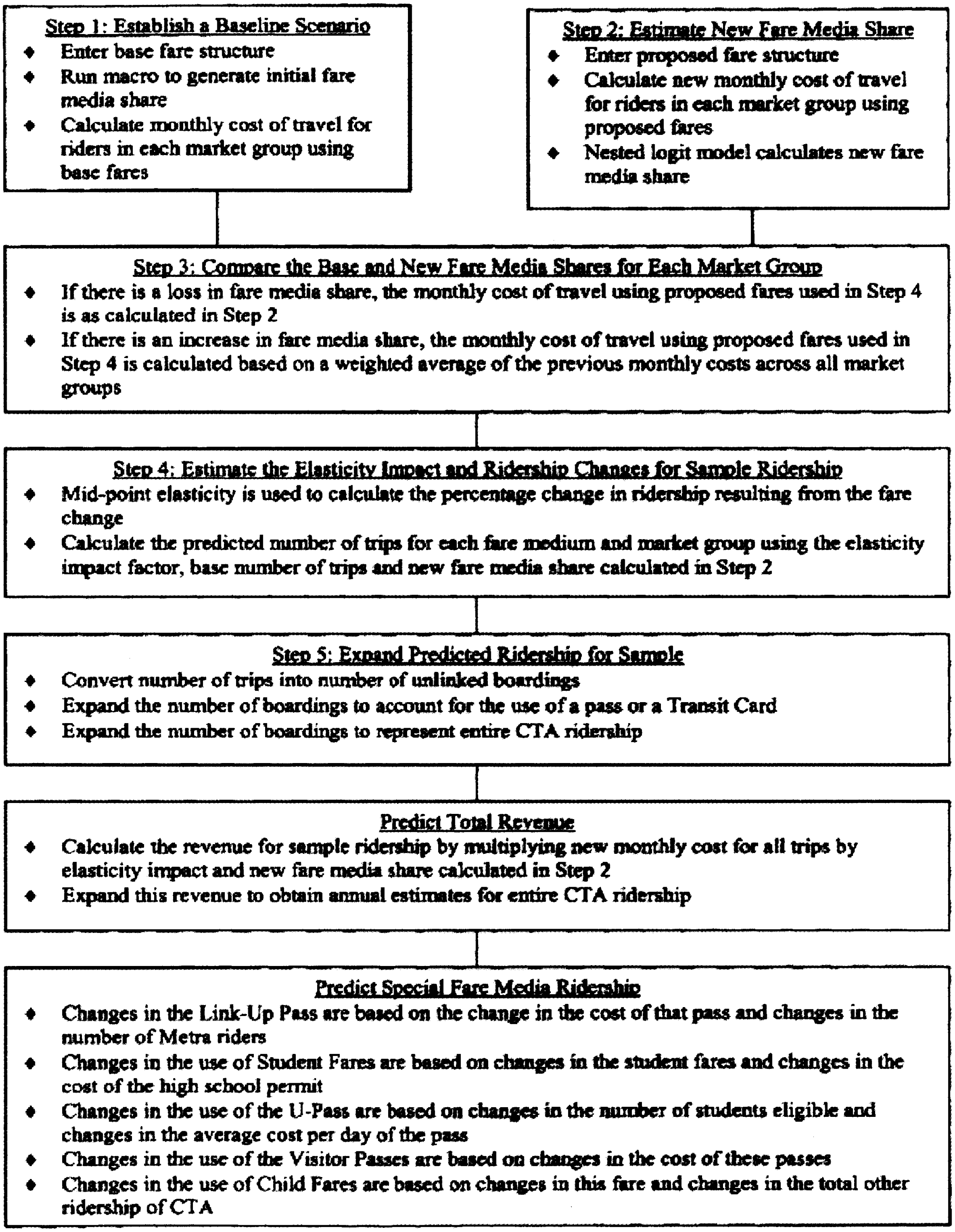
3.2 Elasticity and Fare Modeling

Transit agencies have fare models constructed according to their requirements and estimated elasticity values (as discussed in the previous section) are used as essential components in such fare models. The Chicago Transit Authority (CTA) fare model, a valuable example of the use of elasticities in a fare model to predict the effect of fare policy changes, has been discussed in Hong (2006) and Zureiqat (2008) and is briefly reviewed in this section.

Figure 3-1 shows the flow chart summarizing the CTA fare model which predicts the impact of fare changes on the fare type share, ridership and revenue. There are five steps in this model. The first step of the model relies on gathering data on rider demographics using surveys, and this data is used to categorise CTA riders into market segments (or groups) by their fare types (referenced as fare media in the figure) used and frequency of travel. Using this data and the base fare structure, a macro is run to estimate the base share of each fare type and media specific coefficients to be used in the next step. In step two, the new fare structure is entered and a discrete choice nested logit model (which utilizes the coefficients estimated in step one) is used to estimate the share of the new fare types within each market group.

The third step uses the concept of elasticity by comparing the base and new fare media shares, and there are two different scenarios that emerge. If there has been a loss in the fare medium share within a market group, the elasticity impact is based on the comparison between the monthly cost of travel under the old cost and the monthly cost of travel under new fare as proposed in the second step. If there has been an increase in fare media share for any particular market group, the elasticity impact is based on a comparison of the weighted average of the old costs across all market groups (as in step one) and the new monthly cost of travel (as in step 2).

Figure 3-1: CTA Fare Model Flowchart (Hong, 2006)



The fourth step uses elasticity coefficients, developed from the aforementioned customer surveys, which explain the changes in the CTA ridership caused by fare changes. The elasticity coefficients or impact factors are multiplied by the base trips and new fare media share to get predicted number of trips for each fare medium and market group. The final step in the model expands the estimated trips by using measured transfer patterns to get unlinked boardings. These are then further expanded from the sample ridership to give the total ridership across the CTA. The remaining two steps correspond to predicting ridership for special fare media and predicting total revenue, again with the use of elasticity factors.

As is evident the CTA fare model uses a number of elasticity factors to obtain the change in both ridership and revenue. A drawback of the CTA model is that it does not directly predict ridership and revenue if there are changes in socio-economic demand drivers, and relies only on fare changes. Therefore, estimating these elasticity factors which accurately predict changes only in fare is a critical step before they are further used in forecasting, but other elasticity estimates on population growth, income, employment are also useful.

This chapter briefly reviewed what elasticity means, literature on elasticity estimation and the importance of elasticities in a fare model. These provide an insight into the linear regression model used for our first case study and the use of elasticities resulting from our estimation. The next chapter discusses fare policy in London.

Chapter 4 Public Transport and Fare Policy in Greater London

This chapter provides background information on public transport in London and the fare policies that influence travel on the major modes, the Underground, Buses and National Rail. Section 4.1 describes public transport in London and its central role in travel in London. Section 4.2 focuses on fare policy within TfL, specifically the London Underground and London Buses, and briefly describes the major fare policy initiatives over the last decade and their influence on travel. Section 4.3 describes fare policy and ticket options on National Rail in London. Section 4.4 provides a chronology of major fare policy changes within Greater London over the last decade and finally Section 4.5 presents fare trends and travel patterns.

4.1 Public Transport in London

Transportation in London includes many modes of travel, typical of many major metropolitan areas including car, bus, heavy rail, light rail, tram, bicycle, taxi, ferry and of course walk. All these modes are used by a significant number of people, interchangeably and in conjunction with each other, and make for a complex transportation system. The Greater London Authority is headed by the popularly-elected Mayor of London and has a functional body named Transport for London(TfL), responsible for regulation and planning of all the main transport modes, with the exception of the National Rail network which is operated by government-franchised Train Operating Companies (TOCs) (TfL Legislative Framework, 2011).

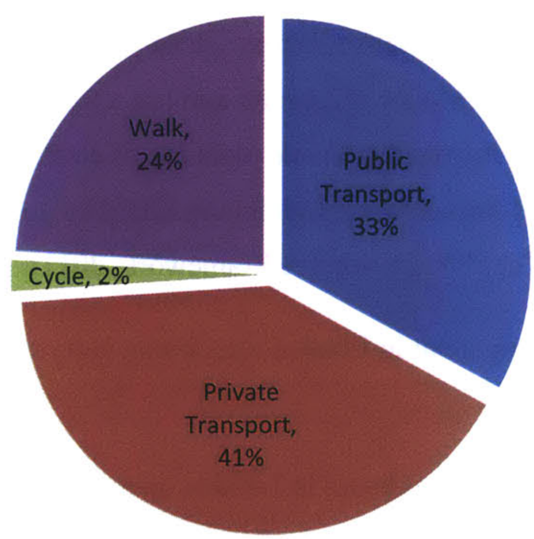
Public transport is a vital component in London's economy carrying a third of all trips on one (or more) of the following modes:

1. Buses – More than 6800 local buses in London operate on a network of over 700 routes (TfL London Buses Webpage, 2011) and carry an estimated 2.1 million daily passenger trips (TfL, 2010).

2. London Undergound – London Underground consists of eleven heavy rail lines, which primarily operate underground in the central zones and on the surface elsewhere, and carry 3.5 million daily passenger trips (TfL, 2010).
3. National Rail – This consists of railway lines operated by 10 different Train Operating Companies (ORR, 2010) which connect London and other parts of the country, and account for an estimated 2.2 million daily passenger trips (TfL, 2010), within Greater London. National Rail is the one public transport mode in London which is not directly the responsibility of Transport for London, though some parts of the network such as London Overground Limited (including the East London Line) are administered by London Rail, which is part of Transport for London.
4. Docklands Light Rail –A light rail line system primarily serving East London.
5. Tramlink – A system of trams operating in South London and connecting at different points to the Underground and National Rail network.

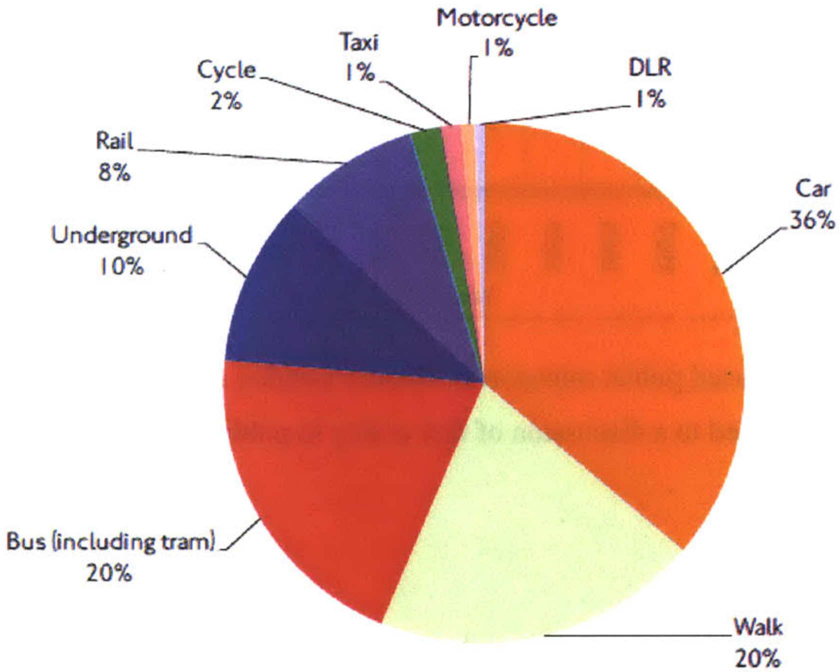
In 2008, an estimated 24.4 million trips were made across all modes in London with the mode classified by the longest distance for multi-stage trips. Figure 4-1 shows the mode share by this definition.

Figure 4-1: Mode Share of Trips in London, 2008 (TfL, 2010)



The definition of trips however does not consider the role played by the shorter linking journey stages made on other modes of travel. For private transport the definition of trips is adequate but in public transport, linking journey stages play an important role, and so a measure of journey stages is an important indicator of travel. Figure 4-2 shows mode share according to this definition.

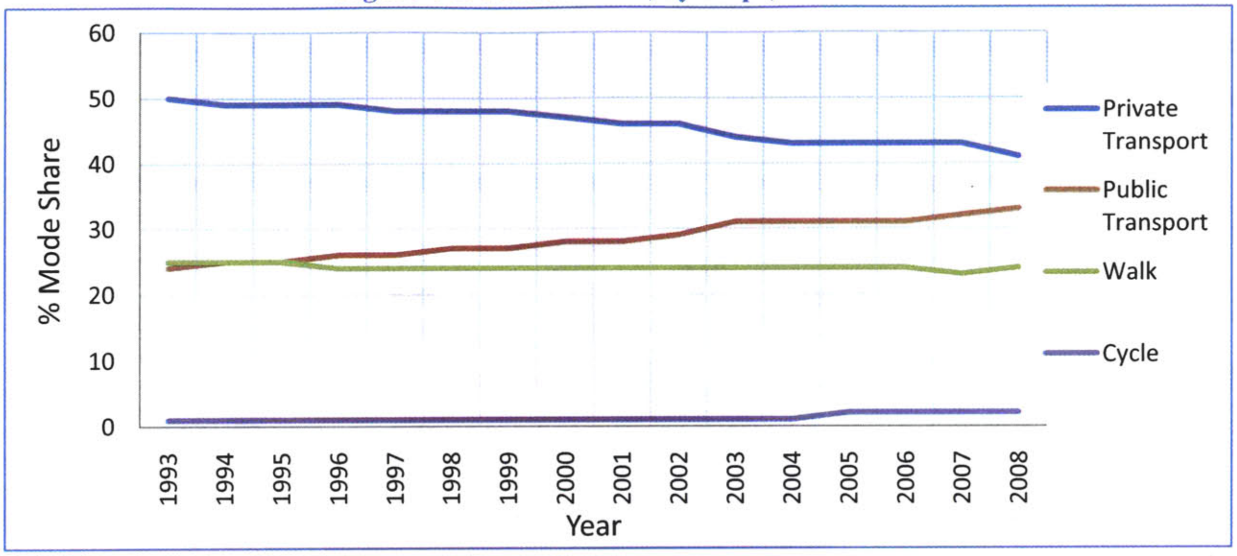
Figure 4-2: Mode shares of daily journey stages in London, 2008 (reproduced from (TfL, 2010))



By this measure, public transport (Bus, Underground and Rail) accounts for 38% of journey stages with the share of bus (and trams) being 20% and that of underground and rail being 10% and 8% respectively. Public transport in London is also becoming increasingly popular relative to other modes of travel, as evidenced by the consistent increase in use over the last two decades, shown in Figure 4-3.

The importance of public transport to London's economy is even greater than would be expected from the figures previously described. The majority of the jobs exist in Central London, which is also where the public transportation system is the most developed, and a large number of commuters make trips daily to Central London from other parts of Greater London. Public transport accounts for 89 percent of travel into Central London in the morning peak (7 to 10 AM), which includes 43% travel using the National Rail mode (TfL, 2010).

Figure 4-3: Mode Shares, by Trips, over time



Now that we have introduced public transport in Greater London and given evidence of its importance, we can proceed to a discussion of fare policy in public transport in the following sections.

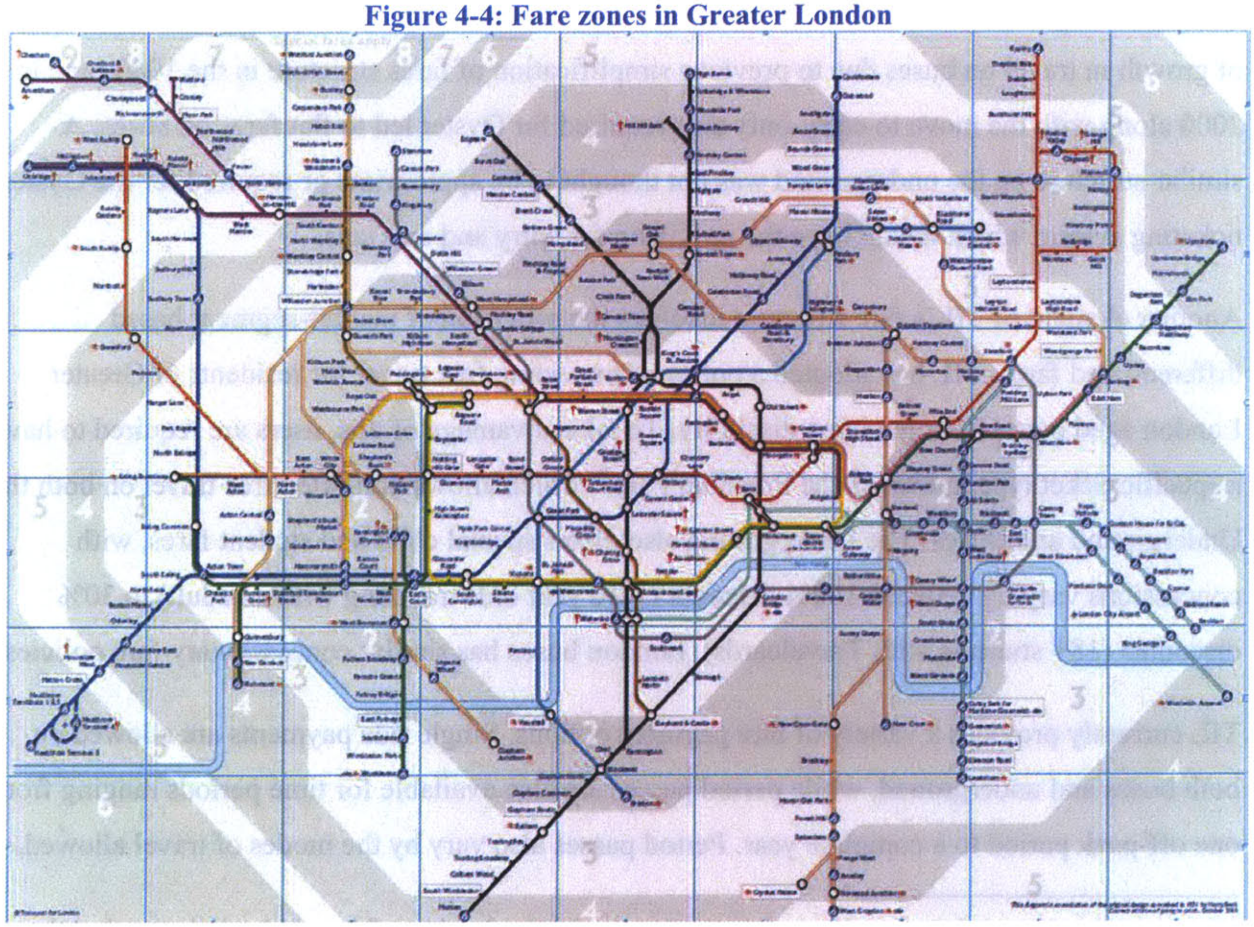
4.2 Fare Policy within Transport for London

As discussed in Chapter 2 of this thesis, fare policy includes fare structure (including fare strategy, fare payment options and fare levels) and fare collection systems and technology. TfL is responsible for fare policy for London Underground and Buses through a combined planning process, after considering the effects of interaction between these modes. Elements of their individual fare policy are therefore described together in this section, but identifying where differences exist. Section 4.2.1 discusses the current TfL fare structure, while section 4.2.2 considers the fare technology aspect. Section 4.2.3 reviews previous fare modeling work conducted in Transport for London.

4.2.1 Fare Structure

The first element of fare policy that will be discussed is fare structure, which is comprised of fare strategy, payment options and pricing levels. The first component within fare strategy is the fare structure. London Underground uses a zonal fare system. The network, as shown in Figure 4-4, consists of nine zones, with Zone 1 covering most of Central London and other zones covering concentric areas around Central London. Over 97% of the 270[1] stations fall within the first 6 zones. Fares are set either according to zones passed through on a trip (in the case of single journeys), or based on zones within which a ticket is valid (for multiple trip tickets). Fares also vary by time of day, with both peak and off-peak fares for single and multiple trip options. This zonal, time-based system on the Underground is complemented by a flat fare system on London Buses. Here, each trip has the same fare regardless of the trip length or time of day, and period tickets are also not based on time or zonal validity.

Figure 4-4: Fare zones in Greater London



In terms of transfer pricing and policy, again different policies apply to the different modes. There is no charge for transfers made within the Underground network, all of whose lines interconnect. This means that trips can involve any number of transfers between origin and

[1] As of January 2011.

destination stations as long as the user does not exit the system[5]. There are exceptions to this rule at some locations where travelers must exit one gated Underground station and enter another to complete their journey. These are known as Out-of-System Interchanges (OSIs), and free transfers are allowed within specified time windows. On the London Bus network, transfers are charged the full fare. This means that any journey on a given bus is charged the flat bus fare, regardless of any other trips made either prior to, or subsequent to, that journey[6]. Multiple trip tickets are formulated taking into account transfer policies, but these will be discussed later where payment and ticket options are discussed.

This dual policy of zonal, time-based fares with free transfers on the Underground and flat fares with full charge transfers on buses evolved due to historical and technological factors[7]. Evidence of growth in travel on buses due to previous simplification of fares structure in the 1980s and in 2000 along with the move to entry-only taps required for Oyster led to flat fares on buses. A similar structure on the underground was not thought to be appropriate or required for the Oyster ticketing system which would have the provision for entry and exit taps.

Another element of TfL's fare structure involves the provision of market-segment based differentiated fares. TfL has adopted a policy of providing free travel for residents of Greater London aged over 60[9] or having a disability. To take advantage of this, users are required to have a specific ticket type known as the Freedom Pass[10] which allows unlimited free travel on both the Underground and Buses. The Underground also offers special child and student fares, with concessions varying between 100% discount (5-10 year olds traveling with an adult) to 30% discounts (18+ students with Travelcards). London buses has similar concessionary fare policies.

TfL currently provides a variety of fare payment options. Single ride payments are allowed on both buses and underground, while period passes are also available for time periods ranging from one off-peak period to a complete year. Period passes also vary by the modes of travel allowed,

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[5] There are also time windows by origin and destination to minimize joy-riding. Trips which take longer than the specified time are charged the maximum fare, i.e. equivalent fare between Zones 1 and 6.

[6] Except when a bus breaks down and a new journey is made on another bus along the same route, in which case the traveler is entitled to a refund for one of the trips.

[7] The information in this paragraph was obtained through correspondence with Tony Richardson at TfL.

[9] First introduced in 1984, the age for the freedom pass has varied, ranging between 60 and 65 years at different points of time.

[10] The London boroughs pay TfL a negotiated amount on each Freedom Pass, to compensate for travel by these users.

with bus passes allowing unlimited travel on buses and Travelcards allowing unlimited travel on both modes (as well as National Rail). There is no period pass available which allows travel only on the Underground. Stored value payment is also allowed on both modes through the smartcard media known as the Oystercard which is discussed in Section 4.2.2. TfL recently also announced the launch of a new mode of post payment allowing the use of debit or credit card media to make payments for any journey (TfL News Archive, 2011).

The final element of fare structure is the fare level. The fare levels for all TfL modes are specified each year based on a comprehensive review process. The current fare levels are given in Appendix A.

4.2.2 Fare Payment and Technology

The other major element of fare policy relates to the fare payment and collection technology comprised of the fare or ticket media, the fare payment or verification systems and the fare administration systems which form the back-end to the system.

The fare media that can be used on the TfL modes are magnetic tickets as well as smartcard ticket media. The policy within TfL over the last decade has been to encourage people to move from magnetic tickets to its Smartcard based electronic ticketing system, the Oyster system. The Oyster system was introduced to the public in a phased manner, starting in 2003, and forms the backbone of all fare payment in TfL with over 75% of public transport journeys in London using the Oystercard. The phased introduction is summarized in section 4.4. This system is comprised of elements centered around the Oystercard, a contactless smartcard which acts as the ticket media interface for users and has the capability to store credit. An Oystercard can be obtained from numerous outlets including TfL stations, authorized Ticket Stops, online and, since 2010, at National Rail stations within Greater London. Credit can be added through manned ticket counters, automatic ticket vending machines across outlets or online.

A major element of the fare payment verification system on the Underground involves the use of fare validators at entry and exit barriers separating the Underground system from the rest of London. This system allows the implementation of a zonal based stored credit ticket type such as

Oyster Pay-as-you-Go (hereafter known as PayG), where the maximum fare is deducted at entry and the appropriate amount is refunded at exit. This system along with the technical capability of the Oystercard also allows daily capping at day travelcard fare levels, a significant feature of the Oystercard.

Table 4-1 presents the most commonly used ticket types, with PayG and Travelcard ticket types of particular importance to this thesis.

Table 4-1: TfL Ticket Types

Ticket Type	Modal Validity	Description	Trip Validity	Time Validity
Single Fare Tickets	Available separately for each TfL mode	Magnetic tickets which can be bought using cash, credit or debit.	Single Trip	Given Day, Anytime during day
Bus and Tram Pass	Bus, Tram	Smartcard based tickets which allow travel for specified time periods on buses and trams.	Unlimited Trips	Available in Weekly, Monthly and Yearly Variants
Travelcard	Underground, Bus, National Rail, Other TfL modes	Magnetic (when sold at National Rail outlets) or smartcard based tickets which allow travel for specified time periods on all TfL modes.	Unlimited Trips	Available in Day Off-Peak, Day Anytime, Weekly variants. Also any other period from 1 month to 1 year.
Oyster PayG	Underground, Bus, National Rail, Other TfL modes	Flexible stored value smartcard ticket type, with appropriate amount deducted for each trip. Has automatic daily capping at Day Travelcard fares.	Fare deduction for each trip	Anytime during day, as per trip

4.2.3 Previous Fare Modeling Work at Transport for London

In the 1980 and 1990s, London Transport developed a times-series linear regression model to obtain demand elasticity measures at an aggregate network-wide level for buses and the underground. The model developed was of a log-linear form with the dependant variable being a proxy for journeys per London resident (calculated as revenue divided by average fare deflated by Greater London population) and factors are included to control for effects of fare, service provided, socio-economic demand drivers and major events etc. This model was estimated on a

1970-1990 dataset and provided estimates of conditional and own mode elasticities which were reported in London (1992) and reviewed in McCollom & Pratt (2004). Figure 4-5 reproduces results on fare elasticities from this work.

Figure 4-5: Estimated London Transport fare elasticities at 1990 fare levels (McCollom & Pratt, 2004)

Elasticity Type	Elasticity (95% Confidence Interval)	Explanation
LT Bus		
Own Mode	–0.62 (±0.04)	Change in demand level if only the bus fare changes within the multi-modal system.
Conditional ("Normal")	–0.35 (±0.06)	Change in demand level if bus, Underground, and British Rail fares all change by the same proportion.
Underground		
Own Mode	–0.43 (±0.05)	Change in demand level if only Underground fare changes within the multi-modal system.
Conditional ("Normal")	–0.17 (±0.06)	Change in demand level if Underground, bus, and British Rail fares all change by the same proportion

Underground elasticities were found to be lower than bus elasticities, a result which would be expected due to the important role the underground plays in Central London and was found to be consistent with previous studies. The model used considers an aggregate index of fare and while it does not explicitly account for changes in fare structure, these are implicit in the aggregate fare function, providing an opportunity to test for impact of fare policies not covered by the fare index. An important fare policy change in the context of fare integration in London was the introduction of the Travelcard. This fare media, introduced in the early 1980s enabled users to travel on buses and underground, and National Rail was also added to the possible modes in 1990. The Travelcard introduction came at the same time as a major change in fare levels, with the average fare on buses decreasing by 19% and that on the Underground decreasing by 28%. The model developed by London Transport was also used to estimate the impact of the Travelcard (until 1990) on demand and revenue. The findings were reported in London Transport (1992) and present an interesting picture of the impact of the Travelcard as shown in Figure 4-6.

The change in fare structure induced an increase in travel and therefore revenue, and this nearly neutralized the reduction in revenue due to the fare level decrease.

Figure 4-6: Estimated Impact of Travelcard and associated changes (McCollom & Pratt, 2004)

Stimulus	Effect on Bus		Effect on Underground	
	Revenue	Passenger Miles	Revenue	Passenger Miles
Change in Fare Level	–11%	+10%	–17%	+15%
Change in Fare Structure	+4%	+20%	+16%	+33%
Total Impact	–7%	+30%	–1%	+48%

Note: "Change in Fare Structure" includes Travelcard and associated fare *structure* changes.

Kincaid et al (1997) extended the data till 1995 and Mitrani et al (2002) till 2000, with new variables and refinements included where possible and used the model to update fare elasticity estimates. Mitrani et al (2002) provided the latest update suggesting an elasticity of -0.64 for buses and -0.41 for the underground at 2000 fare levels. The case study in the following chapter is based on these previous reports and the model developed by London Transport, though new factors have been incorporated and some old factors have been discontinued. Since the model includes data from previous time periods, the results will not be significantly different, yet they will indicate a trend as to in which direction elasticity values are moving, if there are any changes.

4.3 Fare Policy on National Rail within Greater London

National Rail consists of about 20 Train Operating Companies providing passenger services across the United Kingdom, their combined interests represented by the Association of Train Operating Companies (ATOC). There are 10 TOCs operating within the London South-East region, under franchise from the Department of Transport in the UK: c2c, Chiltern, First Capital Connect, First Great Western, London Midland, London Overground, National Express East Anglia, Southern, Southeastern and South West Trains. While the individual TOCs have some autonomy in setting their fare structure and technology, the government sets guidelines they must conform to, such as the RPI+1% rule (tobe explained later). Section 4.3.1 discusses the fare structure National Rail follows in London, while Section 4.3.2 covers the technological aspect. Section 4.3.3 attempts to link fare change and travel patterns for National Rail.

4.3.1 Fare Structure

Within the Greater London region, the TOCs are mandated to follow a fare structure based on the London fare zones, a policy which came about in 2007 as the result of the government's aim of providing a consistent and coherent fare structure across Greater London. While TOCs were initially required to set their fare levels based on the zonal system for single and return tickets they still had freedom to set prices for season tickets, from 2 January 2010 all TOCs follow a common zonal fare system. With a zonal fare system in place, effectively free transfers are allowed on the National Rail system, but transfers to other modes are effectively charged in the form of a higher fare (known as "through fares").

National Rail also provides service differentiated fares, as journeys made on first class cost more than journeys made on standard coaches. Subsidies are also provided to sections of society such as 16-25 year olds, seniors, disabled persons etc through the means of railcards. Fare payment on National Rail can be made for single trips, return trips, as well as multiple trips in a given time period, and now with Oyster PayG stored credit payment is also possible. Aspects of fare payment and ticket media are covered in greater detail in the next section.

Prior to 2010, the majority of the TOCs were also allowed to set their own fares based on the aforementioned RPI+1% rule. This rule restricts all regulated fares within a fare basket to rise by a maximum of RPI+1% and rail fares in Greater London all fall under commuter fares, designated as regulated fares. Individual fares within the basket can rise by 5% more than the rule, but the weighted average can only rise by a maximum of RPI+1% (SRA, 2003; Colin Buchanan Ltd., 2006). From 2010 National Rail fares are set after negotiations between ATOC and TfL with 2 possible fare levels, for journeys made only on National Rail and journeys involving both National Rail and the Underground. Examples of the three types of fares in 2011 are shown in Appendix A.

4.3.2 Fare Payment and Technology

Fare payment and verification technology on National Rail varies across the TOCs, but within Greater London it has been significantly impacted by Oyster on National Rail. The main ticket types valid only on National Rail in Greater London are magnetic tickets, available from ticket counters at most National Rail stations. A description and other details are provided in Table 4-2.

Table 4-2: National Rail ticket types in Greater London

Ticket Type	Description	Location Validity	Trip Validity	Time Validity
Standard Day Single	Paper or magnetic ticket valid for a single trip	Origin and Destination Specified	Single Trip	Given Day, Anytime during day
Standard Day Return	Paper or magnetic ticket valid for a return trip	Origin and Destination Specified for both trips	Single and Return Trip	Given Day, Anytime during day
Cheap Day Return	Paper or magnetic ticket valid for a return trip	Origin and Destination Specified for both trips	Single and Return Trip	Given Day, Off-Peak Periods
Point to Point Season	Paper or magnetic ticket valid for multiple trips within a specified time period.	Journey between a specified set of stations, route or TOC service	Unlimited Trips in given time period	Available in a Weekly variant as well as any time period between 1 month and 1 year.

Apart from the ticket types shown above, the TfL administered Travelcard as well as PayG are also ticket types that can be used on National Rail. As described in Section 4.2, these ticket types can be bought or credit added at Underground stations, ticket stops, National Rail stations or even online and this increased retail ability as well as flexibility in travel is expected to have provided greater utility to the users of National Rail. Prior to OXNR, fare verification on National Rail was not consistently rigorous and users' tickets were checked at entry of station or on the train. As part of OXNR, barriers with Oyster validators were installed at most NR stations in Greater London allowing the implementation of a complete zonal system, and a more rigorous fare verification system. Chapter 6 is a case study dealing with the impact of the introduction of Oyster PayG on National Rail and looks in greater detail at the impacts of the ticket type and the fare integration policy in Greater London.

4.4 Chronology of Major Fare Policy Changes in the past decade[11]

Before moving on to the case studies, it is important to review the major fare policy decisions that have defined the current fare scenario in Greater London. In this context, Oystercards (or simply Oyster) has been a significant influence and all the changes related to this are first highlighted before other major decisions in fares are listed.

- Implementation of Oyster in London
    - September 2002: Oystercards first issued to TfL staff.
    - May 2003: Monthly and Annual Travelcards introduced on Oyster.
    - September 2003: Monthly and Annual Travelcards sold by TfL available only on Oystercards.
    - October 2003: Weekly Travelcards and Bus Passes introduced on Oyster.
    - January 2004: Oyster PayG launched across the London Underground network, Dockland Light Rail and parts of National Rail where Underground fares were valid.
    - February 2004: Freedom Passes first issued on Oyster.
    - May 2004: Weekly Travelcards sold by TfL available only on Oystercards.
    - February 2005: Daily price capping on PayG.
    - November 2006: PayG entry charge on the Underground increased to maximum cash fare. Users failing to tap in or out are charged a maximum cash fare, while other users who validated both on entry and exit are charged appropriate zonal fares.
    - 2 January 2010: PayG extended to vast majority of National Rail stations in Greater London region (OXNR). Sale of Oyster and self service machines also introduced at a significant number of National Rail stations.
- Other major changes
    - January 2004: Bus fares simplified to single fare of £1 regardless of zone and time of travel.
    - September 2005: Free bus travel for all under-16s.

[11] The information in this section was obtained through correspondence with Tony Richardson at TfL.

- January 2006: Carnets[12] withdrawn. Single zone cash tickets withdrawn, except for Zone 1 only. Apart from single tickets including zone 1, prices for other single tickets increased between 30% to 125%.
- September 2006: Free bus travel extended to 16/17 year olds in full time education.
- January 2007: National Rail network in London formally adopts zonal fare system for single and return tickets. Individual TOCs had freedom to set their own zonal fares, independent of TfL fares or other TOC fares.
- 2 January 2010: In conjunction with OXNR, National Rail network switches to a standard zonal fare system with all TOCs moving to the same zonal fares on singles, returns as well as point to point season tickets. Fares are set at a different level to Underground fares, with a third category of joint "train-tube" fares for journeys involving both Underground and National Rail modes.

The changes listed above represent major fare policy initiatives between 2002 and 2010, which would have had varying impacts on public transport travel, some of which will be investigated further in this thesis.

4.5 Fares and Travel on Public Transport in London

4.5.1 TfL Services

Public transport fares in London have changed significantly over the last decade. Within TfL fares are increased every year during the first week of January along with other changes in fare structure. These regular fare changes can impact on changing travel behavior, in terms of mode use, ticket media use and other user choices. Figures 4-7 and 4-8 highlight the changes in number of journeys made on Underground and Buses and compare these with the Gross Yield Index, an indicator used by TfL to represent the average fare change. This fare index is updated based on a gross yield factor calculated and published by Fares and Ticketing each year. The gross yield factor is a percentage value which represents the average increase in fare price relative to the

[12] Set of 10 single tickets.

previous year, making no allowance for switching between ticket types. The basic formulation of the equation for calculating the fare index is as shown:

$$FU_n = FU_{n-1} * \left[\frac{\sum_{t = \text{ticket type}}^{All\ t} (Cost_{t,n}) * TSold_{t,n-1}}{\sum_{t = \text{ticket type}}^{All\ t} (Cost_{t,n-1}) * TSold_{t,n-1}} \right]$$

$FU_n = Underground\ Fare\ Index\ in\ Period\ or\ Year\ n$
$Cost_{t,n} = Cost$ of Ticket Type t in Period n
$TSold_{t,n} =$ Number of tickets sold of type t in Period n

In the equation, the term within the brackets represents "1 + the gross yield factor", i.e. it is the weighted sum of the number of tickets sold in year n-1 for a given ticket type with the weights being the cost of the ticket type in year n, divided by the weighted sum of the number of tickets sold in year n-1 for a given ticket type with the weights being the cost of the ticket type in year n-1. This formulation therefore assumes that there will be no switching between ticket types from year n-1 to year n, though some adjustments are made if new ticket types are introduced or old ones eliminated. The fare index has been deflated by the Retail Price Index, which is an indicator for inflation in the UK and a trend line has been added to the journeys graph to show the general trend, whilst also keeping the seasonal effects visible.

Figure 4-7: London Underground, Journeys and Fare Index

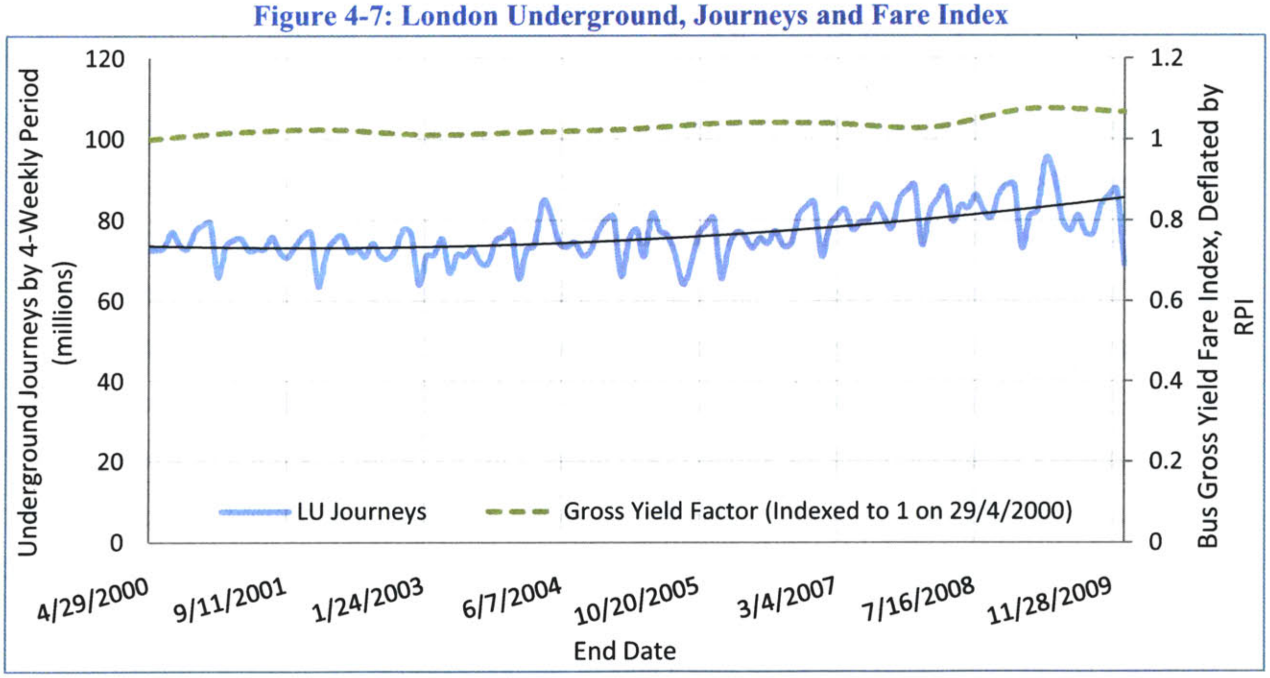
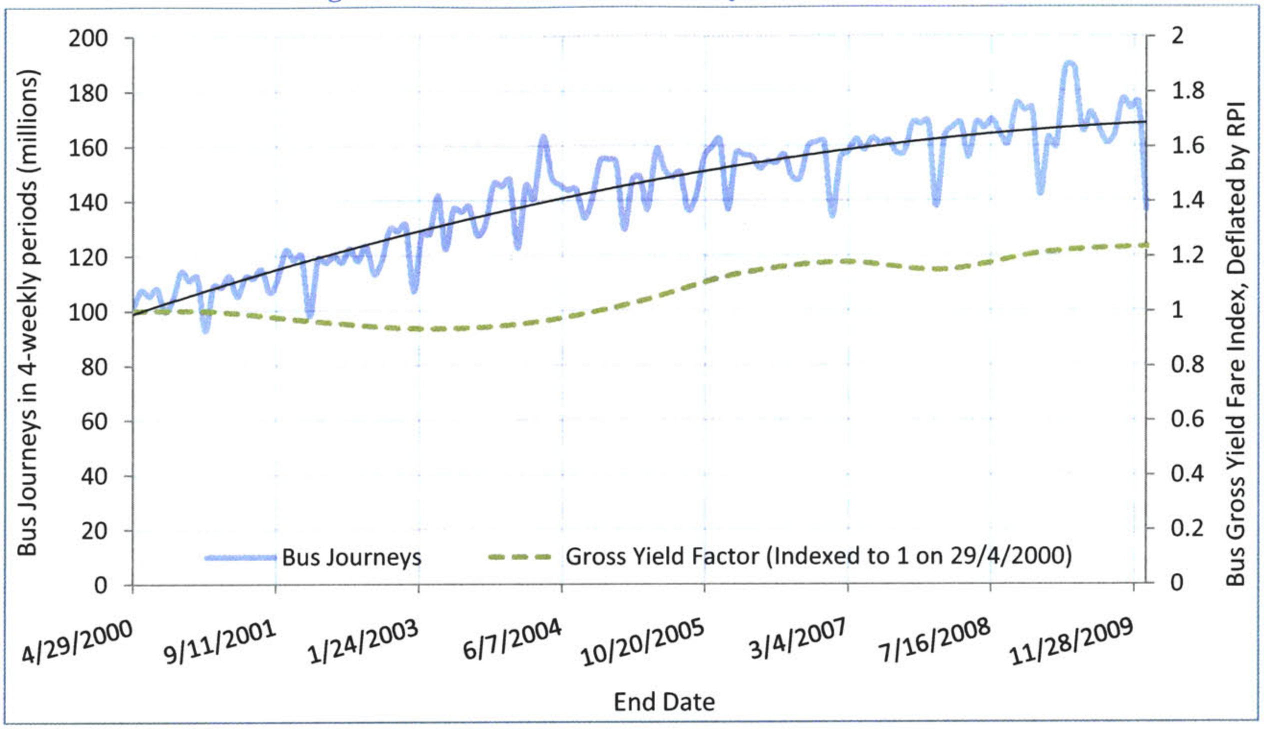


Figure 4-8: London Buses, Journeys and Fare Index



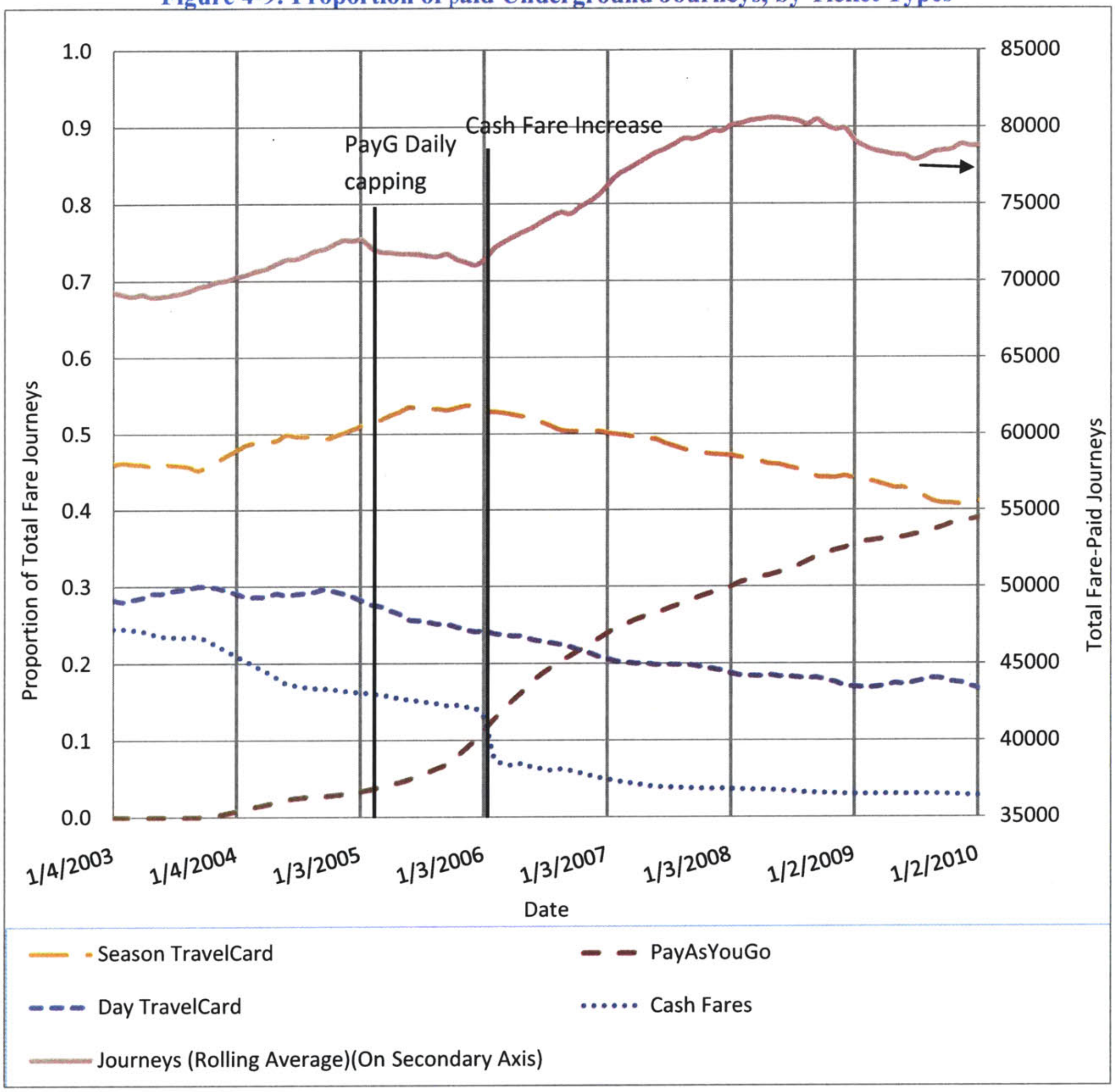
We can see from the graphs that the number of journeys made on both the Underground and Buses has been increasing, even as the real cost of travel (represented in the figure by the RPI deflated Fare Index) has also been increasing. This is contrary to our expectations of travel decreasing with increasing fare, and indicative that this graph shows only a small part of the complete story. Other socio-economic changes, as well as changes in the fare policy scenario have a major role to play, and these will be discussed throughout the thesis.

An example of the changes in travel brought about by fare policy changes is visible in Fig 4-9 which shows the change in the proportion of Underground journeys by ticket type. Some major fare policy changes are shown in the figure and in some cases the effects on travel are quite visible. The implementation of daily capping in Feb 2005 started the decrease in journeys made on day travelcards[13], quite likely with the increasing use of PayG. The increase in cash fares (between 30-100%) and withdrawal of carnet tickets in 2006 led to the further rapid take-up of PayG with users switching from the single ticket types. Further, from this point onwards, there was also a significant growth in travel, though this cannot directly be attributed to the increasing take-up of PayG. January 2004 also saw a major decrease in journeys made on Single tickets and

[13] Smoothing methodology causes changes to appear prior to fare policy change.

carnets, while the use of Season Travelcards increased quite dramatically, though it is not quite clear whether this was caused by fare policy change.

Figure 4-9: Proportion of paid Underground Journeys, by Ticket Types



As becomes clear, fare policy has a significant impact on travel behavior, whether it is in terms of ticket usage or actual travel and this is also true for National Rail.

4.5.2 National Rail

While Chapter 6 highlights the effects of changes that took place in 2010, it is important to have a perspective on the evolution of fares and travel on National Rail over the past decade. Figures 4-10 and 4-11 represent the fare index and passenger journeys as they have changed over the last 10-12 years.

Figure 4-10: National Rail Fare Index, London and South-East operators (ORR, 2010)

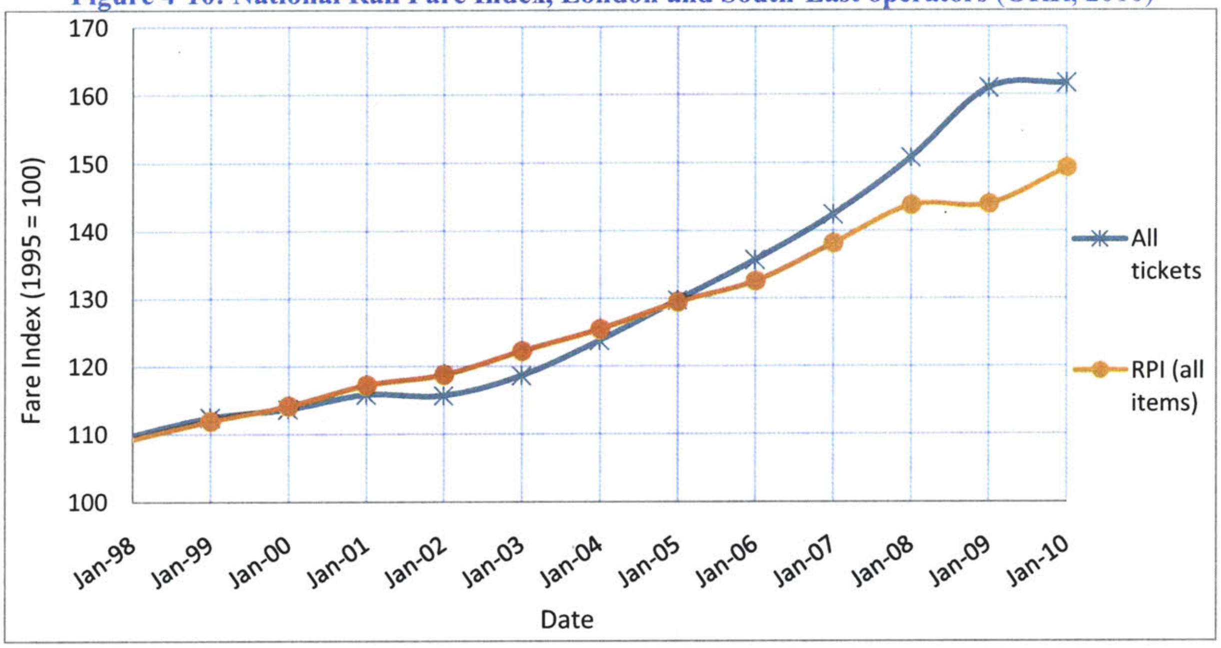
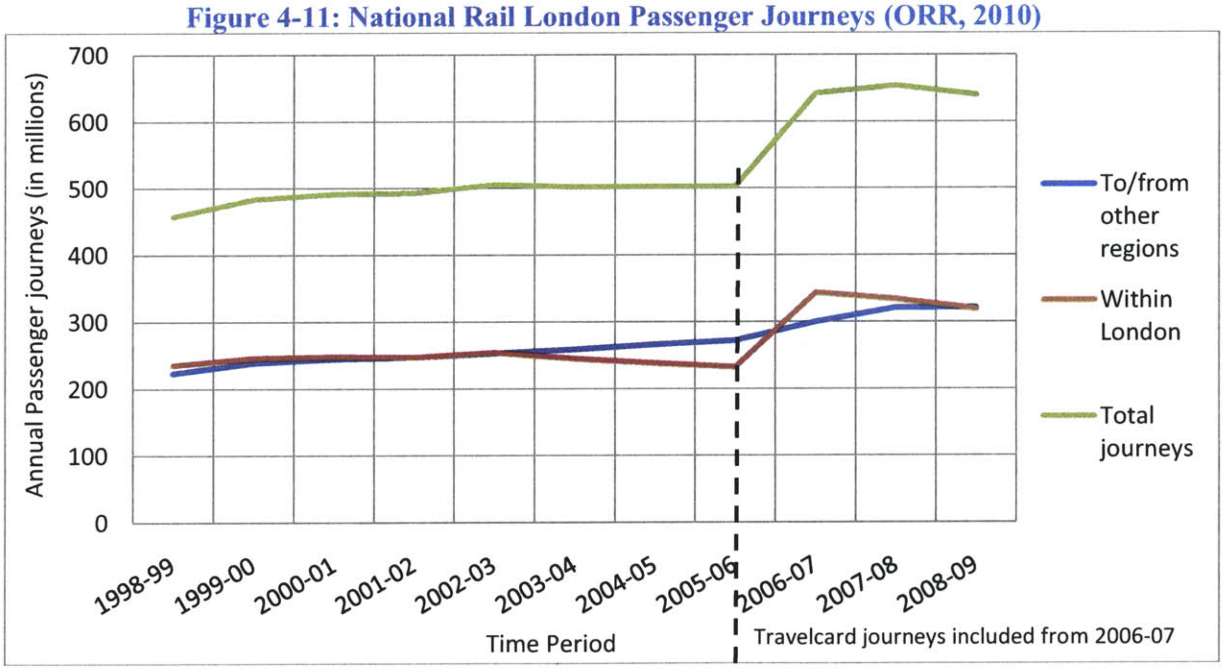


Figure 4-11: National Rail London Passenger Journeys (ORR, 2010)



As seen in fig 4-10, fares have been increasing at a greater rate than the RPI over the past eight years. This would be expected to lead to a decrease in travel, though based on Fig 4-11 it is not possible to directly infer that this is the case, especially since there is a change in the journey estimation method used in 2006-07. It might be possible to estimate the impact of fare policy changes using econometric methods or by before and after studies and the two case studies focus on identifying impacts through these methods.

As part of this chapter we have discussed the fare policy scenario, presented a chronological list of major fare policy changes and finally some trends of fares and travel within London. The next chapter presents an estimation of demand on the Underground and Buses, with the focus being fare elasticities and the impact of fare related policies.

Chapter 5 Fare Elasticity Estimation on London Buses and London Underground

As described in Chapter 4, since the year 2000 TfL has implemented the Oyster ticketing system on buses and the underground, introduced free travel for under-16s on buses, changed the fare structure for buses and made annual changes in fare levels on the major public transport modes. These are expected to have changed user behavior and may have caused changes in elasticities. This chapter explores whether demand elasticity of travel has changed since 2000 and also estimates the impact of the introduction of the Oyster system on buses and underground.

Section 5.1 defines the main questions that are addressed in this chapter, and then proceeds to review previous fare modeling work at TfL and describes factors expected to affect travel demand in London. Section 5.2 is devoted to travel on London buses and introduces the main fare policies that are being tested in the model before proceeding to the results and discussion. Section 5.3 is devoted to travel on the London Underground and introduces the main policies that are being tested in the model before proceeding to the results and discussion. Finally, section 5.4 discusses some of the limitations of the model and section 5.5 summarizes the findings.

5.1 Overview

The focus of this chapter is the impact of recent fare policy changes on the demand for travel in London. Demand is a complex term and may mean different things based on context, and it is also tightly linked to supply. In transportation, demand is a derived good and not an end in itself since it exists mainly because of the need to engage in activities which are accessible only through traveling, and this may vary with geographical, socio-economic and situational factors among others. Demand for travel is also influenced by the options available for travel and this brings into play the fare policy. When multiple modes are available, users may choose how to travel based not only on the existing external factors such as their job and home locations, their income and whether they own a private means of transport, but also on the basis of their experience or expectations with each mode. Fare policy is a significant component of transit and influences user experience in many ways, thereby influencing demand. Therefore, it is important to gain an understanding of what the demand is for a given fare policy scenario and also how fare initiatives can change this demand.

5.1.1 Objectives

The main objectives addressed in this case study are as follows:

1. Fare Elasticity of Demand:
   - What are the current fare elasticities of demand on London Buses and London Underground and have they changed significantly over time?
2. Impact on Demand of structural changes in fare policy:
   - What has been the impact on demand of the introduction of Oyster PayG on buses and underground?
   - What has been the impact on revenue demand in London of implementing free travel on buses by children under 16?

5.1.2 Factors influencing demand for travel in London

There are numerous factors which influence demand for travel on urban public transport which TRL(2004) categorizes as fares, quality of service, demand interactions, income, car ownership, land-use and public transport interaction. The impact of these factors may vary across locations and other dimensions. There are a multitude of factors affecting travel on both buses and the Underground and different variables may be used as proxies to represent each factor. The explanatory factors pertinent to Greater London and used in the existing TfL models (Mitrani et al, 2002) are shown in Table 5-1 for London Buses and Table 5-2 for London Underground. These tables show the expected effect on demand of an increase in the explanatory factor, the reason for hypothesis, possible confounding factors and our chosen variables. Road congestion and bus priority, which are new factors included in the bus model, are shown in Table 5-1.

Table 5-1: Demand Factors for London Buses

Type	Explanatory Factor	Hypothesized Effect of Increase in Factor	Reason	Confounding Factors	Variable Used
Fare	Bus Fares	Negative Impact	The higher the fares, the less people would choose it.		Bus Gross Yield Index
	Underground Fares	Positive Impact	The underground is a competing mode to buses and so higher fares would mean people are more likely to choose to travel by buses.	LU and buses can also be complementary modes.	[Bus Gross Yield Index - UG Gross Yield Index] / Bus Gross Yield Index
	National Rail Fares	Positive Impact	National Rail and buses are competing modes and higher fares on Rail would encourage a switch to buses.	Rail and buses can also be complementary modes.	National Rail Price Index
Service	Bus Miles	Positive Impact	The more service is operated, the more people are likely to choose buses.		Smoothed Bus Miles Run
	Underground Miles	Negative Impact	The more service the Underground operates, the more likely people are to choose it over bus travel.	There might also be a complementar-ity effect.	Underground Miles Run
Socio-Economic Demand Drivers	Income / Spending	Positive Impact	The more money people have or spend, the more they are likely to spend on travel.		Retail Sales Index
	Employment	Positive Impact	Greater number of employed people will mean more commuting trips.	.	Total Employment in Greater London
	Unemployment	Negative Impact	The unemployed will not make as many commuting trips resulting in lower trip rates.	Unemployed people may also have to travel more.	Greater London Unemploy-ment
	Car Ownership	Negative Impact	The more cars people own, the less likely they are to use bus.		Private Cars in London
Weather	Temperature	Unclear	This should have little impact in a 4-weekly comparison, except for exceptional weeks which could be treated separately.		Temperature Index
	Rainfall	Unclear	This should have little impact in a 4-weekly comparison, except for exceptional weeks which could be treated separately..		Rainfall Index

Quality of Service	Road Congestion	Negative Impact	The more road congestion, the poorer bus service and of the more likely are shifts to auto or LU.		Inner London Road Speeds
	Bus Priority	Positive Impact	Prioritizing buses improves service and should attract more users.		Priority Bus Lane Miles
One-Off Factors	Holidays	Negative Impact	The more holidays in a period, the less people will travel.		UK Public holiday
	Strikes	Negative Impact	Service is affected and so people will choose other modes.		Dummy
	Other factors	Case by Case			Dummy

Table 4-2: Demand Factors for London Underground

Type	Explanatory Factor	Hypothesized Effect of Increase in Factor	Reason	Confounding Factors	Variable Used
Fare	Underground Fares	Negative Impact	The higher the fares, the less people will travel.		UG Gross Yield Index
	Bus Fares	Positive Impact	Buses are a competing mode to the underground and so higher bus fares would mean people are more likely to choose the underground.	LU and buses can also be complementary modes.	[UG Gross Yield Index - Bus Gross Yield Index] / UG Gross Yield Index
	National Rail Fares	Positive Impact	National Rail and underground are competing modes so higher fares on Rail would encourage a switch to underground.	Rail and underground can also be complementary modes.	National Rail Price Index
Service	Underground Miles	Positive Impact	The more service operated, the more people are likely to choose the underground.		Underground Miles Run
	Bus Miles	Negative Impact	The more service bus offered, the more people are likely to choose buses over the underground.	There might also be a complementar-ity effect.	Bus Miles Run

Socio-economic Demand Drivers	Spending	Positive Impact	The more money people have or spend, the more likely they are to travel.	.	Retail Sales Index
	Employment	Positive Impact	Greater number of employed people will mean more commuting trips.	.	Total Employment in Central London
	Unemployment	Negative Impact	Unemployed people will not make as many commuting trips resulting in a lower trip rate.	Unemployed people may also have to travel more.	Greater London Unemploy-ment
	Car Ownership	No impact	Parking in Central London is very costly and most underground trips start or end in Central London.		Private Cars in London
	Tourism	Positive Impact	The more tourists, the higher usage of underground.		Overseas visitor nights in London
Weather	Temperature	Unclear	This should have little impact, except for exceptional case weeks which could be treated separately.		Temperature Index
	Rainfall	Unclear	This should have little impact, except for exceptional case weeks which could be treated separately.		Rainfall Index
One-Off Factors	Holidays	Negative Impact	The more holidays in a period, the less people will travel.		UK Public holidays
	Strikes	Negative Impact	Service is affected and so people will choose other modes.		Dummy
	Other factors	Case by Case			Dummy

5.1.3 Definition of Fare Model

The models used by London Underground for both Buses and Underground are annual difference semi- logarithmic models, with the data points aggregated at the period level (Mitrani et al, 2002). A TfL period is 4 weeks and this gives rise to a minor discrepancy since a year is (typically) one day longer than 52 weeks. While there might exist some minor differences between weeks compared in an annual difference model, they are broadly the same and where there are expected to be major differences, these are controlled for either by adjusting the data or omitting a given data point. While the specific models used for buses and the Underground are defined in the corresponding sections, the general model form is as follows:

$$\Delta \ln(REV) = a + b * \Delta(FO) + b * \Delta(FOS) + d * \Delta(FO' - FOT') + e * \Delta(FNR) f * \Delta \ln(MO) + g * \Delta \ln(MOT) + h * \Delta(RS) + i * \Delta(EMP) + j * \Delta(UNEMP) + k * \Delta(TEMP) + * \Delta(RAIN) + o * \Delta(HOLS) + p * \Delta(DUMMY) + \ldots$$

where

a, b, c, d...	=	Model Parameters to be Estimated
Δ	=	Annual Differenced
REV	=	Dependent Variable (Own Mode Revenue per Person at constant fare)
FO	=	Own Mode Fare Index
FOS	=	Smoothed Own Mode Fare Index
FO'-FOT'	=	Difference of Own Mode and Other Mode Fare Indices, normalized by Own Mode Fare Index
FNR	=	National Rail Price Index (London operators)
MO	=	Own Mode Miles Run
MOT	=	Other Mode Miles Run
RS	=	Retail Sales Index
EMP	=	London Employment
UNEMP	=	London Unemployment
TEMP	=	Temperature Index
RAIN	=	Rainfall Index
HOLS	=	Holidays
DUMMY	=	Dummy Variables
...	=	Other Mode Specific Variables

Within the given model there are variables representing different factors, as discussed in the previous section. The form of the model also affects the elasticity values estimated. The model allows estimation of arc elasticity values, with the elasticity depending on the magnitude of the fare change, rather than point elasticity estimation which considers demand elasticity due to very small changes in variables. Thus, fare elasticity estimates have to be multiplied by the current fare levels, and so to compare an estimate from a 2000 study we would have to adjust elasticity using 2009 fare levels. Service and retail sales elasticity estimates are treated directly as elasticity values due to their log formulation. Elasticity due to all other variables is treated similar to central London employment, with the estimates having to be multiplied with appropriate deflator values necessary to bring them to current levels.

The impact of simply dummy variables (1 during given time periods, 0 during the remaining time periods) can be estimated by multiplying directly by 100 to give the percentage impact they had. If a dummy variable has a slightly different form, with the minimum value being 0 and maximum value being 1, then multiplying the estimate by 100 gives the peak impact due to that dummy variable. The impact during any period, with respect to a period 13 periods prior (equivalent to 1 year prior) can be modeled by multiplying the change in the dummy variable with the estimate. As an example, if a dummy is being used to model the impact of a train derailment which affected demand negatively for the year 2005 before service was restored in 2006, the dummy would be 0 prior to 2005, 1 for all periods in 2005 and 0 for all periods after 2005. For a model estimate 'y', the percentage impact on demand in 2005 would be 100y, and the percentage impact on demand in 2006 would be -100y. This methodology will be used to model the impact of PayG (which happens across a period of 5-6 years) and the 2005 London terror attacks among others.

The main variables used in the model are discussed below.

a) Dependent Variable

A dependant variable based on revenue was chosen since revenues were the best available proxy for system-wide journeys. As discussed in Mitrani et al (2002), fares affect revenue both directly and indirectly: the direct effect determining the total revenue and the indirect effect being the influence of fares on demand for travel. For the model, the dependant variable was formulated by dividing the total receipts by the average fare levels and then further dividing by the London population. The resultant variable represents the demand underlying the revenue (Mitrani et al, 2002) and it is representative of total journeys by a London resident in a given period. Deflating by population is equivalent to assuming fixed demand elasticity with respect to population and in Kincaid et al (1997) and Mitrani et al (2002) adjustments were made to restrict the population elasticity[14]. This was done since the population is only available yearly and has to be interpolated to the TfL period and further over the 1970s the Greater London population was in steady decline, causing the population

[14] For buses, this value was fixed to 1.0 and for the Underground it was fixed to 0.45. E.g. for the Underground model, this would represent a demand increase of 0.45% on the Underground due to a 1% increase in population.

variable to be highly correlated with the constant time-trend term. As part of the modeling, this was found to be reasonable and the methodology continued.

Another caveat here is that the average fare level is represented by a proxy variable, a fare index whose value is set to be 100 in 1965. The fare index was described in Chapter 4 and will be further discussed in the next sub-section on fare variables since it forms an important part of the model being estimated. However this means that the dependant variable and consequently the models only reflect fare paying users. While this issue does not affect the underground model greatly, on buses the policy allowing children under 16 to travel free was implemented in 2005 September, and this might have impacted estimation. A dummy variable has therefore been included to account for the impact of this change.

For the purposes of this study, other variables representing journeys made within Greater London were also explored. For the underground, gate counts at a subset of underground stations within London was considered a credible proxy and this data was investigated to ascertain its usability. It was found that this data contained many missing data points, with an average of 26% of days missing data, and with only 5 of 321 stations having less than 10% invalid data between 2001 and 2010. This proxy was therefore unsuitable for an annual difference model containing information for every period over 40 years.

b) Fare Variables

It is important to have a clear idea of the variables representing the average fare level in a given year. Firstly, the proxy for fares on both the underground and buses is the gross fare index (defined in section 3.5), with the value set to 100 in 1965. The formula is repeated here for clarity.

$$FU_n = FU_{n-1} * \left[\frac{\sum_{t = \text{ticket type}}^{All\ t} (Cost_{t,n}) * TSold_{t,n-1}}{\sum_{t = \text{ticket type}}^{All\ t} (Cost_{t,n-1}) * TSold_{t,n-1}} \right]$$

$FU_n = Underground\ Fare\ Index\ in\ Period\ or\ Year\ n$
$Cost_{t,n} = Cost$ of Ticket Type t in Period n
$TSold_{t,n} =$ Number of tickets sold of type t in Period n

This formulation therefore assumes that there will be no switching between ticket types from year n-1 to year n, though adjustments are made if new ticket types are introduced or others eliminated[15]. This inability to account explicitly for ticket switching is a significant shortcoming of using the gross yield factor, especially since the past decade saw very high switching with the introduction of Oyster and structural fare policy changes.

An alternative measure of revenue per journey was considered as a replacement for the gross yield factor since this would effectively take switching into account. While this variable more simply captures the effect of the average ticket price a person experiences, it is highly dependent on the reliability of journey estimates. Models using this variable were estimated and were not satisfactory and thus rejected for the purposes of this study.

Fares however are not directly represented by the fare index since these represent nominal fares, but they are further deflated by earnings (a proxy for income levels) to get a real fare estimate. While deflating by Retail Price Index (RPI) might be a more standard approach, in the case of Greater London it was found that the standard of living has increased faster than RPI, resulting in greater variability in elasticities estimated using RPI deflated fares. Earnings are therefore thought to be a better indicator for the real fare level and result in more stable elasticity estimates. Further, over the last decade, TfL has also followed the policy of maximum average fare increases of RPI+1% on underground and RPI+10% on buses (for the early part of the decade), and this results in high correlation between the fare index and RPI which complicates model estimation.

It is also important to clarify the various fare elasticity values resulting from model estimation:

i. Own Fare Impact Elasticity – The short term (or immediate change) in demand from an increase in own mode[16] fares. In the model, earnings deflated fare indices were used for bus and underground.

[15] New ticket types are compared with their closest available alternatives (e.g. Oyster single fare with Cash) and estimates are made of the amount of ticket switching between these ticket types.
[16] Own mode refers to the mode being considered in the model. E.g. for the underground model, own fare elasticity depends on change in underground fares.

ii. Own Fare Smoothed Elasticity – The medium term change in demand due to an increase in own mode fares, where medium term represents the approximate change in demand happening within one year of a fare change, irrespective of change in other mode fares. In the model, smoothed earnings deflated fare indices were used for bus and underground.

iii. Cross mode Elasticity - The change in demand due to an increase in the other mode fares.

a. Underground with respect to bus fares (underground model) – The variable used is the relative change between earnings-deflated underground and bus fare indices divided by earnings-deflated underground fare index, as shown:

$$\frac{(Underground\ Fare\ Index - Bus\ Fare\ Index)}{Underground\ Fare\ Index}$$

Throughout the 1970 to 2009 period, bus and underground fares have tended to move together (i.e. are highly correlated) and using absolute values of both in the same model would give unreliable estimates. The variable of Underground fare relative to bus fare is used to overcome this problem, since it minimizes the effect of correlation while still giving an estimate of the cross elasticity (Mitrani et al, 2002). Since this is a relative fare variable of the Underground fare with respect to bus fare, the elasticity estimate would be expected to have a negative value.

b. Bus with respect to underground fares – In the bus model, for the reasons mentioned above, the variable used is the relative change between earnings-deflated bus and underground fare indices divided by earnings-deflated bus fare index:

$$\frac{(Bus\ Fare\ Index - Underground\ Fare\ Index)}{Bus\ Fare\ Index}$$

Again, a negative elasticity estimate would be expected for this variable.

c. National Rail – In both the bus and underground models, an earnings-deflated National Rail fare index (specifically for the London region) was used. National Rail fares were not found to be correlated with Underground and bus fares and therefore a relative measure is not required. Since National Rail is thought to be a competing mode, a positive elasticity estimate would be expected.

iv. Own Mode Elasticity – This represents the total change in demand over a period of one year if own mode fares increased by 1%. Typically, a demand model should be able to separate the impact of the own mode elasticity from cross elasticity and in such a case, own mode elasticity would simply be the sum of (i) and (ii). But for the reasons mentioned in (i), the relative cross mode elasticity[17] picks up some of the effect of the change in own fare. In the underground model, this is the sum of estimates of (i), (ii) and (iii)-(a) and for the bus model it would be the sum of (i), (ii) and (iii)-(b).

v. Conditional Elasticity – The total change in demand if fares on all modes increased by the same proportion (in the same direction). Here, the relative cross elasticity[14] would not be included since underground and bus fares increase proportionally. In the model, this is the sum of estimates of (i), (ii) and (iv).

It is also important to note with the model formulation, the fare elasticities are proportional to real fare levels (Mitrani et al., 2002) and so estimates from 2002 would need to be updated to 2009 fare levels for comparison.

c) Other Variables

The models also include variables representing service on buses and underground in miles of service, socio-economic variables such as Greater London population, unemployment, retail sales, tourism, holidays, major event information as referenced in Table 5-1 and Table 5-2. Some variables not used in the previous London Transport studies have also been tested to capture road congestion and bus priority effects and these will be mentioned where appropriate.

[17] as in (iii)-(a) and (iii)-(b).

5.2 London Buses

5.2.1 Overview

As described in chapter 4, there have been numerous fare policy changes that have occurred on London buses in the past decade. This section builds on the bus model used by Mitrani et al (2002), and introduces the following new factors:

a) Road Congestion – Research has shown that it is unclear whether congestion is likely to cause a general increase in bus demand, due to its effect on both buses and cars (TRL, 2004). However, due to the high cost of parking as well as the recently introduced congestion charging zone in London, it would be expected that a decrease in congestion would increase bus demand. Since this effect would be particularly seen in Central London, a series was constructed to model congestion using traffic speeds in Inner London. This series has been measured from 1965 to the present over 3-year periods with the results published at the end of each 3-year period. This was supplemented by recent more detailed ANPR (Automatic number plate recognition) camera data, measured as a monthly series, to indicate the seasonal effects. Using speed of traffic in Inner London is a measure of the time that buses would take, and this means that higher traffic speeds reduce bus travel time and increase demand. Therefore, the estimate based on this series is expected to be positive.

b) Bus Priority – Since 2000, TfL has implemented an aggressive policy of creating priority bus lanes. Data on cumulative priority bus lane miles on the London network is available annually from 2000 and to use this in our model, interpolation was used within each year to obtain a 4-week period series. This was used to approximate the effect of bus priority, and elasticity estimates are expected to be positive since having more bus priority lane miles should improve service and increase demand for buses.

Apart from the new factors, there have also been some major changes influencing travel. The terror attacks on the TfL network in July 2005 led to a temporary decrease in both underground and bus demand. The impact was modeled within Transport for London and estimates of the reduction in revenue are presented in Appendix B.

The model used was as follows:

$$
\begin{aligned}
\Delta \ln(REV) = {} & a + b * \Delta(FB) + b * \Delta(FBS) + d * \Delta(FB' - FU') + e * \Delta(FNR) + f * \Delta \ln(MB) \\
& + g * \Delta \ln(MU) + h * \Delta(RS) + i * \Delta(EMP) + j * \Delta(CAR) + k * \Delta(TEMP) \\
& + l * \Delta(RAIN) + m * \Delta(CONGN) + n * \Delta(BUSPR) + o * \Delta(HOLS) \\
& + p * \Delta(DUMMY)
\end{aligned}
$$

Δ	=	Annual Differenced
a, b, c, d...	=	Model Parameters to be Estimated
REV	=	Dependent Variable (Bus Revenue per Person at constant fare)
FB	=	Bus Fare Index
FBS	=	Smoothed Bus Fare Index
FB'-FU'	=	Difference of Bus and LU Fare Indices, normalized by Bus Fare Index
FNR	=	National Rail Price Index (London operators)
MU	=	Bus Miles Run
MB	=	Underground Miles Run
RS	=	Retail Sales Index
UNEMP	=	Greater London Unemployment
CAR	=	Car Ownership per head
UNEMP	=	Greater London Unemployment
TEMP	=	Temperature Index
RAIN	=	Rainfall Index
CONGN	=	Inner London Road Speeds (Congestion Proxy)
BUSPR	=	Bus lane miles
HOLS	=	Holidays
DUMMY	=	Dummy Variables

Before proceeding to an estimation of the change in demand using the elasticity model, it is important to consider the changes in bus travel resulting from the fare policy changes in London. Figures 5-1 (a) and (b) depict estimates of journeys made on London buses by the main ticket types used over the past decade. Significant switching between ticket types is seen throughout this period. In the early part of the decade, prior to 2004, there was significant growth in bus journeys and while this growth might have been due to factors other than fare policy, such as the improvement in service associated with the introduction of the congestion charge, it is quite striking that much of the growth seems to have been from journeys on period bus passes, with a small contribution from one day bus passes. This growth was likely triggered by the elimination of some zonal combinations and a significant decrease in prices for bus passes, in a mid-year fare revision in May 2001.

Other than this, journey changes due to the introduction of PayG are also quite clearly seen, with reduction in journeys made on ordinaries, saver tickets and one day bus passes all occurring at around the same time. Growth of PayG journeys on buses seems to have been given a push by significant fare increases on all period bus passes during the 2006 fare revision, which also resulted in a decrease in journeys made on period bus passes. During this same period however, there was a decrease in paid journeys, due to the policy of free bus travel for all under 16s implemented in September 2005. This policy was further extended to include free travel for 16/17 year olds in full time education in September 2006, the impact of which is not as clearly visible in Figure 5-1 (a), which shows the fare-paid journeys on buses by ticket type. Figure 5-1 (b) shows the free journeys by children under-16 (and 16/17 year olds in education) and freedom pass users. The freedom pass which allows free travel for London residents who are over the age of 60 or have a disability, was introduced in 1984. While the exact definition of eligibility has changed over time (in terms of age, and eligible disabilities), journeys made on this ticket type are estimated to follow a fairly steady trend over the previous decade, as seen in Figure 5-1 (b).

So, as can be seen from the graphs of estimated journeys, fare policy seems to have had a significant impact on travel in London buses. What is not as clear is the impact of the fare changes on the demand for bus travel, which is the main focus of this chapter. It is quite likely that apart from the annual fare revision, the other policies which caused switching between ticket types might also have influenced demand for travel and this shall be explored in greater detail in the next section.

Some important fare policies would not have been captured by any variable in the model and are thus included in the model as dummy variables, these being:

i. January 2004 fare structure simplification – In 2004, PayG fares and bus pass fares were simplified from a zonal structure to a complete flat fare structure. At the same time, under 11s were allowed to travel free on buses and trams, though this was expected to have a negligible impact compared to the fare structure simplification.
ii. May 2004 Oyster PayG introduction on London buses.
iii. March 2005 introduction of daily capping on PayG, on both buses and underground.
iv. September 2005 implementation of free travel on buses for under 16 year olds.

v. September 2006 implementation of free travel on buses for 16/17 year olds in full time education.

Figure 5-1: Bus Journeys, by ticket type
(a) Fare-pay tickets

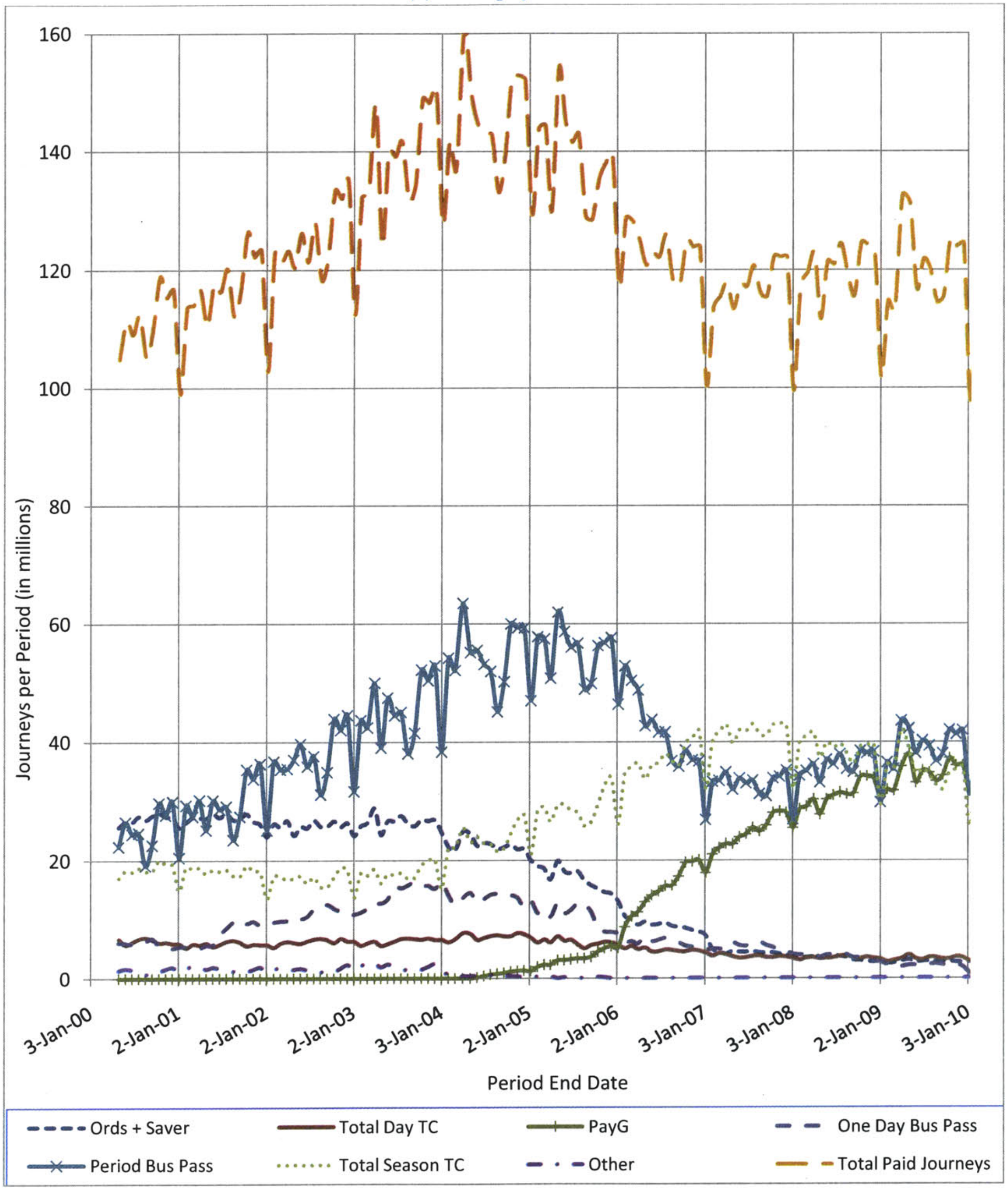
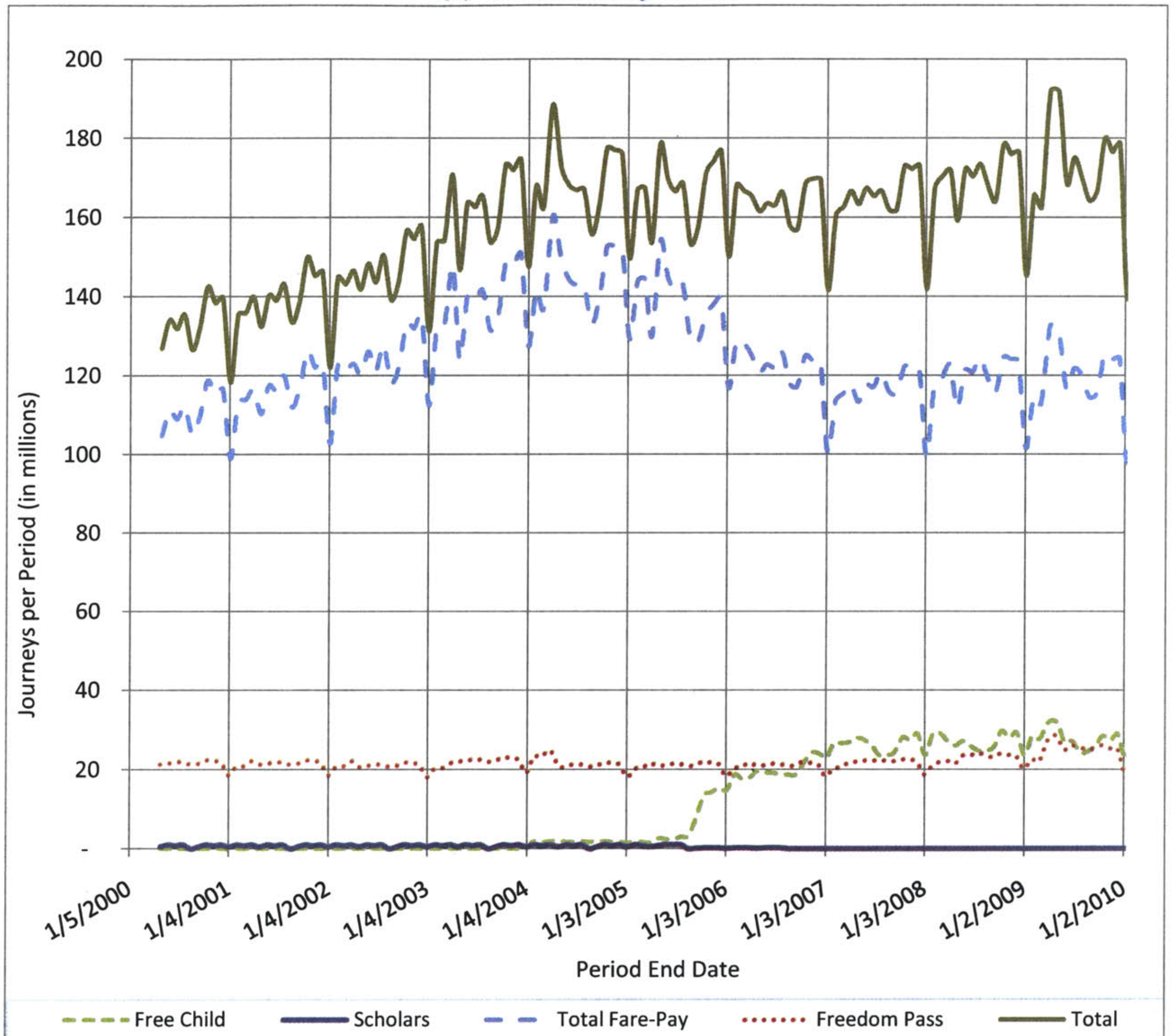


Figure 5-1: Bus journeys, by ticket type
(b) Concessionary tickets



The bus model elasticity estimation results are presented in the following sections.

5.2.2 Elasticity Results

The bus model was estimated on period-level data from 1970 to 2009, containing 440 data points with 34 explanatory variables and 405 degrees of freedom. The model achieved an adjusted r-

squared value of 0.8922 which suggests that the model explains the data well[18]. The discussion of the model results is divided into parts, first the fare elasticities and a comparison with the values in 2000 to assess whether they have changed, and second, a section on the impact of PayG on bus demand. Detailed model estimation results from the model are shown in Appendix C.
A model was also estimated using data from 2000-2009, but while the model achieved a good overall fit (r-square value > 0.8), the fare elasticity estimates were not significant. This is further discussed in Section 5.4.

a) Fare Elasticity Results and Comparison with previous studies

Table 5-3 shows fare elasticity results for the 2009 model along with the reliability of the estimate and the associated confidence limits.

Table 5-3: Bus Fare Elasticities, at 2009 Fare Levels

Year		Estimate	Std Error	t-value	95% +ive limit	95% -ive limit
Own Fare Impact Elasticity[19]	(a)	-0.35	0.013	-25.87	-0.372	-0.319
Own Fare Smoothed Elasticity[20]	(b)	-0.17	0.046	-3.75	-0.262	-0.082
Cross Elasticity with Underground Fare[21]	(c)	-0.12	0.033	-3.55	-0.179	-0.052
Impact effect of rail fare change	(d)	0.17	0.034	4.97	0.101	0.234
Own Price Elasticity[22]	(a+b+c)	-0.63				
Conditional Price Elasticity[23]	(a+b+d)	-0.35				

All the results from the model conform to our expectations: negative values for all variables except rail fare. National Rail and underground are both found to be competing modes with respect to buses based on this evidence. The t-values are all greater than 2.58 (or smaller

[18] The corresponding study in 2002 using data from 1970 to 2000 with 323 data points, 31 explanatory variables had an adjusted r-squared value of 0.897.
[19] Instant effect of fare change, without lag
[20] Lagged effect of fare change with effects occurring over an year
[21] Relative fare elasticity
[22] This represents the total elasticity due to an increase in bus fares when both underground and rail fares don't change. It includes both instant and medium term effects.
[23] This refers to the elasticity when fares for underground, buses and rail change by the same proportion (in the same direction).

than -2.58) indicating that the estimates are significantly different from 0 at a 99% confidence level. This is consistent with previous studies. Table 5-4 compares estimates for the earlier model (data upto 2000) with the currently estimated model.

Table 5-4: Bus fare elasticity timeline comparison, at 2009 fare levels

Year		1970-2000 Estimates (95% confidence limits)	1970-2009 Estimates (95% confidence limits)
Impact Fare Elasticity	(a)	-0.355 (-0.385 to -0.326)	-0.346 (-0.372 to -0.319)
Smoothed Fare Elasticity	(b)	-0.199 (-0.298 to -0.101)	-0.172 (-0.262 to -0.082)
Elasticity with Respect to Bus	(c)	-0.146 (-0.220 to -0.072)	-0.116 (-0.179 to -0.052)
Impact effect of BR fare change	(d)	0.159 (0.089 to 0.229)	0.168 (0.101 to 0.234)
Own Price Elasticity	(a+b+c)	-0.701	-0.633
Conditional Price Elasticity	(a+b+d)	-0.396	-0.350

The results from the table suggest that there has been no change in elasticity from 2000 to 2009. While there have been small changes in the cross elasticities with underground and national rail, these are not significant and to all intents and purposes elasticities do not seem to have changed from 2000 to 2009.

b) Impact of PayG

PayG was introduced on buses in May 2005. This was expected to have increased demand for buses due to improvements such as lower boarding times and less fraud. The impact of PayG on buses is tested in the bus model using a dummy variable. The data available to represent growth due to PayG were revenue and journeys, as shown in Figure 5-2. The dummy variable was modeled by smoothing the Bus PayG journey series, as shown in Fig 5-3. The hypothesis is that demand increased in the form of a logistic curve.

Figure 5-2: Bus PayG Journeys and Revenue

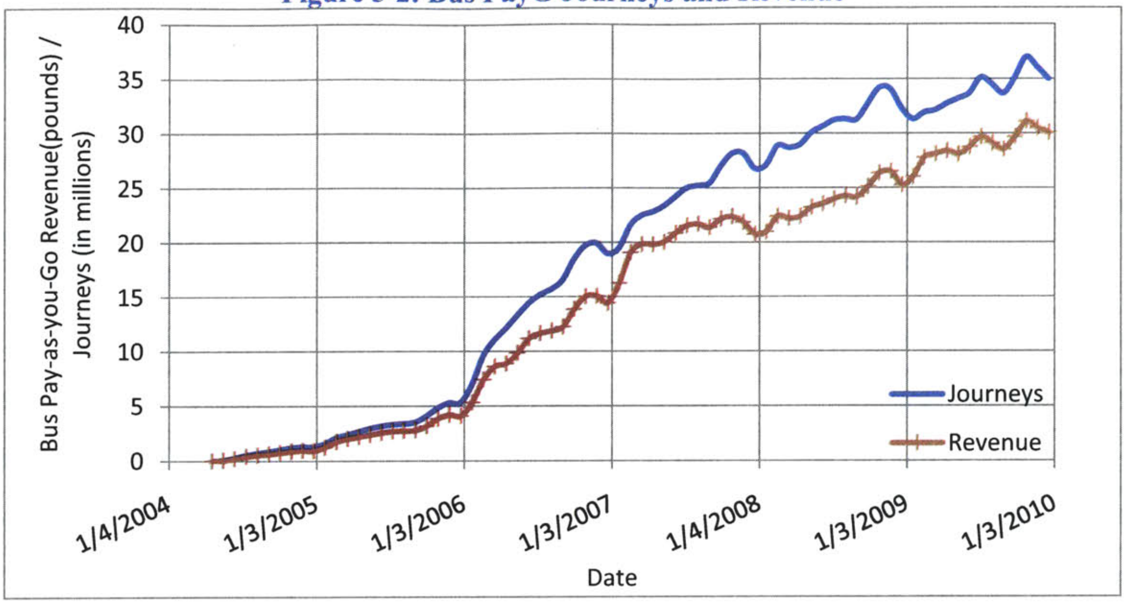
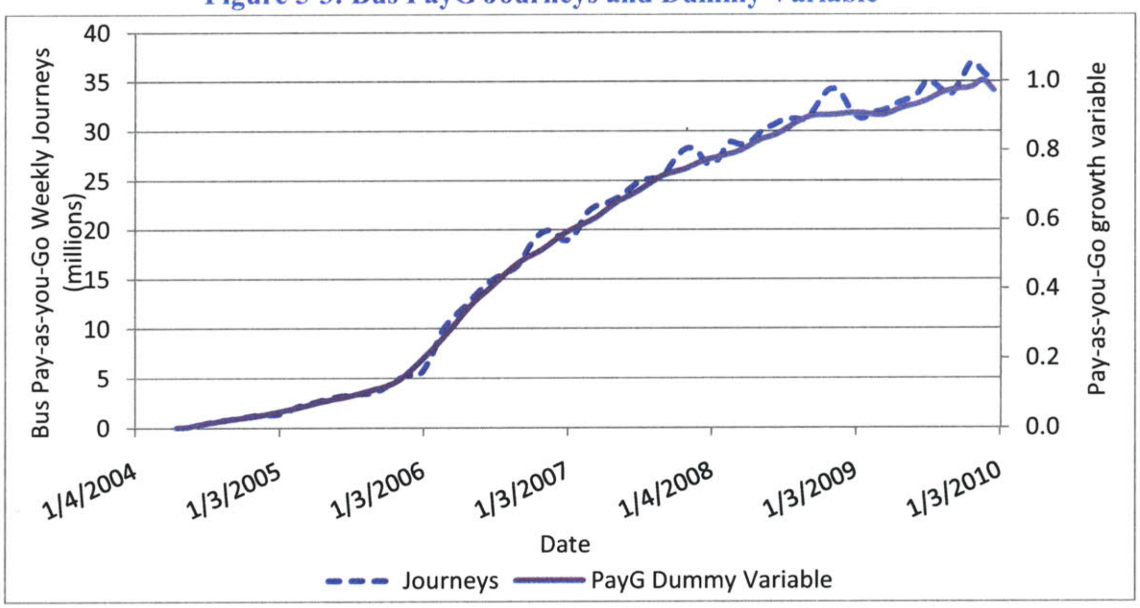
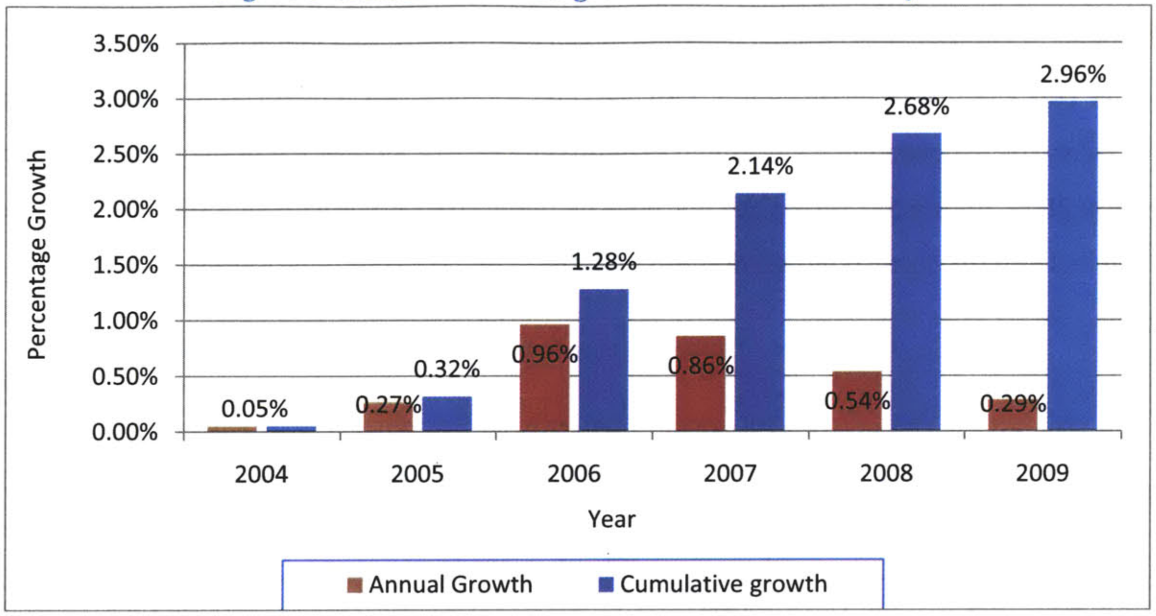


Figure 5-3: Bus PayG Journeys and Dummy Variable



The PayG estimate from the model results does not demonstrate conclusively that PayG had a significant influence on increasing demand on buses. The estimate was positive but the t-statistic had a value of 1.21 which is lower than the 95% probability significance limit suggesting that the model cannot assert with 95% probability that PayG increased demand on buses. However, if we accept the estimated value to be the true value, then PayG had the annual impact on demand shown in Figure 5-4.

Figure 5-4: Annual demand growth on buses due to PayG



While the model is not able to conclusively demonstrate the increase in demand due to PayG, it suggests that there was an increase of 2-3%. This is not pursued further in this case study and is left as an area for further research.

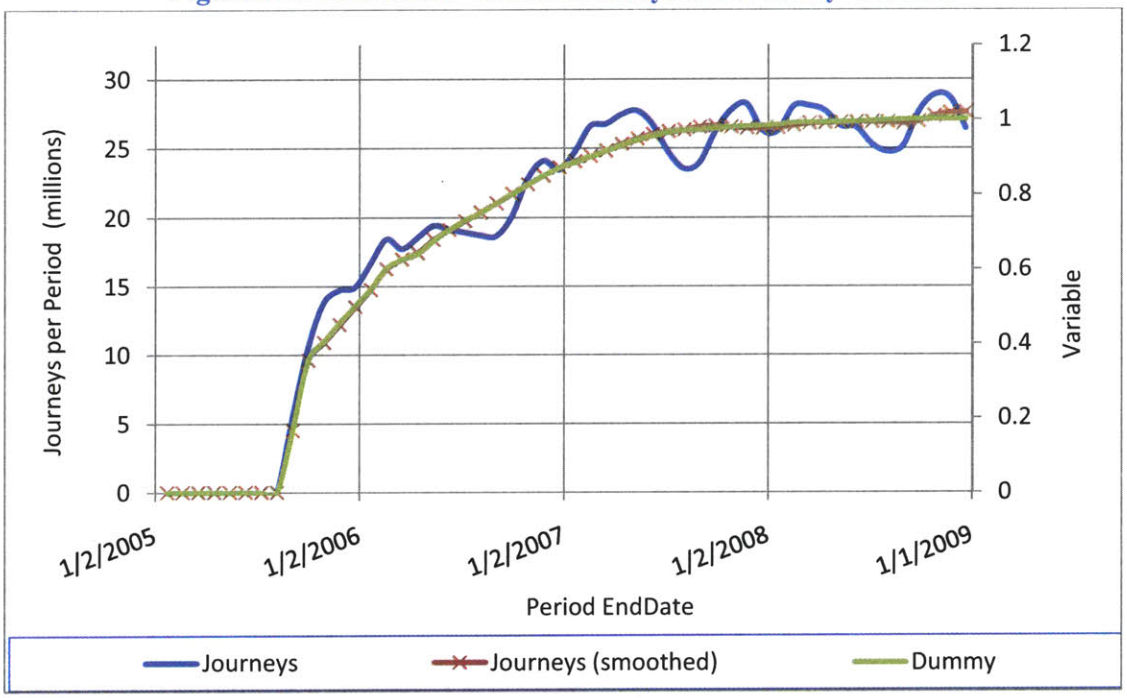
c) Impact of 2004 Bus Fare Simplification

Another factor which may have affected this result was the implementation of the flat fare structure on buses in 2004, which was tested using a simple dummy variable (with a value of 0 prior to January 2004 and 1 thereafter). The model estimated that this resulted in 5.4% (with 95% probability limits of 4.2% and 6.6%) increase in demand over the expected change due to the fare increase. However, this might have reflected some of the growth due to PayG on buses.

d) Impact of Free Travel for Under-16s and 16/17-year olds in Education

Free travel for under-16s was introduced in September 2005 on recommendation of the Mayor of London (Colin Buchanan Ltd., 2006), and was followed by free-travel for 16/17 year olds in education from September 2006. Both of these policies resulted in a gradual move of these categories of users under the age of 16 from fare tickets to concessionary tickets. Since the model is for fare paying traffic only, the effect of this policy change would be to reduce fare-paying demand. To represent the effect of switching away from paid tickets, a variable was created which matched estimates of bus journeys made by Under-16s and 16/17 year olds in education. This variable assumes that movement to free travel by Under-16s happened in a sinusoidal fashion with nearly 99% of the impact happening by July 2007. Figure 5-5 shows the journeys by under-16s (and 16/17-year olds in education) on bus and the corresponding dummy variable.

Figure 5-5: Free Under-16 Bus Journeys and Dummy Variable



From the model, the estimate for this variable was found to be significant (with a 95% confidence interval) with a t-statistic of 3.19 (>1.96). Based on the estimates, the annual decrease in revenue demand is shown in Figure 5-6 with a total decrease of 6.19% with 95% significance limits from 2.54% to 10.62%. Table 5-5 summarizes the annual changes due to this policy.

Figure 5-6: Annual Bus Revenue Demand Decrease due to Free Child Policy

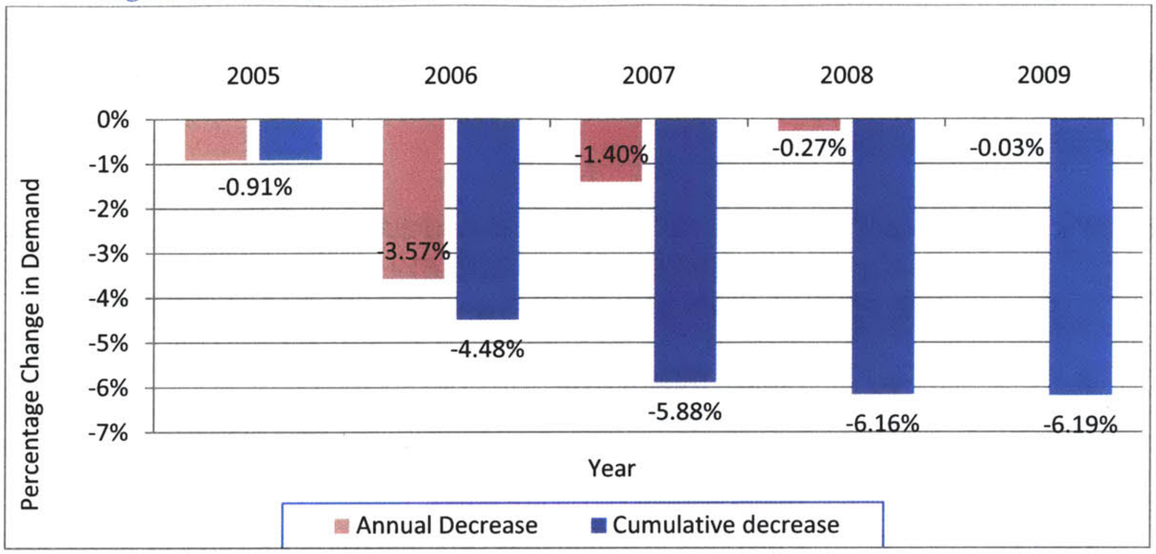


Table 5-5: Annual Bus Revenue Demand Decrease due to Free Child Policy

Year	Estimate	Std Error	t-value	95% -	95% +
2005	-0.91%	0.30%	3.19	0.37%	1.56%
2006	-3.57%	1.19%	3.19	1.46%	6.13%
2007	-1.40%	0.47%	3.19	0.57%	2.41%
2008	-0.27%	0.09%	3.19	0.11%	0.47%
2009	-0.03%	0.01%	3.19	0.01%	0.05%
Total	-6.19%	2.06%		2.54%	10.62%

The direction of the change is as expected as is the annual breakdown, but it is interesting to compare the magnitude of the decrease in demand with the current proportion of bus journeys that are made by children under 16 and 16/17 year olds in education. Journey estimates from TfL's journey data suggest that by the end of 2009, around 19% of total journeys (fare-paid and free but excluding journeys made on freedom passes) are made by these users. This figure of 20% is significantly higher than the 6.19% overall decrease estimated by the model. One possible reason for this might be that the demand by "free users" has increased. A statistic further supporting this is that the total number of bus journeys in 2005 and 2009 are roughly the same even with increases in free child journeys and small increases in freedom pass journeys.

Further results from the model are not directly applicable to the aim of this chapter and are shown in Appendix C.

5.3 Results for London Underground

5.3.1 Overview

The model used was as follows:

$$\begin{aligned}\Delta \ln(REV) = {} & a + b * \Delta(FU) + c * \Delta(FU' - FB') + d * \Delta(FNR) + e * \Delta \ln(MU) + f * \Delta \ln(MB) \\ & + g * \Delta(RS) + h * \Delta(UNEMP) + i * \Delta(CAR) + j * \Delta(TEMP) + k * \Delta(RAIN) \\ & + d * \Delta(CONGN) + d * \Delta(BUSPR) + d * \Delta(HOLS) + d * \Delta(DUMMY)\end{aligned}$$

Δ	=	Annual Differenced
a, b, c, d...	=	Model Parameters to be Estimated
REV	=	Dependent Variable (LU Revenue per Person at constant fare)
FU	=	Underground (LU) Fare Index
FU'-FB'	=	Difference of LU and Bus Fare Indices, normalized by LU Fare Index
FNR	=	National Rail Price Index (London operators)
MU	=	Underground Miles Run
MB	=	Bus Miles Run
RS	=	Retail Sales Index
UNEMP	=	Greater London Unemployment
CAR	=	Car Ownership per head
UNEMP	=	Central London Employment
TEMP	=	Temperature Index
RAIN	=	Rainfall Index
HOLS	=	Holidays
DUMMY	=	Dummy Variables

Similar to the analysis for buses, it is important first to understand the changes in journeys for the main ticket types. From Figures 5-7 (a) and (b) which show estimates of journeys on the Underground it is interesting to note that the variation across ticket types is lower for the Underground than for bus. This indicates that the effect on ticket use of individual changes is less on Underground travel than bus travel which could be attributed to travelers facing less of a choice (in terms of ticket options) on the underground than on bus.

The most significant fare policy change on the Underground was the introduction of PayG at the start of 2004, with a market share which has steadily increased to approximately 40% of the journeys made on the Underground by the end of 2009. This was discussed in Chapter 4 where a timeline of changes on Oyster was also provided. Some of these points in the timeline are clearly visible in Figure 5-7 (a), since they give rise to sudden changes in ticket usage behaviour while other changes do not have a clear effect on ticket switching. An example of the former is the large fare increase on cash and ordinary tickets (while PayG fares were kept constant and lower than equivalent magnetic tickets) which led to an increase in use of PayG and a decrease in other ticket types. Similarly, the introduction of daily capping on PayG also seems to have led to switching from Day Travelcards to PayG.

Figure 5-7: Underground Journeys, by ticket type
(a) Fare Paid tickets

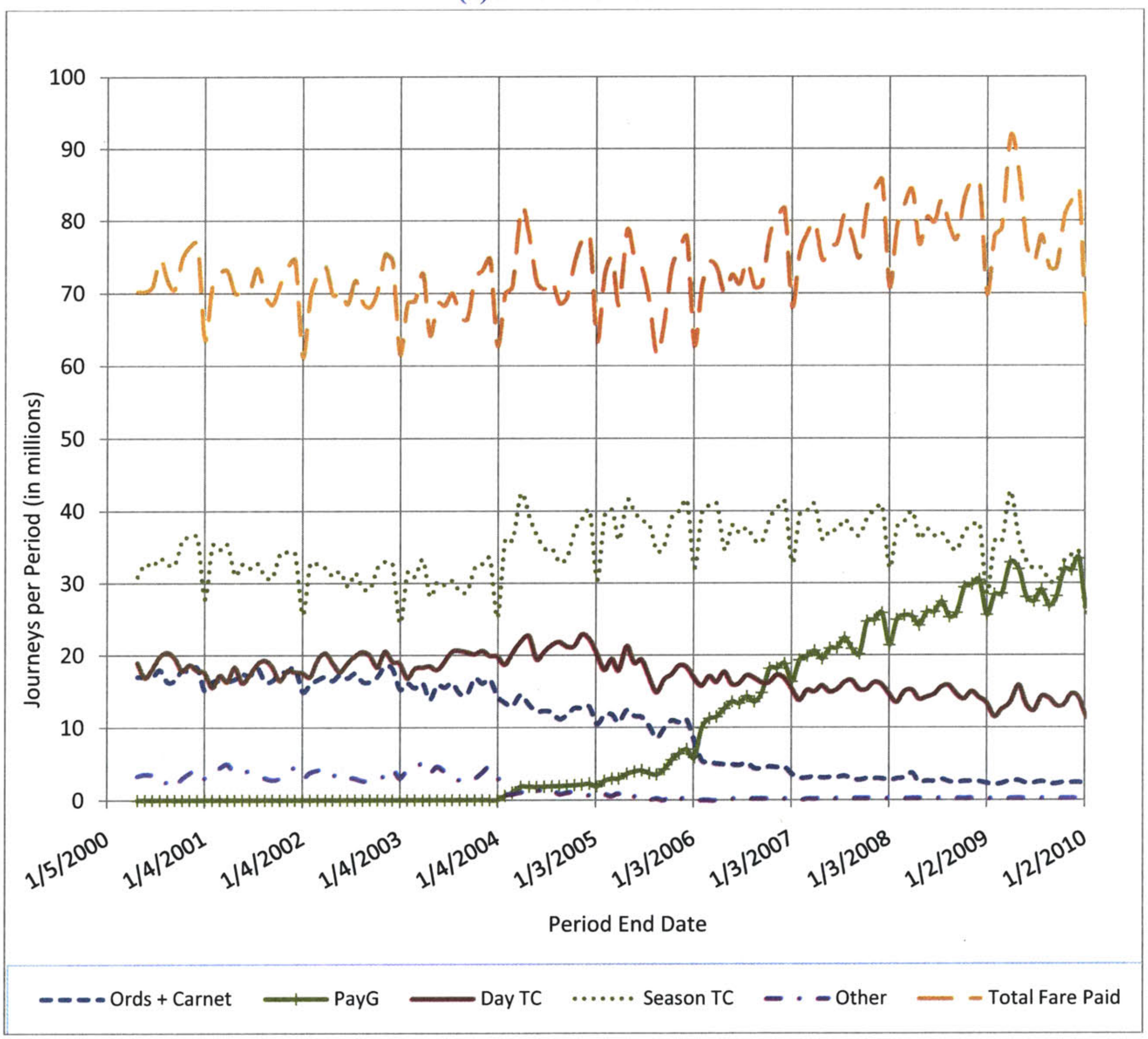
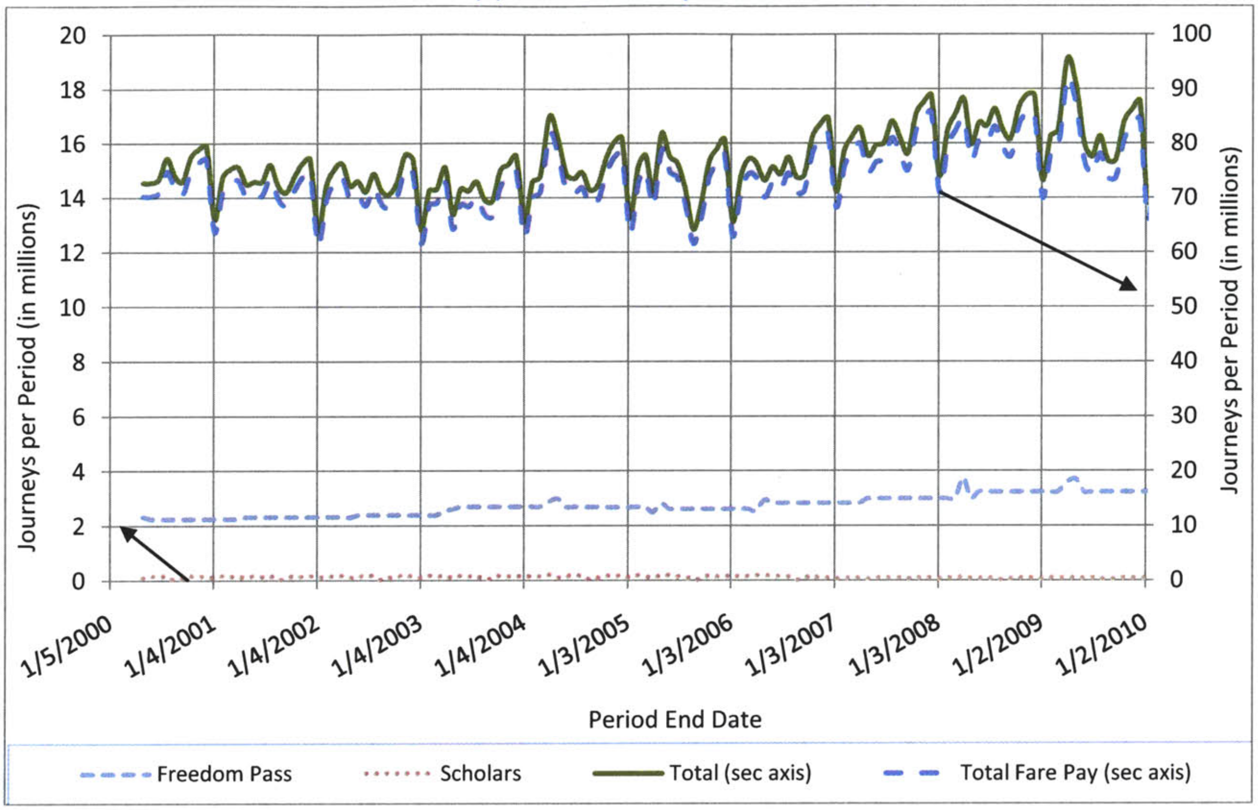


Figure 5-7: Underground Journeys, by ticket type
(b) Concessionary tickets



While these changes are indicative of ticket switching, there is no evidence of growth in travel due to PayG with the focus of this chapter being changes in demand, this is explored in the elasticity estimation results and discussion presented in the next sub-section.

5.3.2 Elasticity Results

The Underground model was estimated on period-level data from 1970 to 2009, containing 441 data points with 38 explanatory variables and 402 degrees of freedom. The model achieved an adjusted r-squared value of 0.908 which suggests that the model explains the variation in the data well[26]. As in Section 5.2.2 the model results are presented and discussed first in terms of the fare elasticities and a comparison with the previous estimated values (for 1970 -2000 data), and second, a section on the impact of PayG on Underground demand. Detailed results from the model are shown in Appendix D.

[26] The corresponding study in 2002 used data from 1970 to 2000 with 330 data points, 34 explanatory variables and an adjusted r-squared value of 0.925.

a) Fare Elasticity Results and Comparison with previous studies

Table 5-6 shows fare elasticity results for the 2009 model along with the estimates of the reliability of the estimate and the 95% confidence interval.

Table 5-6: Fare Elasticities of Demand, at 2009 Fare Levels

Year		Estimate	Std Error	t-value	95% -ive limit	95% +ive limit
Own Fare Impact Elasticity	(a)	-0.26	0.01	-20.20	-0.29	-0.24
Own Fare Smoothed Elasticity	(b)	-0.04	0.04	-0.90	-0.13	0.05
Cross Elasticity with Bus Fare	(c)	-0.13	0.04	-3.76	-0.20	-0.06
Impact effect of Rail fare change	(d)	0.11	0.03	3.13	0.04	0.17
Own Price Elasticity	(a+b+c)	-0.43				
Conditional Price Elasticity	(a+b+d)	-0.19				

The results from the model are consistent with our expectations; though the smoothed fare elasticity is not significant even with only a 50% confidence interval (this is consistent with previous studies). Rail and bus are competing modes with respect to the underground based on this evidence. Table 5-7 compares estimates for 2000 model with the new model.

Table 5-7: Comparison of Underground fare elasticities at 2009 fare levels

Year		1970-2000 Estimates (95% confidence limits)	1970-2009 Estimates (95% confidence limits)
Impact Fare Elasticity	(a)	-0.267 (-0.295 to -0.239)	-0.261 (-0.286 to -0.235)
Smoothed Fare Elasticity	(b)	-0.032 (-0.121 to 0.058)	-0.040 (-0.128 to 0.047)
Elasticity with Respect to Bus	(c)	-0.124 (-0.209 to -0.039)	-0.132 (-0.201 to -0.063)
Impact effect of NR fare change	(d)	0.086 (0.015 to 0.157)	0.107 (0.034 to 0.174)
Own Price Elasticity	(a+b+c)	-0.410	-0.433
Conditional Price Elasticity	(a+b+d)	-0.211	-0.194

The results from the table suggest that there has been no significant change in elasticities from 2000 to 2009. While there have been small changes in the cross elasticities with buses and national rail, these are not significant and for all purposes elasticity values do not seem to have changed from 2000 to 2009.

b) Impact of Introduction of PayG

As mentioned in Chapter 4, PayG was introduced on the Underground at the start of 2004. This was expected to have increased demand due to greater ease in travel and convenience. While no direct evidence is available on how it may have increased demand, it is possible to test its impact using a dummy variable. The dummy variable was created by smoothing Underground PayG journeys. Figure 5-8 shows the Underground PayG revenue and journeys while the dummy variable is shown with the PayG journeys in Figure 5-9.

Figure 5-8: Underground PayG Journeys and Revenue

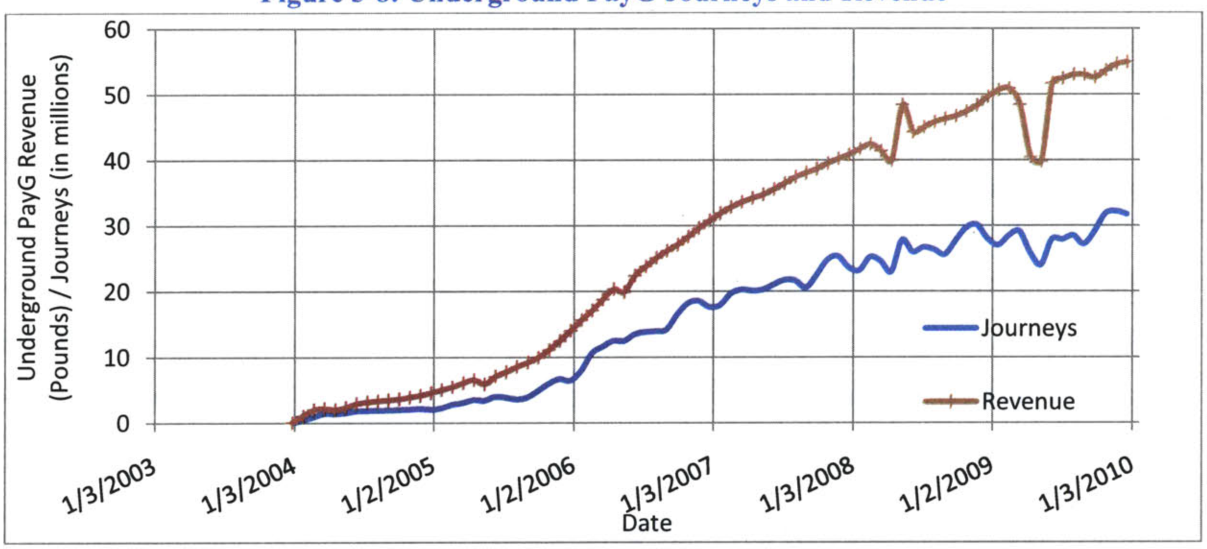
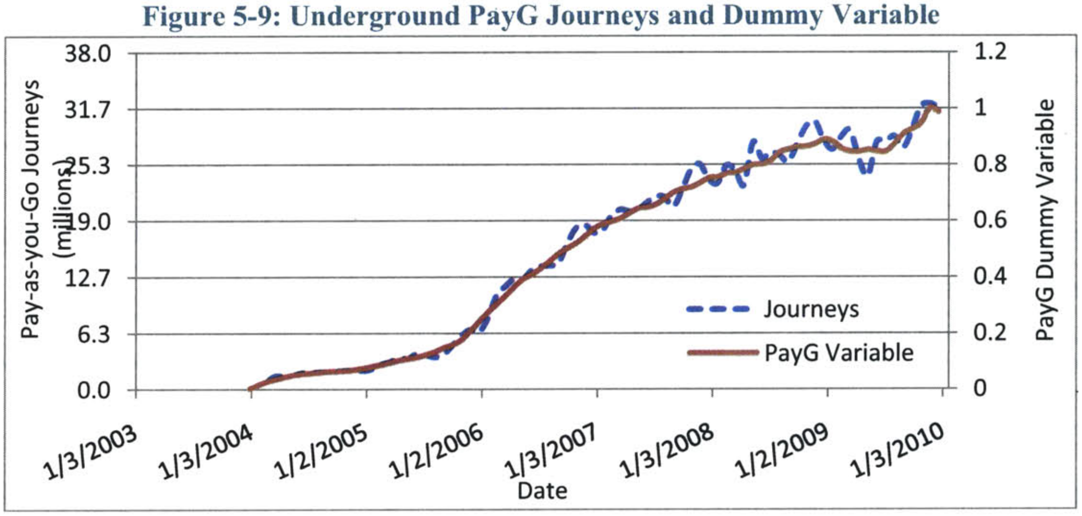


Figure 5-9: Underground PayG Journeys and Dummy Variable



Based on this hypothesis, the model estimated that PayG had increased demand, with a t-statistic of 2.29 representing that with more than 95% probability it can be said that there was an increase in demand. Figure 5-10 represents the growth in demand both by year and as a cumulative function. Further details of this result with standard error and 95% confidence intervals are shown in Table 5-8. While other formulations predicting greater growth due to PayG can be used in the model, there is no evidence supporting them and so these are not discussed.

Figure 5-10: Annual Demand growth on Underground due to PayG

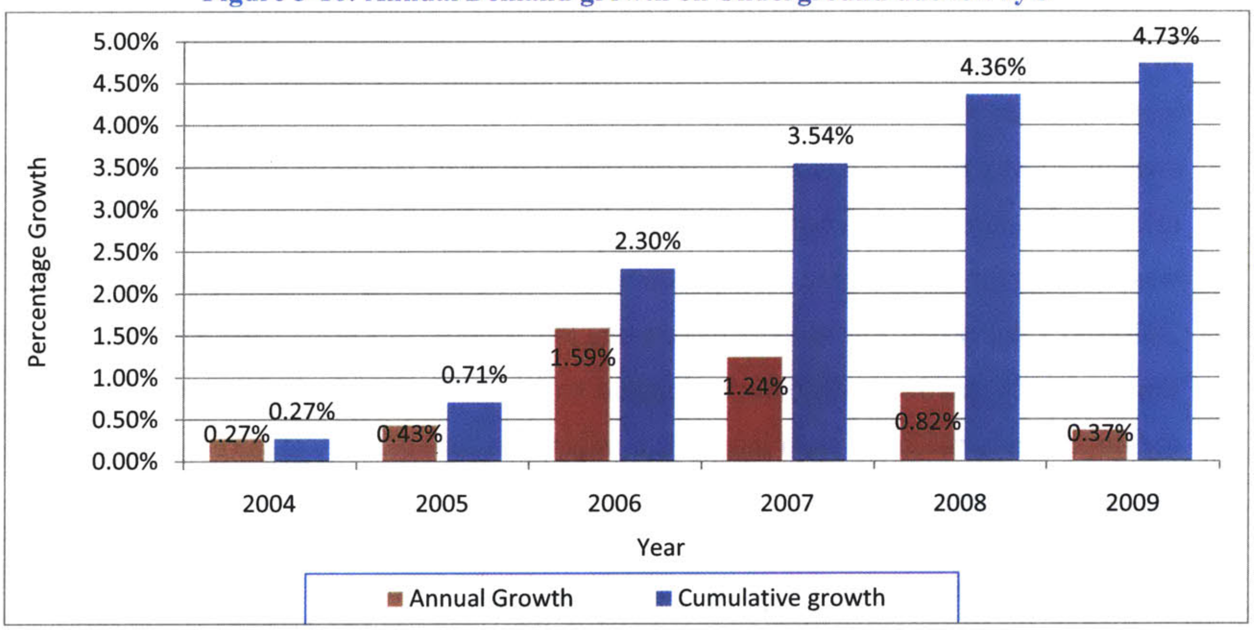


Table 5-8: Annual Underground Demand Decrease due to PayG

Year	Estimate	Std Error	t-value	95% -ive confidence interval	95% +ive confidence interval
2004	0.27%	0.12%	2.29	0.04%	0.51%
2005	0.43%	0.19%	2.29	0.06%	0.81%
2006	1.59%	0.69%	2.29	0.23%	2.95%
2007	1.24%	0.54%	2.29	0.18%	2.31%
2008	0.82%	0.36%	2.29	0.12%	1.52%
2009	0.37%	0.16%	2.29	0.05%	0.68%
Total	4.73%	2.06%		0.69%	8.77%

What must be noted here is that this formulation assumes that once there has been an increase in demand due to PayG, this does not disappear in following periods but simply continues to build up. Thus, based on this model and within 95% probability limits, if PayG had not been introduced on the Underground, demand would have been between 0.69% and 8.77% lower than it actually was by the end of 2009.

c) Impact of 2006 Cash Fare Increase

In 2006, in order to incentivize people to switch to PayG, cash fares for the underground were increased by a factor of between 30% and 100%, which resulted in significant switching away from cash fares. The gross yield fare index would be expected to capture the effect of this fare increase, but due to its limitation in accounting for ticket-switching this was tested in the model using a simply dummy variable, having value of 0 prior to January 2006 and 1 thereafter. The model predicts that this resulted in a 4.2% (with 95% probability limits of 2.4% and 5.9%) decrease in demand during 2006. This might be representative of the limitation in the gross yield index, or it might also be indicative of the actual impact of the cash fare increases.

Further results from the model are not directly applicable to the aim of this chapter and are shown in Appendix D.

5.4 Model Limitations

The model used for both the Underground and buses have some limitations.

- Use of Revenue as the dependent variable – Fare elasticity represents the change in journeys due to changes in fares, and so models generally have journeys as the dependent variable. The models used in this study (and previous studies by Mitrani et al(2002), Kincaid et al(1997)) uses revenue since it represents the best available proxy for journeys but is highly dependent on the fare levels.

- Use of Gross Yield Index - The first limitation stems from the use of the Gross Yield Indices, as was mentioned in Section 5.1. This is unable to accurately take into account ticket switching and while a different model formulation, revenue per journey, was used, this was found to give estimates not matching with the expectations.
- Estimation of model using shorter time periods of data – The model relies heavily on the data from the 1980s for the fare related effects, because of the "Fares Fair" period which happened in the early 1980s. There were large changes in fare over a period of 3-4 years which affected demand very significantly. If this period of data is not used in estimation, the overall fit of the model for both buses and the Underground remains high (r-squared values are above 0.8), but the model does not give accurate estimations for the fare coefficients. If we consider only the last 10 years from 2000 to 2009, the Underground and bus smoothed fares were highly correlated with the impact fares due to the RPI+1% restriction. The correlation with National Rail fares was also high (correlation coefficient>0.8). Other variables also show high correlation, with the smoothed bus miles being correlated with Unemployment and Employment. Thus, the existence of the multicollinearity problem necessitates the use of a larger data set, including data from earlier years.

5.5 Summary

5.5.1 Buses

There have been changes in both the fares structure and ticketing system on London Buses between 2001 and 2010. These were expected to have changed user travel behavior and were tested in a demand model. The model results indicate that (within 95% confidence limits) the bus fare elasticity estimates are unchanged from previous models. The own elasticity is -0.63 (for the elasticity effect occurring within a year) while the conditional elasticity is -0.35.

The model is unable to determine whether the introduction of PayG increased demand on buses, but this may be due to the other changes that happened simultaneously, specifically the move to a flat fare structure in January 2004. The model suggests that the policy of providing free travel for children under 16 has decreased revenue demand by 6% while the actual number of journeys being made by this market segment was 16% by the end of 2009. This would suggest that the policy of providing free travel for under-16s has increased their use of buses quite significantly.

5.5.2 Underground

Over the last decade, the ticketing system on the Underground underwent a complete overhaul but there were not as many changes in the fare structure as on buses. The model was again used to test for any changes in travel behavior. The elasticity estimates from the model suggest that (within 95% confidence limits) elasticity values have not changed significantly. The own elasticity value (for the elasticity effect occurring within a year) is -0.43 and conditional elasticity value is -0.19. These values are nearly identical to the previous estimates by Mitrani et al (2002).

The model suggests that PayG seems to have had the impact of increasing demand on the underground. PayG has increased travel by nearly 4.7%. This would suggest that the introduction of the electronic ticketing system with stored credit smartcard payment has increased travel demand. The model further predicts that large cash fare increases in 2006 decreased demand by nearly 4.2%.

Chapter 6 Fare Technology Impact of Oyster PayG on National Rail

The implementation of Oyster PayG on all National Rail services within Greater London (OXNR) represented a major change in the fare structure and ticketing technology on these National Rail services. OXNR was motivated by the desire to provide users with an integrated fare system and ticketing technology for London's complex public transportation network. Some level of integration had already been achieved in 1989, through the London Travelcard which allowed users to travel on the Underground, London buses and National Rail. OXNR further integrated the system by allowing users to use the flexible and popular PayG option on National Rail. The PayG ticket option, introduced on the Underground and Buses in 2003, now accounts for 40% of all journeys made on the Underground and 30% of all paid journeys made on Buses, and as was discussed in Chapter 4, led to growth in travel. Its introduction on all National Rail services within Greater London was expected to have a similar effect, with some users switching from other ticket options to PayG as well as some movement between modes and some growth in journeys. The focus of this chapter is to evaluate the changes in travel on National Rail which happened as a result of OXNR.

Section 6.1 of the chapter briefly describes the implementation of Oyster PayG on National Rail and discusses expected changes in ticket and mode usage. It further defines the main questions that are being addressed in this chapter. Section 6.2 describes the methodology and data for analysis and data processing involved. Section 6.3 presents the control factor results and the network-wide changes observed while section 6.4 deals with results of analysis at chosen stations along specific rail corridors. Section 6.5 highlights changes in behavior of existing Oystercard users and section 6.6 summarizes the conclusions from this case study and their fare policy implications.

6.1 Implementation of Oyster PayG on National Rail

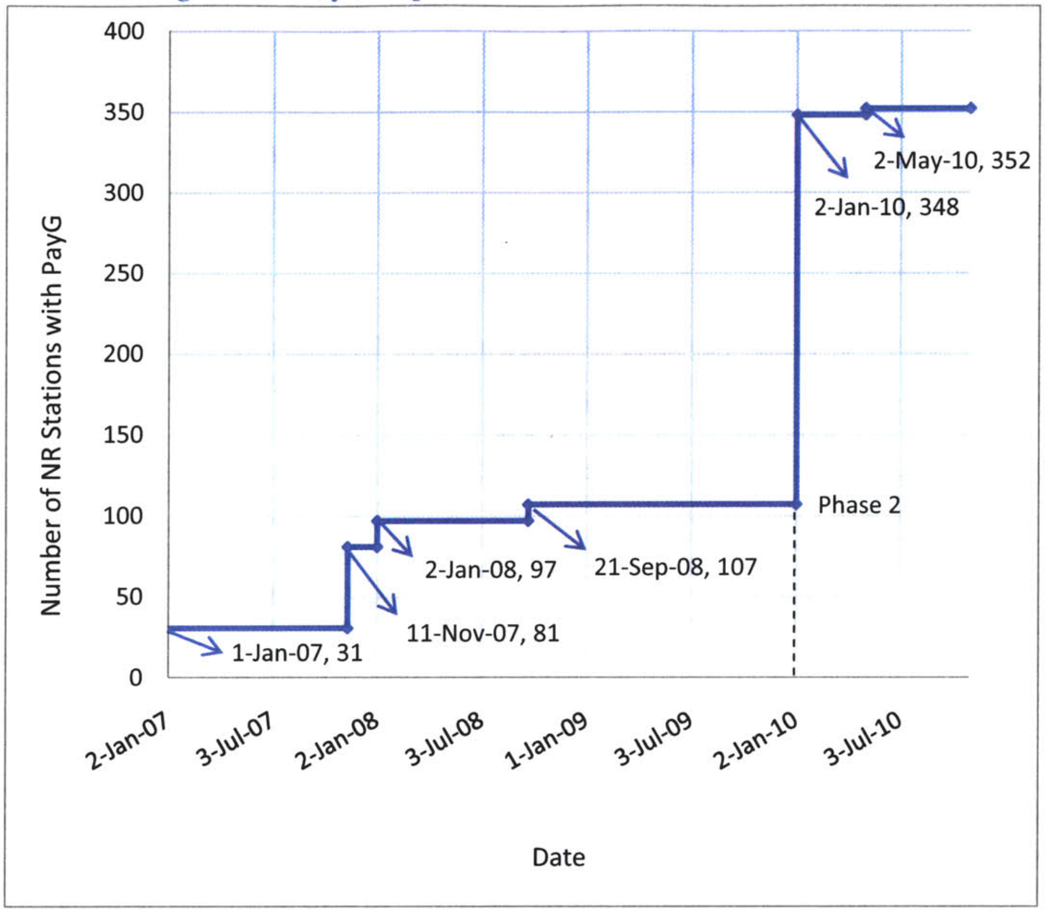
As described in Chapter 4, the Oystercard is administered by TfL and the National Rail stations and services within Greater London are administered by Train Operating Companies (TOCs). In order to implement Oyster PayG on National Rail within the Greater London region, there were extensive negotiations between TfL and ATOC leading to a phased implementation of Oyster PayG. Table 6-1 illustrates the stations added by date and their distribution among the TOCs.

Table 6-1: PayG Implementation phases

Date	No of Stations added to PayG	PayG Implementation - Breakup by TOCs		
		Train Operating Companies	No of Stations	Comment
Pre 2007	31	c2c	5	Implemented at stations on Inter-available routes, ie routes shared or parallel to TfL routes.
		Chiltern	6	
		First Capital Connect	13	
		National Express East Anglia	5	
		First Great Western	2	
11-Nov-07	50	London Overground Limited	50	Silverlink taken over by TfL, becomes LOROL.
2-Jan-08	16	c2c	2	Phase 1
		Chiltern	5	
		National Express East Anglia	9	
21-Sep-08	10	First Great Western	10	
2-Jan-10	241	c2c	4	Phase 2
		Chiltern	1	
		First Capital Connect	27	
		London Midland	2	
		London Overground Limited	11	
		National Express East Anglia	27	
		Southeastern	71	
		Southern	54	
		South West Trains	44	
2-May-10	4	London Overground Limited	4	East London Line

Figure 6-1 shows the introduction graphically with the cumulative number of NR stations having PayG capability. As can be seen, the major increase in availability of PayG occurred on 2 January 2010, with 241 stations, or 68% of the total, being made PayG operational on this date.

Figure 6-1: PayG Implementation on National Rail stations

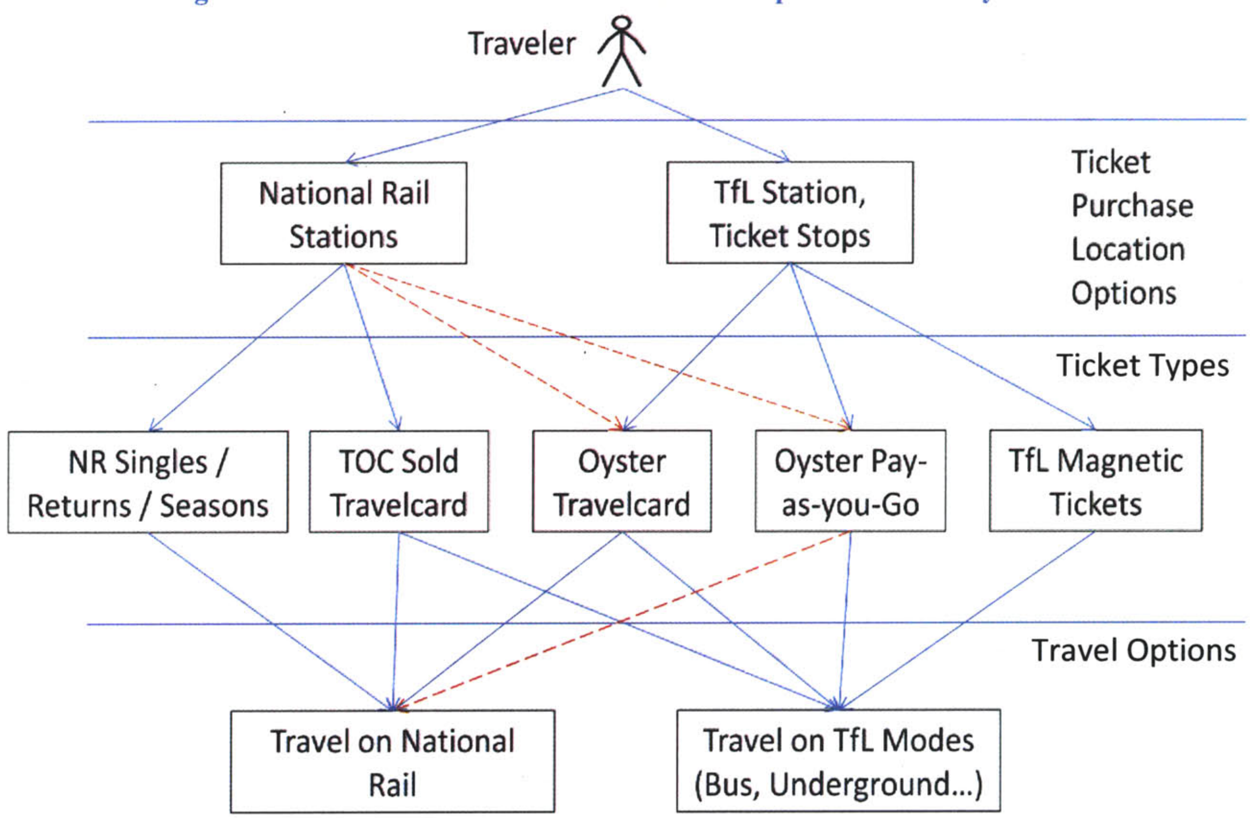


Of the 241 stations which were part of Phase 2 of OXNR, 169 stations were operated by the 3 major TOCs south of the river, South West Trains, Southern and Southeastern. The majority of these stations are south of the Thames, in areas not well served by the Underground.

6.1.1 Expected Changes

The introduction of Oyster on National Rail produced structural changes in both ticket purchase options as well as ticket capabilities. TfL stations and authorized Ticket Stops sell Travelcards on Oyster which are valid on National Rail. It is also possible to buy and top-up PayG credit on Oystercards at these locations. Prior to 2010, most National Rail stations issued tickets which allowed travel only on National Rail, these being single journey tickets, return tickets, seasons valid on National Rail or magnetic Travelcard tickets valid on all modes served by the Travelcard within the specified zones. With OXNR, some National Rail stations also started to issue Oystercards with Travelcard and PayG capabilities. Furthermore with an Oystercard, users have the option to add credit or load a Travelcard online, and the card gets updated the next time it is validated at a PayG enabled validator. These options greatly enhance the flexibility of travel experienced by a user. Figure 6-2 illustrates the increase in user options, with arrows (in blue) representing the scenario before OXNR and dashed arrows (in red) representing the additional options due to OXNR.

Figure 6-2: Ticket Purchase Location and Use Options affected by OXNR



This increased flexibility and choice may lead to a perception that PayG is a superior option to the National Rail Single, Return or Season tickets, and similarly that a Travelcard on Oyster is a superior option to the National Rail Travelcard on magnetic. This case study assesses whether the evidence from journeys (or ticket sales) supports such a perception, and if so how it affects behaviour.

6.1.2 Objectives

The main objectives and questions that are addressed through this analysis are as follows:

1. Journey growth:
   What (if any) journey growth has occurred on National Rail as a result of Phase 2 of Oyster PayG on National Rail?
   Is this growth trend similar across corridors and stations?
   What factors affect the growth?
2. Ticket switching:
   What (if any) ticket switching occurred due to Phase 2 of Oyster PayG on National Rail?
   Is this switching similar across corridors and stations?
3. Mode Switching:
   How much (if any) mode switching has occurred between the Underground and National Rail?

6.2 Methodology

6.2.1 Data

Different kinds of data were used in this case study as discussed below:

1. ATOC ticket sales data: The LENNON revenue system is used by the TOCs and contains ticket sales for all the TOCs. ATOC provided the weekly ticket sales data from the week ending 23 August 2008 to the week ending 9 October 2010. This data contains the following information relevant to this study:

   - Week of ticket sale
   - Origin of ticket sale (for Travelcards and season tickets) or origin of trip (for point to point tickets)

- Zonal validity of ticket (for Travelcards) or destination of trip (for point to point or season tickets)
- Ticket product
- Number of tickets sold/issued
- Journeys: Number of journeys made on tickets sold. These are estimated using journey per ticket factors developed by the TOCs.

This data also contains the Oyster PayG journeys made to/from National Rail stations in the same format as above. This data is based on actual journeys made between stations and is input by TfL into the LENNON system which assigns every journey as a ticket issued (i.e. ticket issue per journey is taken to be one, which is equivalent to a journey per ticket factor one). This data has actual origin and destination stations and is assigned multiple ticket products including categories of "Mix", "Traintube" and "Rail" journeys according to the type of journey made. The "Mix" and "Traintube" codes indicate that these are journeys on National Rail services linked to an underground journey[27], while all other PayG journeys are purely National Rail journeys, not linked to journeys on other modes.

2. Encrypted 100% Oystercard data: As described in Chapter 4, the Oyster ticketing system in London involves users validating their payment for any journey by "tapping" their Oystercard. This data is maintained for all modes in a Central Data System. Data from this system has been made available by TfL to MIT for certain weeks across every year for this (and other) analysis. This data contains all journeys made on Oyster and includes the following information.

    - The (encrypted) Oyster ID which is the unique ID of the smartcard used to make a journey
    - Origin location which is a record of the entry validation for the journey
    - Destination location which is a record of the exit validation for the journey (for Underground trips and National Rail trips from 2 Jan 2010).

[27] For example, if someone travels from Twickenham NR station to Richmond NR station (using National Rail services) and then, as part of the same trip, continues from Richmond Underground station to West Kensington on the district line (using Underground services), this would count as one Traintube (or Mix) journey on National Rail.

- Date and time of entry and exit of the given journey
- Product or ticket type used to make the journey
- Subsystem-id which indicates the mode(s) used during a journey

3. Network-wide National Rail PayG journeys: Transport for London estimates PayG journeys made on National Rail from its Central Data System. These are estimated weekly and contain estimates of both National Rail only journeys as well as joint journeys shared between National Rail and other modes (as for the "Mix" and "Traintube" journeys described above). This is TfL's aggregate PayG data and while it is not available at the same disaggregate level as data contained in LENNON, it is considered to be more accurate[28].

4. Travelcard journeys: Transport for London has also provided estimates of journeys made on Travelcards and PayG journeys on National Rail for 4-10 October 2009 and 26 Sept-2 Oct 2010. The Travelcard journeys are broken down by Travelcard type and location of sale while the PayG journeys are aggregate values.

6.2.2 Analysis Methodology

There are three main components to the analysis being carried out - Network-wide journeys, Station-specific journeys and Station-specific Oystercard journeys. The network-wide journeys component forms the base of the analysis, with the station-specific and Oystercard components helping improve our understanding of the changes indicated by the network-wide study. These three main study components are linked by the station/corridor selection process which is a precursor to the station-specific studies as shown in the Figure 6-3. Each research component fulfils different objectives. The matrix shown in Table 6-2 shows the objectives addressed by each component.

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[28] The Pay-as-you-Go data on National Rail is estimated using a detailed origin-destination query. The estimation method was improved in January 2011 based on a year's experience and previous data was updated at an aggregate level resulting in downward revision for joint journeys. (TfL Fares and Ticketing, 2011)

Figure 6-3: Case Study Analysis Components

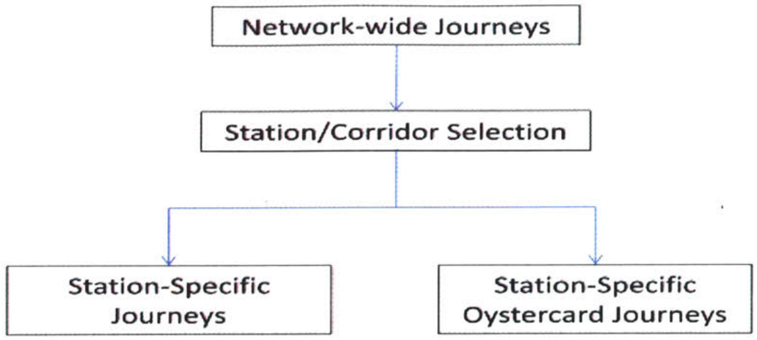


Table 6-2: Link between Objectives and Analysis Components

Objective → V Study Element	Journey Growth	Ticket Switching	Mode Switching
Network-wide Journeys	Total growth	All possible ticket switching	-
Station-specific Journeys	Journey growth at station	Ticket switching at station	-
Oystercard Panel Journeys	Oystercard Panel Growth	PayG - Travelcard Switching	Underground - National Rail

To control for changes other than Oyster on National Rail, a control factor needs to be estimated. This will be used in both the network-wide journey and station-specific journey component, and the chosen control factors will be discussed after a description of the other three study components.

a) <u>Network-wide Journeys Component</u>

The network wide journeys analysis estimates the change in journeys over the entire National Rail network in London, by comparing journeys made on main ticket types for a week in 2009 with a corresponding week in 2010. The chosen weeks were 4-10 October in 2009 and 26 Sept-2 Oct in 2010, both in similar periods of the year to control for any seasonal effects. In order to account for any natural year-to-year changes affecting journey patterns, a control factor was estimated and applied to the 2009 figures, thus enabling comparison and identification of OXNR's actual effect on journey growth. The objectives covered by this component of the methodology includes net journey growth on the National

Rail network in Greater London and ticket switching between the major ticket types due to OXNR. The aim was to find out if there has been ticket switching only from the expected ticket types (tickets which are directly comparable with PayG) or if there is evidence to suggest that users may also have switched from other ticket types.

b) Station-Specific Journeys Component

The station specific journeys component highlights specific changes across several OXNR corridors, using ticket sales to estimate journeys at several stations along each corridor. Along corridors expected to have been affected by OXNR stations were chosen based on criteria that will be defined in Section 6.4. Journeys made at the selected stations were compared over time to understand the effects of OXNR and further, journey growth at different stations along the corridors were compared to understand the variation in the impact of OXNR. Furthermore, journey growth at stations across the chosen corridors was also compared over time to understand the impact across National Rail corridors serving London.

The comparison examined changes that took place between 2009 and 2010 across the stations, by comparing various weeks in 2009 with corresponding weeks in 2010. The weeks were chosen based on data availability as well as validity of the data during each period. The chosen time period of comparison in 2009 is from the week ending 10 January 2009 to the week ending 3 October 2009, and corresponding weeks in 2010 are from the week ending 9 January 2010 to the week ending 2 October 2010. Each week was compared with the corresponding week in the previous year to eliminate any seasonal effects. A control factor was also applied to the journeys undertaken in 2009, to account for any natural growth that may have taken place.

The main objectives fulfilled by this component of the research include journey growth at stations, as well as highlighting ticket switching patterns that took place at each of the stations. Inferences were drawn on whether OXNR had an impact on travel and ticketing patterns.

c) Station-Specific Oystercard Study

The Oystercard study supplements the estimated journey analysis with analysis of actual journey data using the 100% Oystercard data set. This study examines a panel of Oystercards which are active throughout the chosen periods of our study, and identifies if there have been any major changes due to OXNR. This was done by choosing a station having an alternative Underground service at the same facility and analyzing Oystercards which use that station. It was necessary for the station to have Underground service prior to OXNR Phase 2 to allow for the identification of mode switching between the Underground and National Rail. The study further looks at the ticket usage patterns for the Oystercard panel to identify switching between Travelcards and PayG and a combined mode and ticket usage was also estimated to identify whether switching was particular to National Rail or also seen on the Underground. The methodology and data issues encountered are further discussed in Section 6.5.

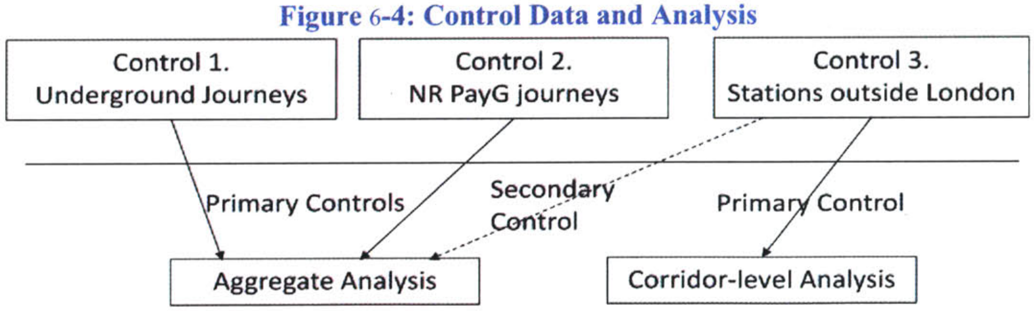
d) Control Factor Analysis

Control factor estimation is an important part of this study which helps account for any changes in aggregate journeys due to exogenous effects, to improve the year-on-year analysis. There are three control factors considered for the study:

i. Network-wide Underground journeys
ii. Journeys on NR corridor/stations having PayG prior to 2 Jan 2010
iii. Journeys from stations outside London to London

These control factors are not uniformly applicable to both our journey studies. Figure 6-4 shows the mapping between them.

Figure 6-4: Control Data and Analysis



The chosen control factors are described below.

i. Underground journeys

Underground journeys form the main control for the network-wide analysis as they are a good indicator of the changes in travel in London, being influenced by the common demand drivers such as population, inflation and GDP. The Underground is both a competing and a complementary mode to National Rail, and this would suggest that it might not be an ideal control for our analysis of the effects of OXNR. However, this case study examines Phase 2 of OXNR, which was centered on fare policy improvements to the south of the Thames river in London. The Underground primarily serves areas north of the river with only 5 of its 11 lines providing any services south of the river. Approximately 14% of the total journeys on the underground originate in boroughs South of the river with 10.5% of these originating in the four central London boroughs of Lambeth, Lewisham, Southwark and Wandsworth (TfL, 2010). The underground services also have minimal competing services or concurrent stations to National Rail south of the river. Underground journeys are therefore thought to be a good control for any changes other than Oyster on National Rail, but other controls still need to be considered.

ii. Journeys on NR corridors having PayG prior to 2 Jan 2010

The second control factor is the journeys between the National Rail PayG stations which were operational before 2 Jan 2010. All of these stations had PayG operational prior to 2009, and so they are not expected to have been influenced by OXNR. Furthermore, all of these stations are north of the river and while some stations along these corridors had PayG implemented only in 2010, no major effect is expected. If anything, growth would be higher than expected and this control would then provide an upper bound making it a reasonable control for our analysis.

iii. Journeys from stations outside London to London

The third control factor is the journeys from stations outside London to London. The criteria for choosing such stations were:

- There should be a high number of commuting journeys to London. This ensures that the effect of any major changes in London is reflected in the change in travel from this station.
- Station should be outside the Greater London PayG region, i.e. the Travelcard zones. This minimizes any possible impact on travel patterns due to OXNR.

Table 6-3 shows the top 15 stations located within the government districts of East or South-East England but outside the Travelcard zones ranked by number of entries and exits in 2008-2009.

Table 6-3: Major National Rail Stations near London but outside Greater London zones

Ranking (by traffic volume)	Station Name	Station Owner	2008-09 Entries & Exits	Time to London Terminal at Peak (minutes)
1	Reading	First Great Western	14,384,236	25-30
2	Brighton	Southern	13,806,628	50-60
3	Gatwick Airport	Network Rail	11,695,308	30-35
4	Guildford	South West Trains	8,051,842	37-42
5	Cambridge	National Express East Anglia	7,571,838	55-80
6	Chelmsford	National Express East Anglia	7,375,452	36-41
7	Southampton Central	South West Trains	5,835,958	85-105
8	Stansted Airport	National Express East Anglia	5,241,384	52-57
9	Oxford	First Great Western	5,080,934	55-70
10	Basingstoke	South West Trains	4,807,902	47-56
11	Milton Keynes Central	London Midland Trains	4,551,538	43-56
12	Colchester	National Express East Anglia	4,502,739	55-63
13	Stevenage	First Capital Connect	4,257,732	24-37
14	Tonbridge	Southeastern	4,211,562	40-49
15	Peterborough	East Coast Main Line	4,099,754	53-66

Since the only available data was the total number of entries and exits at a given station and not the origin and destination, another method was found to ensure that only stations with significant travel to London were included. Commuting journeys form the majority of the journeys to London and would be expected to be most significantly impacted by changes in London, and so the criteria chosen was that during the morning peak, selected stations should be within 40 minutes travel time to the Central London terminal station.

Based on these criteria, the following control stations outside London were selected: Reading, Guildford, Chelmsford and Stevenage. Gatwick Airport which would otherwise qualify was excluded because of its sensitivity to air travel. The selected control stations are shown circled in the map in Figure 6-5. Each of these stations has direct, frequent and fast service into London, and also has a high number of passenger journeys, comparable to major National Rail stations within Greater London.

Figure 6-5: Control Stations outside Greater London
(Greater London area is within box and possible stations are circled)

It is expected that travel patterns from these stations would reflect the actual changes in travel behavior in London, as reflected in the station selection criteria. This is then expected to be a reasonable secondary control for the network-wide analysis and is also used in our corridor-level analysis.

6.2.3 Data Processing

The analysis methodology uses ticket sales data from LENNON, the revenue system used by the TOCs, supplemented by ticket sales or journey data from Transport for London. This section describes the data processing and the method for estimating journeys from ticket sales data. Figure 6-6 shows the data processing work needed to obtain journeys from the LENNON system.

Figure 6-6: ATOC Data Processing
(Processes are shown in rounded green boxes and data inputs/outputs in square blue boxes)

The raw data from ATOC contained data on both tickets sold by the TOCs, as well as data from TfL on Travelcards and PayG journeys. While some of the input TfL data had a unique product code and description (an example of this is Product Code ="2JTW" and Product Description = "TfL Inward Annual 2JTW"), some of the input data had a product code shared with TOC sold ticket types. An example of this was Product Code="2BDY" and Product Description=" CHEAP DY RTN HI 2BDY" which represented both a Cheap Day Return ticket sold by the TOCs as well as an Off-Peak Day Travelcard sold either by the TOCs or inputted by TfL. The data on Travelcard sales by TfL is typically input from a specific location and can therefore be distinguished by the origin location which belongs to a set of possible origin locations, such as "AUTHORISED INPUT LOCATION 0732". The TOC sold ticket data was therefore separated from the TfL input Travelcard ticket sales data.

The next step in data processing was to separate out the data on Travelcard sales by the TOCs from the TOC sold tickets and here too the issue of data with same product type arises. Travelcard sales can be distinguished from TOC point to point tickets by their destination location. The destination location for TOC sold Travelcards is a zonal location such as "ZONE R1256 LONDON" and so we can further separate out the TOC Travelcard sales from the TOC point to points based on the destination locations. At the end of this step data on TfL sold Travelcard tickets, TOC sold Travelcard tickets and TOC sold point to points were available, which constituted our initially processed data. This was necessary since different Journey per Ticket factors are appropriate for each ticket type.

The next step was to aggregate the data by product type and week. This step gives the total number of tickets issued during each week for each product type. Once this was done for all the product types, they were assigned to the appropriate weeks for which journeys were to be estimated. The result at this stage was a dataset with the tickets sold (issued) for all product types for every week of the period being analyzed. There were still a few complications such as missing data for some dates which was the case for roughly every 4th week of input TfL data. Closer analysis revealed that the week prior to the week with missing data contained data for both weeks together and so these could be appropriately distributed.

The next step was journey estimation from ticket sales data which involved the use of journey per ticket factors. The journey per ticket factor is based on the number of journeys made, on average, on a given ticket type. These factors are estimated both by ATOC and TfL on the basis of surveys on ticket usage.

The factors used by ATOC are not estimated as frequently as corresponding ones for TfL tickets. This is primarily since the TOC tickets can only be used on NR services between defined stations (or groups of stations), while TfL Travelcards can be used an unlimited number of times across multiple modes in the given time period. They are still thought to be reasonable since the year on year change in ticket usage is small for TOC sold tickets, and this issue is not expected to affect our analysis. Table 6-4 shows the commonly used journey per ticket factors for major ticket types.

Table 6-4: TOC-sold Ticket Journeys per Ticket Factors

Singles	Returns	7 Day Season	Monthly Seasons	Annual Seasons
1	2	10.3	45	480

TfL carries out an ongoing Travelcard Diary survey which attempts to estimate the number of journeys made on a travelcard. This survey provides results based on the location of ticket sale, whether it is made at a TfL outlet (including ticket stops), a TOC outlet within the Travelcard zones in London or a TOC outlet outside the Travelcard zones. The results are further disaggregated by off-peak day travelcards, peak day travelcards and weekly travelcards. The monthly and yearly travelcards use appropriate multiples of the weekly estimates. These factors are then used to estimate the number of journeys made on a ticket. The survey results are compiled quarterly with the usage factors as shown in Table 6-5.

The factors shown in the table were used in the analysis. Period travelcards show the number of weekly journeys, i.e the number of journeys made during 7 days of ticket validity and these were converted to factors for monthly, annual and any other period travelcards by multiplying by a factor of the number of days in the period. Furthermore, the factor was assigned to the last week of the shown month, and for weeks between each of the assigned periods, a linear interpolation of the factors was used. Multiplication of the journey per ticket factors by the number of tickets issued in any week provided estimates of the number of journeys made on tickets issued within a given week.

Table 6-5: Travelcard Journeys per Ticket Factors

Date	Sales at TfL Outlets			Sales at TOC Outlet Within Travelcard Zones			Sales at TOC Outlet Outside Travelcard Zones		
	Period	Off Peak	Peak	Period	Off Peak	Peak	Period	Off Peak	Peak
Jan-09	2.93	0.42	0.35	8.39	1.75	1.92	9.53	1.83	1.87
Apr-09	3.05	0.38	0.36	8.20	1.72	1.94	9.36	1.83	1.86
Jul-09	3.09	0.39	0.36	8.14	1.72	1.96	9.27	1.85	1.86
Oct-09	3.15	0.39	0.47	8.16	1.72	1.93	9.22	1.87	1.87
Jan-10	3.25	0.35	0.49	8.21	1.73	1.93	9.27	1.91	1.90
Apr-10	3.34	0.34	0.51	8.14	1.80	1.94	9.38	1.98	1.96
Jul-10	3.30	0.33	0.53	8.21	1.81	1.96	9.46	2.00	1.97
Oct-10	3.23	0.30	0.49	8.25	1.80	2.01	9.43	2.01	1.98

The final step involved the distribution of the journeys across a number of weeks and summation to estimate the number of journeys made during a given week. This was done by simply taking the average of journeys for tickets sold in the appropriate number of weeks. As an example, the number of journeys made by annual season tickets during week 'i' would be an average of journeys due to annual season tickets sold from week 'i-51' to week 'i'. A similar method was followed for all other ticket types.

PayG Journey Calculation

In the previous section, we discussed the estimation of journeys using ticket sales data and since National Rail stations were generally un-gated prior to OXNR, this is expected to be the most reliable source of data available for National Rail journeys made using magnetic or paper tickets, both prior to and after OXNR. For journeys made using Oystercards and especially the PayG faretype, we have a more reliable source of data. These journeys are directly determined from the central database server which has data on all journeys made using Oystercards. The journeys are calculated and input into the LENNON revenue system, as a means of recording the revenue from PayG journeys accruing to the TOCs.

At some stations users have a choice of travel mode, and in general they can use multiple modes to make a single journey. Thus, there can be more than one journey segment (by mode) made during any trip. The method used to calculate National Rail journeys recognizes this fact and the journey calculation attempts to account for this using origin and destination data for each trip. Based on this methodology, if a trip involves using only National Rail, it is counted as one National Rail journey segment. If the trip involves using both National Rail and Underground, it is counted as one National Rail journey segment and one Underground journey segment. This definition is broadly consistent with the definition used for journeys made on Travelcards and also TOC-sold tickets.

There are however further complications involved in using this data. The PayG journey data being used at a station-level involves the use of data entered into the LENNON system every week or every fortnight. But the calculation methodology has evolved over time and so the LENNON PayG data being used might not be consistent over time. To update such data, revised[29] NR PayG journey estimates from TfL were compared with the LENNON PayG data and this data was then corrected for any inconsistencies.

Exploration of data from both sources revealed that the Rail-only journeys are broadly consistent from both sources, with differences ranging from -2% to +2% and an average difference of 0.3%. For mixed journeys (involving both Underground and National Rail modes), there is a significantly larger error range. During the first week of estimation (week ending 9 January 2010), the revised journey estimate was found to be only 53% of the journeys from the LENNON data. This figure ranges between 57% and 59% until the week ending 10 May 2010, and then jumps to around 90% +/- 4% for the rest of the periods. The PayG journey data from LENNON has therefore been divided into rail-only and mixed journeys and corrected by using an appropriate correction factor, wherever necessary.

The estimate of PayG journeys on NR is thought to be more reliable than journeys estimated from ticket sales since it involves actual journey data. This can create complications when we combine the journey estimates from both data sources as each has a different level of accuracy. While this is recognized, it is assumed that the journey-per-ticket factors are fairly reliable and we can proceed with combining the two data sources. It is possible that our results might reveal evidence that this is not the case, but this will be mentioned where it is thought to be the case.

[29] as of 19 January 2011

Once journeys made on all ticket types are estimated for all our chosen weeks, we can proceed to the comparison stage. For comparison, we can either use absolute figures as they are or apply our control factors by multiplying the data for the periods in 2009 with the appropriate control factors estimated as previously discussed.

6.3 Network-wide Journeys Results

In the previous sections we have discussed the main questions this case study is addressing and the methodology and data issues arising. This section first introduces the control data results which inform any further analysis and thereafter results from the network-wide journeys estimation analysis are discussed.

6.3.1 Control Factor Results

a) Underground Journeys

The first control factor, primarily applicable to the aggregate analysis, is the underground journey growth. Journeys on the underground are estimated using the same definition of a journey as on National Rail, this being that any journey stage or segment that was made completely on one mode is counted as one journey. Thus, a trip involving one journey segment on the Underground with a transfer to National Rail as the next journey segment would count as one journey each on the Underground and National Rail. Journey data provided by TfL were analyzed for the two selected weeks and the growth was estimated to be 1,001,931 journeys, from 20,431,032 journeys (for 4-10 Oct 2009) to 21,432,964 journeys (for 26 Sept-2 Oct 2010). Based on this, our control factor for the journey growth percentage was found to be 4.9%.

b) National Rail PayG Stations prior to OXNR Phase-2

The second control, again applicable only to the network-wide journey analysis, was journeys between NR stations which were PayG capable prior to 2 Jan 2010. Prior to Phase

2 of OXNR, 107 stations were already PayG capable and based on ticket sales at these stations an estimate of journeys was made.

Estimation of journeys between a group of stations from the ticket sales data involves certain assumptions. While some ticket types (point to points, TOC seasons and PayG) include both the origin and destination locations, the majority of tickets sold at these locations were Travelcards which only specify a location of sale and zonal validity. The assumption was made that all journeys made on these ticket types were between the chosen set of stations. This assumption is thought to be reasonable since the majority of National Rail journeys begin or end at major London terminals, and the terminal stations serving PayG capable lines were all PayG capable. Ticket sales from Underground stations within 0.2 miles of the chosen set of National Rail stations were also included in the estimation, and for ticket sales at these locations the journey per ticket estimate used was an average of tickets sold at TfL outlets and TOC outlets in the Travelcard zones.

Based on this analysis it was estimated that there were 1.504 million journeys made during 4-10 Oct 2009 and 1.574 million journeys made during 26 Sept-2 Oct 2010, a 4.64% increase. It was also estimated that PayG journeys increased by 17% (from approx. 464,000 to 526,000 journeys). There also appeared to be some switching between ticket sales locations with journeys made on Travelcards sold at National Rail outlets increasing by 8.2% (35,678 journeys) and journeys made on Travelcards sold at Underground outlets decreasing by 4.5% (26,284 journeys). The control factor from this analysis was found to be 4.64%, though variation in growth was seen across ticket sales locations and ticket types.

c) Journeys from stations outside London to London

The third control was journeys between stations outside London and Greater London and for selected control stations. Journeys were estimated on a weekly basis from the week ending 10 January 2010 to the week ending 9 October 2010. Thereafter, a year-on-year percentage change was calculated at a weekly level, with the first set of weeks compared being 4-10 January 2009 and 3-9 January 2010 and the last set of weeks compared being 4-10 October 2009 and 3-9 October 2010. The first and last weeks of the financial accounting year were omitted from the analysis since ticket sales periods end on the 31st of March and start on 1st

April respectively distorting our weekly ticket sales data and making year-on-year comparison unreliable for these weeks. Figure 6-7 illustrates the weekly percentage change in the number of journeys in 2010 over 2009 for all the chosen stations. Apart from the first and last weeks of the financial years mentioned above, no other weeks are omitted because they illustrate important details and should be considered and used in the corridor-level analysis.

Figure 6-7: Weekly Journeys Change (2010 over 2009), by Station

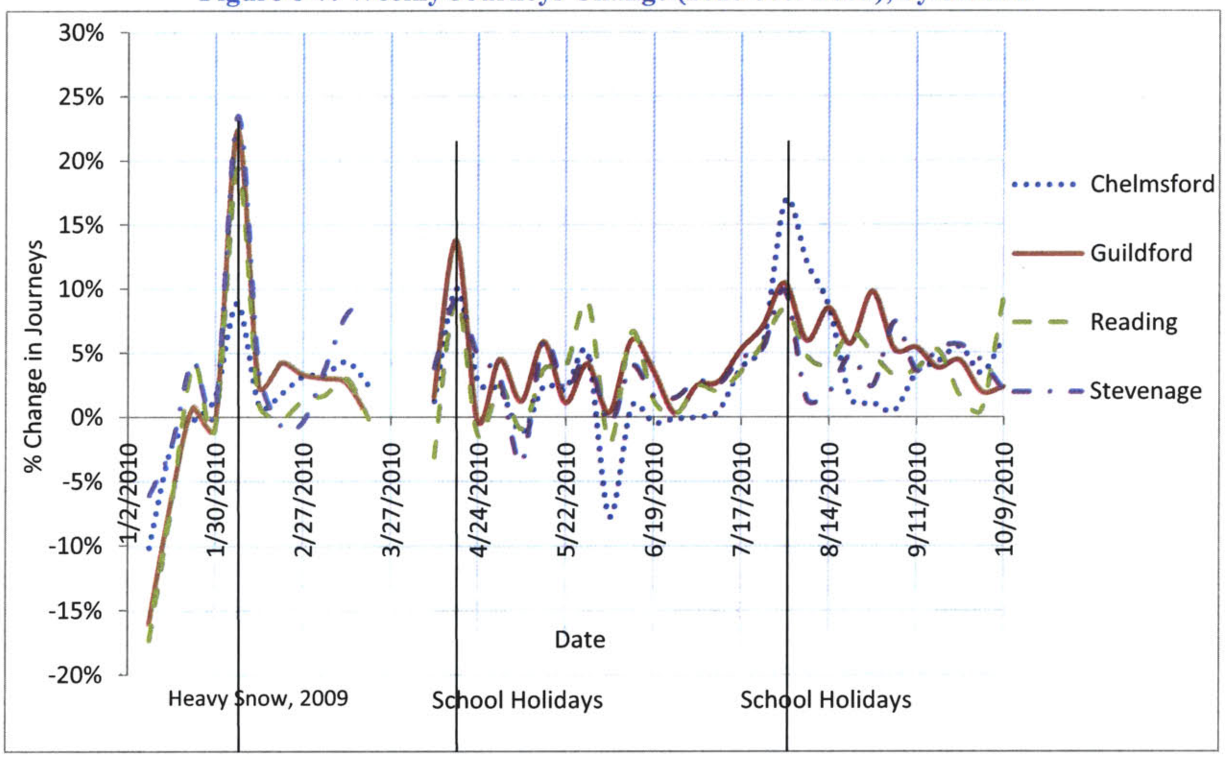


Figure 6-7 shows considerable week to week variation in the year-on-year journey changes, which is to be expected due to events that occur over the course of a two year period. A few dates are noteworthy (as shown in Fig. 6-7) and for each of these dates, journeys in 2009 were lower than would be expected. The expected reasons for this are heavy snow in Feb '09 and less leisure travel during school holiday terms for April '09 and August '09 due to the recession. From Figure 6-7 it can be seen that the change trend is similar across all the control stations. The correlation coefficients for each pair of stations range from 0.74 (for Chelmsford and Stevenage) to 0.89 (for Guildford and Reading). These values will be used for the station-level controls.

For a more reliable comparison of the year as a whole the average or median of the yearly changes might serve better. Table 6-6 shows the descriptive statistics and Fig 6-8 is a histogram for these results, with the column in Fig 6-8 corresponding to the frequency from the percentage shown below to the next higher value on the axis. For the chosen weeks of comparison of the aggregate analysis, i.e. 4-10 October 2009 and 26 Sept – 2 Oct 2010, the change in number of journeys is as shown in Table 6-7.

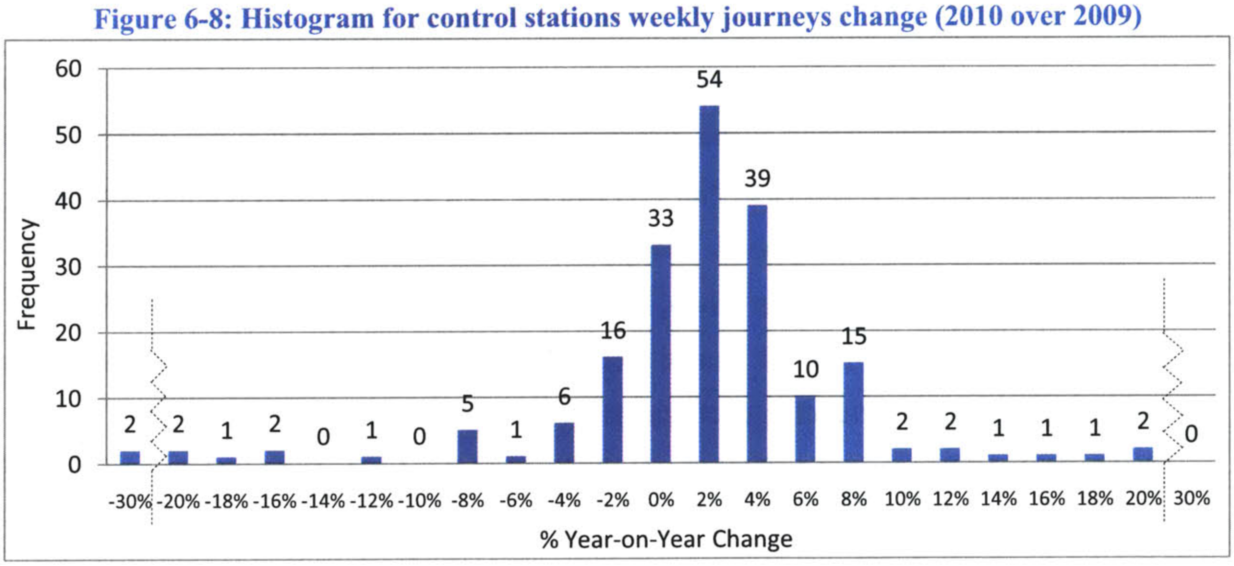
Table 6-6: Descriptive statistics for weekly journeys change (2010 over 2009) for control stations

Details	Chelmsford	Guildford	Reading	Stevenage	All
Average	2.8%	3.7%	2.6%	3.7%	3.2%
Minimum	-10.1%	-16.0%	-17.3%	-6.2%	-17.3%
Maximum	16.9%	22.4%	19.4%	23.4%	23.4%
25th Percentile	0.6%	1.3%	0.3%	1.7%	1.0%
Median	2.3%	3.5%	2.7%	3.6%	3.0%
75th Percentile	4.4%	5.7%	4.9%	5.1%	5.2%
Standard Deviation	4.7%	5.7%	5.5%	4.7%	5.2%

Table 6-7: Journey Percentage Change between 3-10 Oct 2009 and 26 Sept – 2 Oct 2010

Journey Percentage Change between 3-10 Oct '09 and 26 Sept-2 Oct '10			
Chelmsford	Guildford	Reading	Stevenage
4.59%	1.97%	0.80%	3.19%

Figure 6-8: Histogram for control stations weekly journeys change (2010 over 2009)



From Table 6-7, the average growth in the number of journeys between 2009 and 2010 is around 3.2%. It is also evident from the histogram in Figure 6-8 that the percentage growth from 2009 to 2010 is centered between 2% and 4%. For the chosen week, there is a significant amount of variation, with growth from 0.8% to 4.59%. From the table on descriptive statistics, it can also be seen that the 75th percentile of journey change for all weeks is 5.2% growth. All of these values are in the same range as our two primary controls suggesting that these are reliable estimates.

Our primary control factors suggest a growth of 4.6% and 4.9%, and as a slightly conservative estimate we select 5% journey growth as the control factor for the network-wide analysis. For the station/corridor level analysis the control factor needs to be based on the variation over time as these would be indicative of the actual changes over time. Where possible, a station along the same corridor is chosen as the control, otherwise an average value over the 4 stations is selected as the control.

6.3.2 Network-wide Changes in Travel

Using the methodology outlined above, the journey estimates for National Rail in London were calculated. As mentioned, the chosen weeks for comparison were 4-10 Oct 2009 and 26 Sept-2 Oct 2010. The choice of September- October allows a 10 month adjustment period since the introduction of OXNR. Further, there were no major holidays during these two weeks. The weeks were also chosen so as to eliminate any obvious errors within the raw data, which prevented the choice of 27 Sept-3 Oct 2009 and 3-9 Oct 2010 as possible corresponding weeks for yearly comparisons. It is not expected that any seasonal effects would affect this analysis. Table 6-8 shows the estimated National Rail journey segments for the selected weeks by ticket type.

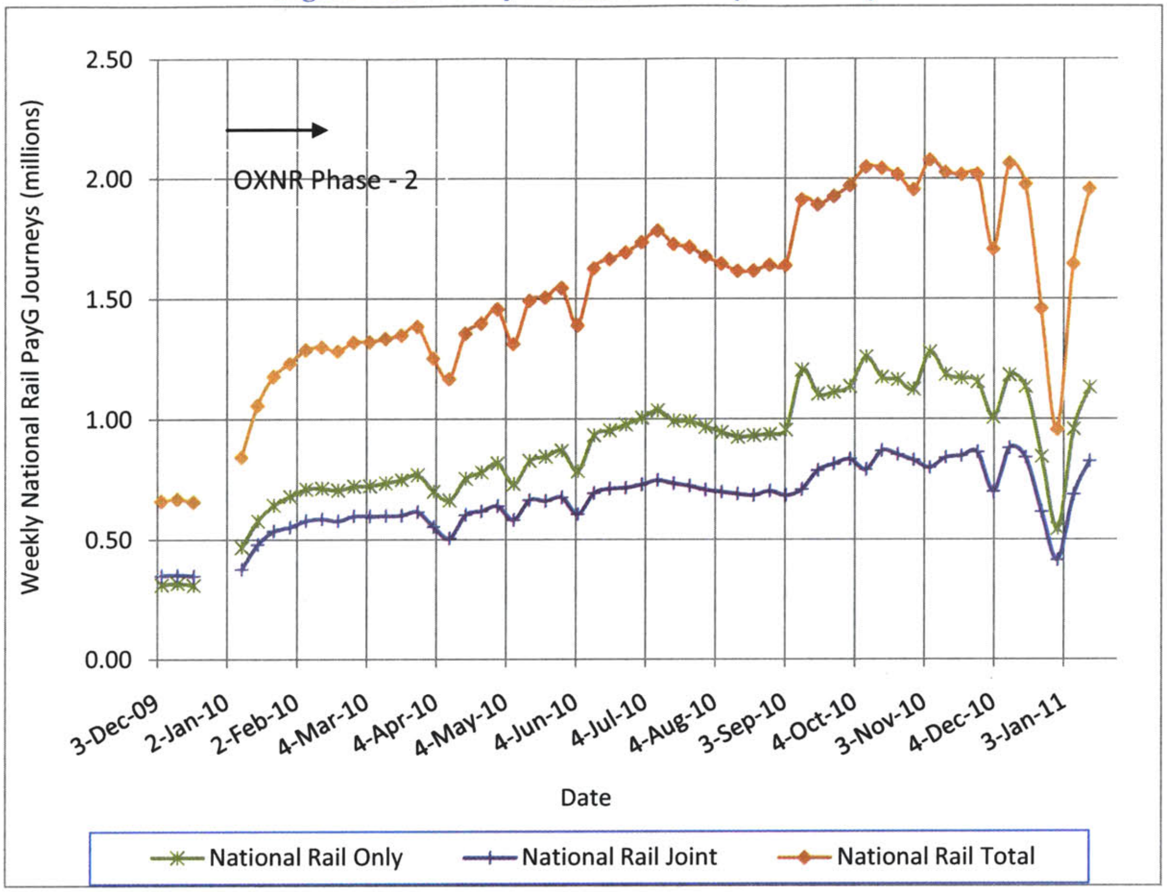
Table 6-8: National Rail Journeys Comparison[30]

Ticket Type	Ticket Detail	4 - 10 Oct 2009	26 Sept - 2 Oct 2010	Change	% Change	% Change Relative to PayG
TOC Day Tickets	Standard Single	436,864	238,954	-197,910	-45.3	-13.0
	Cheap Day Return[30]	409,340	16,974	-392,366	-95.9	-25.7
	Standard Day Return	318,892	288,960	-29,932	-9.4	-2.0
TOC Point to Point Seasons	7 Day Seasons	276,207	217,619	-58,587	-21.2	-3.8
	Monthly Seasons	373,734	329,185	-44,549	-11.9	-2.9
	Annual Seasons	318,635	298,542	-20,093	-6.3	-1.3
	Other Seasons	44,544	44,122	-422	-0.9	0.0
Off-Peak Day Travelcards	TfL sold	263,980	192,444	-71,536	-27.1	-4.7
	TOC-In sold	578,712	583,372	4,660	0.8	0.3
	TOC-Out sold	538,265	588,322	50,057	9.3	3.3
Anytime Day Travelcards	TfL sold	46,743	30,791	-15,953	-34.1	-1.0
	TOC-In sold	170,129	147,744	-22,385	-13.2	-1.5
	TOC-Out sold	194,619	208,203	13,584	7.0	0.9
7 Day Travelcard seasons	TfL sold	1,093,314	1,140,477	47,163	4.3	3.1
	TOC-In sold	576,640	672,609	95,969	16.6	6.3
	TOC-Out sold	224,671	240,487	15,816	7.0	1.0
Monthly Travelcard seasons	TfL sold	773,351	794,010	20,659	2.7	1.4
	TOC-In sold	371,181	398,161	26,980	7.3	1.8
	TOC-Out sold	293,817	299,856	6,039	2.1	0.4
Annual Travelcard seasons	TfL sold	294,744	306,825	12,082	4.1	0.8
	TOC-In sold	414,523	422,495	7,971	1.9	0.5
	TOC-Out sold	431,750	441,038	9,288	2.2	0.6
Pay-as-you-Go		446,006	1,971,886	1,525,880	342.1	100.0
Total		8,890,661	9,873,076	982,415	11.0	64.4

There are numerous striking figures in Table 6-8. First and foremost is the tripling of PayG journeys to a figure of almost 2 million journeys over the course of 2010. Figure 6-9 shows PayG journeys on National Rail, with a breakdown by joint and NR only. Here a clear growth trend over time is seen across 2009. PayG on National Rail data was not estimated prior to 3 December 2009 and the 4-10 October 2009 figure was an estimate provided by TfL.

[30] This data contains a small number of stations outside the Greater London fare zones, accounting for <0.5% journeys. This results in a small number of Cheap Day Return journeys in 2010, even though as part of OXNR, the Cheap Day Return ticket type was eliminated in Greater London. These stations do not bias the results.

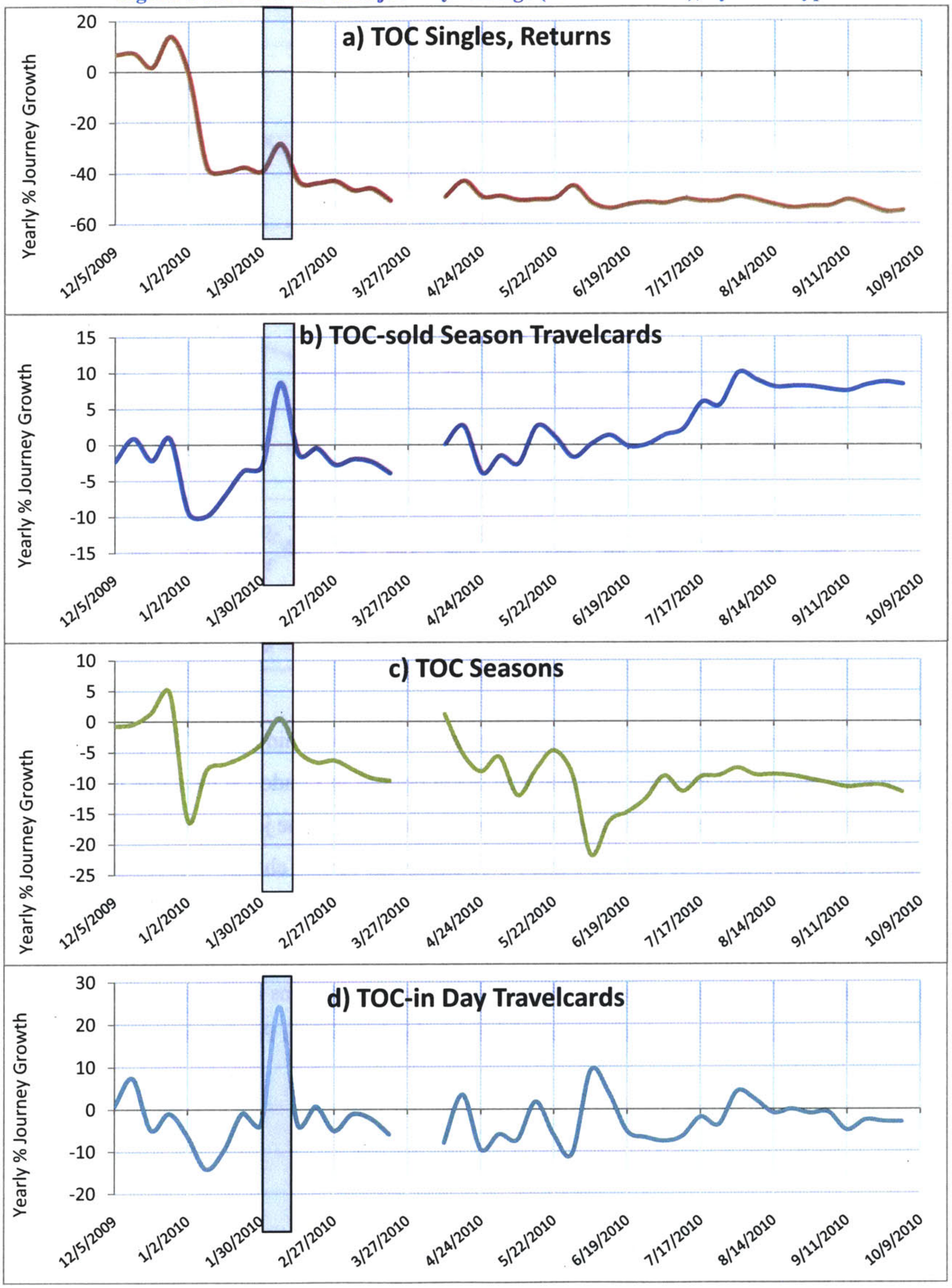
Figure 6-9: Weekly National Rail PayG Journeys



A large proportion of the initial increase can be attributed to switching from Cheap Day Returns which were eliminated from the National Rail ticket options in London at the same time as OXNR Phase 2[31]. Further there is also a sharp initial decrease in the journeys made using single tickets, again attributable to OXNR. Figure 6-10 shows the annual change in journeys for the main TOC-sold tickets, with TOC-in representing TOC sales within the London Travelcard zones. For Singles, there is a very clear decreasing trend evident in January 2010, around the same time as OXNR was introduced. This confirms our expectations regarding ticket switching. What is not evident however is the cause of the sustained growth in PayG journeys.

[31] A small number of stations not part of the London Travelcard zones and accounting for less than 0.3% of total journeys are included in this data. These do not affect the analysis.

Figure 6-10: Network-wide journeys change (2010 over 2009), by ticket type



Examining other ticket types from which people might have switched to PayG, there was a clear decrease in journeys made on TfL sold Day Travelcards (peak and off-peak), with a decrease of around 28% for our chosen weeks. Much of this decrease occurred in January 2010 and is likely attributable to OXNR. However, for Day Travelcards sold by TOCs within London no such trend was seen. For journeys made on TOC seasons, there seems to be some evidence of switching due to OXNR. For 35 out of the 37 weeks, there is a year-on-year decrease in journeys made on TOC seasons, most in the range of 8-12%. It is also worth noting that a decrease is also visible during the last week before OXNR (ending 2 Jan 2010) while the other weeks in December 2009 showed between -0.7% and 4.5% growth from 2008. A portion of this decrease in TOC seasons might also be due to a growth in 7-day and monthly seasons sold by TOCs (on Oyster), which both show increases. However, the increase is not evident at the start of OXNR and only becomes clear from July, after which time all the year-on-year journeys on National Rail sold Travelcards show positive growth. For the other ticket types, there is no clear evidence of switching.

We have however simply been comparing journeys made in 2009 with those made in 2010 and to inform the journey growth analysis, we need to apply our control factor to the journeys made in 2009 and adjust them to the expected 2010 level. As previously mentioned, the control factor for the network-wide analysis is 5% growth. This factor was estimated for total journey growth and while it is not likely that growth would have been uniform across all ticket types, it is worth estimating what the ticket change figures would be if this was the case. Table 6-9 shows journeys in 2009 adjusted by a factor of 1.05.

The table indicates that it is likely that there has been switching away from Day Travelcards, with decreases of 5.7% and 3% for the Off-Peak and Anytime variants respectively. Journeys made on TOC seasons show a 16% decrease, a figure which further strengthens the belief that there has been switching away from these ticket types. The main intent of this table however, is to assess the level of growth in journeys due to OXNR. This figure would appear to be around 5.8% or an increase of 0.54 million journeys. However, this table still does not tell the complete story since the East London Line increased service substantially during this period, and this impact must be considered as discussed below.

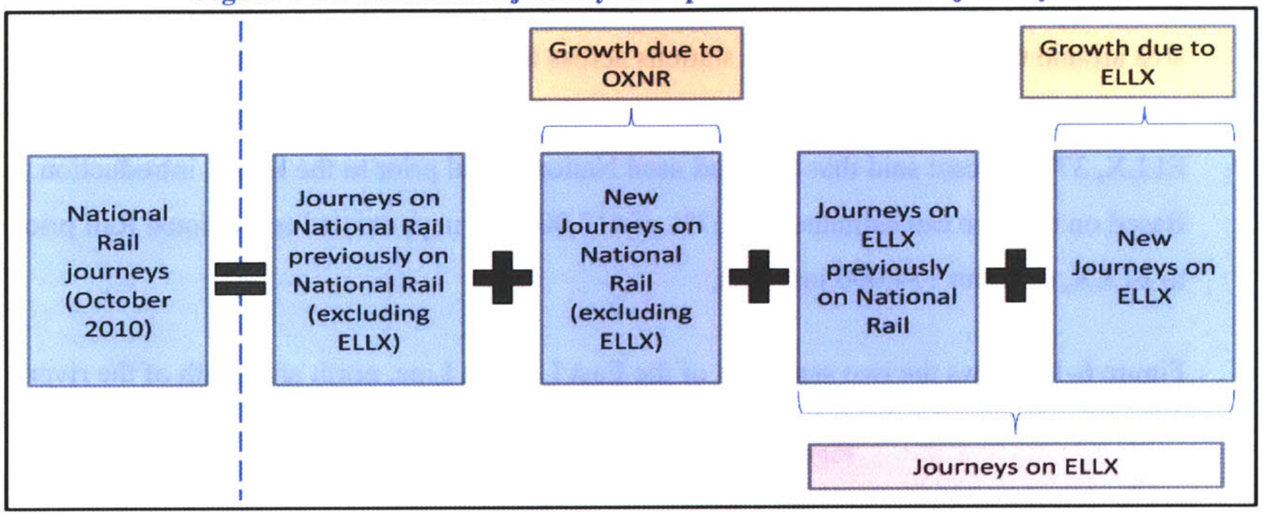
Table 6-9: Control factor adjusted National Rail journeys comparison

Ticket Detail	4-10 Oct 2009 with 5% growth (millions)	26 Sept - 2 Oct 2010 (millions)	Change (millions)	% Change	Change as % of PayG
TOC Day Tickets	1.22	0.54	-0.68	-55.5	-45.1
TOC Point to Point Seasons	1.06	0.89	-0.17	-16.4	-11.6
Off-Peak Day Travelcards	1.45	1.36	-0.09	-5.9	-5.7
Anytime Day Travelcards	0.43	0.39	-0.04	-10.5	-3.0
7 Day Travelcard seasons	1.99	2.05	0.06	3.2	4.3
Monthly Travelcard seasons	1.51	1.49	-0.02	-1.2	-1.2
Annual Travelcard seasons	1.20	1.17	-0.03	-2.3	-1.8
Pay-as-you-Go	0.47	2.06	1.59	321.1	100.0
Total	9.33	9.87	0.54	5.8	35.8

a) Estimation of New Journeys on East London Line extension

The comparison of our figures between 4-10 Oct 2009 and 26 Sept-2 Oct 2010 is not directly valid in terms of journey growth since this period has been affected not only by OXNR, but also by the introduction of the East London Line extension (ELLX). The East London Line is part of the London Overground and is therefore also a part of the National Rail network in London. Part of this line runs parallel to the National Rail network (from West Croydon to New Cross Gate), while the remainder is along a new corridor (New Cross Gate to Dalston junction). Prior to May 2010, construction work was being carried out and this line was not operational. On May 23 2010, this line was reopened resulting in an increase in services along the corridor. While this service increase was accompanied by some service decreases on Southern, it is expected to have had a significant impact on journey growth. As shown in Fig 6-11, not all the growth on this line is due to new journeys, i.e. journeys not previously made on National Rail. Some of these journeys would previously have been made on National Rail and so we need to separate these out to arrive at a better estimate of the new journeys made on ELL. We can then further separate them out to arrive at a better estimate of the actual journey growth due to OXNR.

Figure 6-11: 2010 ELLX journeys as a part of National Rail journeys



From October 2010 manual counts, it was estimated that approximately 70,000 journeys were made on the East London Line on a typical weekday (Ng, 2011). Given 47,000 and 20,000 journeys on a Saturday and Sunday respectively, the weekly journey total is 417,000. Now we need to estimate the number of journeys which are new to the National Rail system (alternatively we can estimate the number of journeys which existed on National Rail prior to the East London Line extension). Ng (2011) analysed the impact of the East London Line and estimated new journeys made on public transit modes using data from manual surveys conducted in late June and early July 2010 to understand the changes due to the East London Line (Accent MR, 2011). The estimation here follows a broadly similar method with the differences being due to the different aims of this estimation and that of Ng (2011).

The surveys were conducted by 2 methods – telephone interviews and interviews at bus stops or rail stations. As part of both of these surveys, the following questions on travel behavior prior to the ELL opening, relevant to our estimation, were asked:

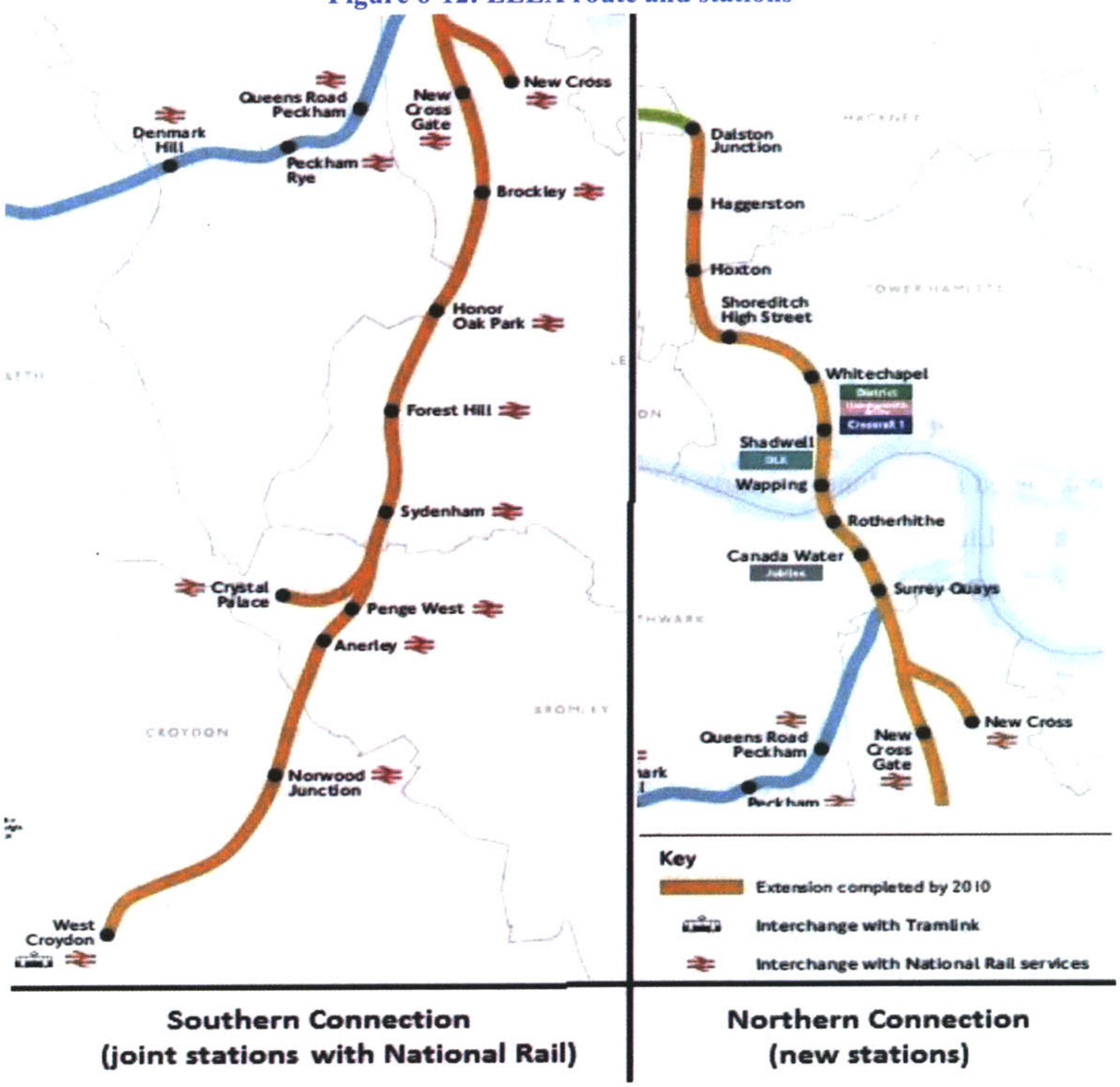
- Have you changed your journey patterns since the London Overground service from Dalston Junction to West Croydon, Crystal Palace and New Cross opened?
- Which means of transport did you use before the new service opened?

We will use responses to these questions in our estimation of the journeys that existed on National Rail prior to ELLX.

The telephone interviews were conducted with individuals living within a 1000m catchment area around the ELL stations, with stations across the whole ELL chosen as part of the survey method. Of t hose individuals who said that their journey patterns had changed since ELLX, 37% percent said that they had used National Rail prior to the ELLX introduction. Based on this, we can estimate that 37% of 417,000 journeys existed on National Rail prior to ELLX, or about 154,000 journeys.

Figure 6-12 shows the two segments of the East London Line, north and south of the river.

Figure 6-12: ELLX route and stations



The other survey method involved interviews at National Rail stations south of the river, as well as interviews at bus stops north of the river. From the station interviews, of the interviewees who said they had changed journey patterns, 76% said they used National Rail prior to ELLX. From the bus stop interviews, of those who said they had changed their journey patterns, 46% said they had used National Rail prior to ELLX. Based on boarding and alighting data from the manual counts, it was estimated that 285,000 and 132,000 journeys were along the Northern (non-National Rail) and Southern segments respectively. If we assume that the surveys at bus stops are applicable to journeys made on the Northern end, and those at National Rail stations are applicable to the Southern end, 231,420 ELL journeys came from National Rail.

Thus, based on the two survey methods, between 154,000 and 231,000 journeys of the 417,000 journeys had previously been made on National Rail. This would indicate that between 186,000 and 263,000 journeys are new National Rail journeys due to the introduction of the East London Line extension.

b) Results and discussion after subtraction of ELL Journeys

From our estimate of the total increase in journeys from 2009 to 2010, we have assumed a natural growth of 5%, and also estimated that an increase of between 186,000 and 263,000 journeys was due to the East London Line extension. Since there have been no other major changes during this period, our total increase in journeys after accounting for both these factors is attributable to OXNR. OXNR would then have accounted for an increase of between 275,000 and 352,000 journeys per week, from a base of 9.3 million journeys per week, representing an increase of between 2.9% to 3.8%.

There were three stages in the journey estimation process discussed in this section. Table 6-10 shows these sequential stages and the corresponding network-wide journey estimates.

Table 6-10: National Rail network-wide journeys estimation summary

Estimation Stage	Before (2009)	After (2010)	Change	% Change
Actual Estimated Journeys	8.89	9.87	0.98	11.0
Journeys with Control	9.34	9.87	0.54	5.8
Journeys with Control, excluding ELL	9.34	9.65	0.31	3.4

The first stage is a simple journey estimation based on the ticket sale data, while the second stage uses a control factor to estimate what the journeys would have been without Oyster on National Rail. However, this figure still included journey growth due to the reopening of the East London Line which is accounted for in the final stage, which suggests that journey growth due to OXNR was around 0.3 million journeys or 3.4%.

6.4 Station-specific Journeys Analysis

In the previous section the focus was on network-wide journeys while this section supplements the previous inferences with an analysis of individual corridors or stations which came under the PayG regime. Within this section, station and corridor selection is first discussed before moving on to analysis and discussion of results.

6.4.1 Corridor and Station Selection

For the corridor and station choice, this study is restricted to the 3 TOCs (Southeastern, Southern and South West Trains) which implemented PayG on all their stations within Greater London on 2 January 2010. All these TOCs operate south of the river where the coverage of the London Underground is far lower than for most regions north of the river and where National Rail is the dominant public transport commuting option. Table 6-12 shows the major stations operated by these TOCs, and the main London terminals serving them, ranked by 2008-09 entries and exits. The first 5 stations (and London Waterloo East) are the London terminals, and are included to present an idea of the scale of use of the other stations[32].

[32] London Waterloo is the busiest railway station in Britain in terms of entries and exits.

Table 6-11: Major stations operated by Southern, Southeastern, South West TOCs, and their London terminals

Ranking	Station Name	Station Facility Owner	2008-09 Entries & Exits	2008-09 NR Interchanges
1	*London Waterloo*	*Network Rail*	*87,930,076*	*4,587,154*
2	*London Victoria*	*Network Rail*	*70,157,115*	*4,498,079*
3	*London Bridge*	*Network Rail*	*49,703,152*	*4,971,470*
4	*London Charing Cross*	*Network Rail*	*36,659,932*	*1,677,852*
5	*London Cannon Street*	*Network Rail*	*21,646,380*	*200,318*
6	East Croydon	Southern	20,581,318	6,371,478
7	Clapham Junction	South West Trains	17,445,432	16,354,822
8	Wimbledon	South West Trains	15,171,750	1,333,795
9	Vauxhall	South West Trains	14,581,929	0
10	Putney	South West Trains	8,793,398	0
11	Surbiton	South West Trains	8,385,738	1,304,636
12	*London Waterloo (East)*	*Southeastern*	*6,707,128*	*891,236*
13	Richmond	South West Trains	6,628,372	1,082,422
14	Lewisham	Southeastern	6,260,836	2,765,614
15	Sutton (Surrey)	Southern	6,059,260	671,266
16	Bromley South	Southeastern	5,796,166	830,504
17	Kingston	South West Trains	5,160,632	0
18	Twickenham	South West Trains	5,108,980	459,364
19	Balham	Southern	5,084,538	270,275
20	Orpington	Southeastern	4,970,528	487,781

There are two stations to be selected for this analysis - a major station with underground service and a major station without underground service. These are discussed below.

a) National Rail Station with Underground Service

The aim of analyzing this station is to try and identify whether the presence of underground service has any effect on ticket switching and on growth. Apart from the previously defined general criteria for corridor selection, the sub-criteria for the specific type of corridor is that there should be underground service serving the same area or destination stations as the National Rail service at that station.

Wimbledon station was selected as the station for analysis, being the third busiest station in the South, outside the Central London terminal stations. Further, as a point of comparison, another station is chosen along the same corridor which provides a control to the main station of analysis. Surbiton, which lies along the same corridor but is further from Central London, was chosen for this purpose. Both of these major stations are served by South West Trains, and have regular peak and off-peak services to Central London. The locations of the stations are similar in that they are both suburban, even though Wimbledon is more commercial than Surbiton.

Figure 6-13 shows both Surbiton and Wimbledon relative to Central London (Waterloo station) on the South West corridor. One of the control stations outside London, Guildford, also lies along this corridor as shown in Figure 6-14.

Figure 6-13: Location of Wimbledon and Surbiton stations within Greater London

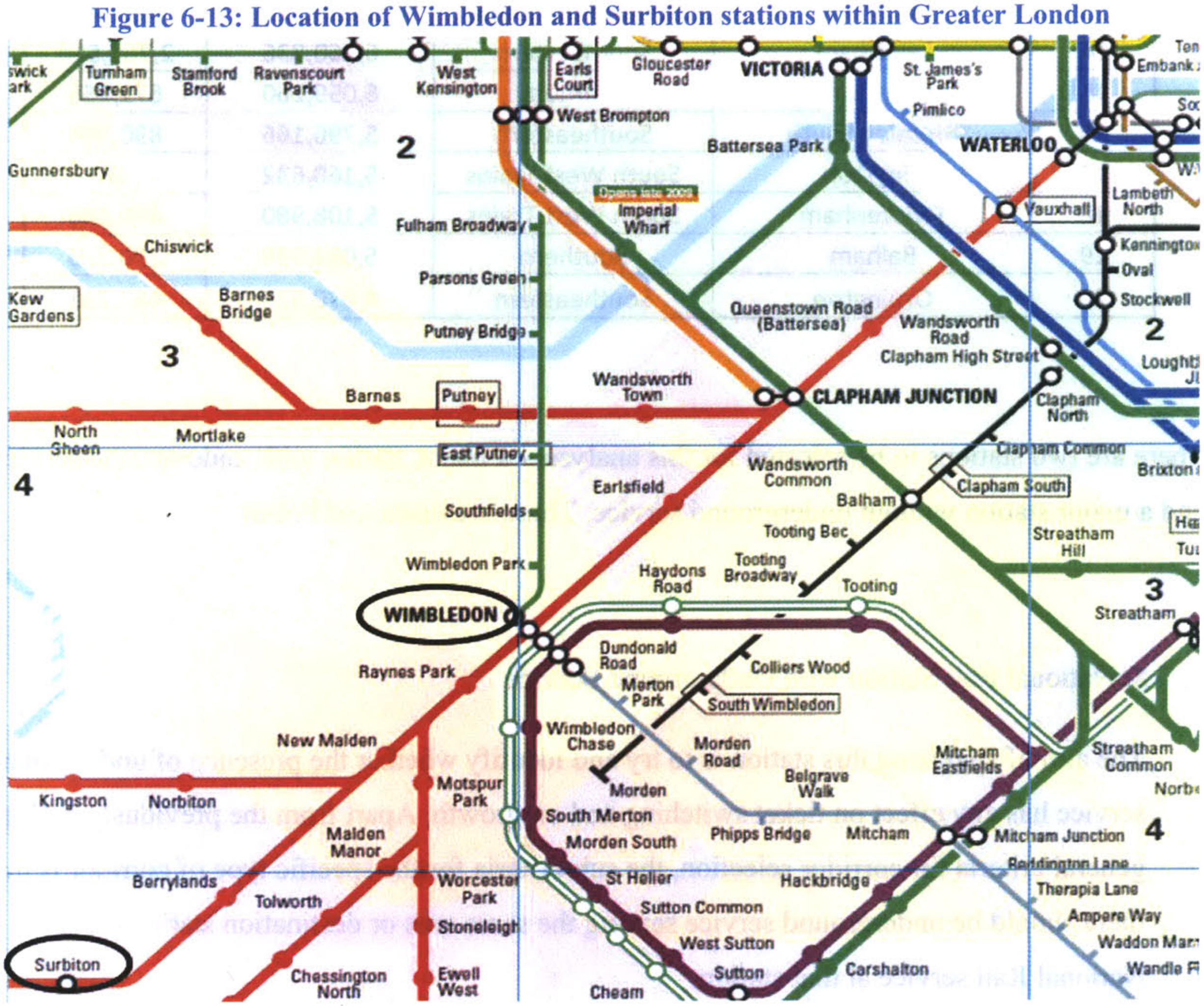
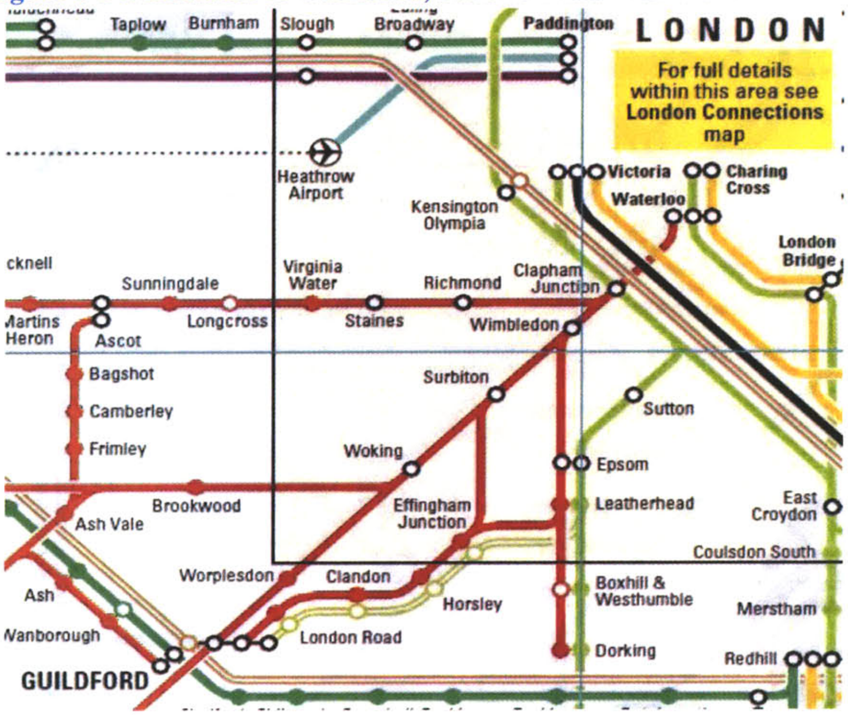


Figure 6-14: Location of Guildford, Surbiton and Wimbledon stations

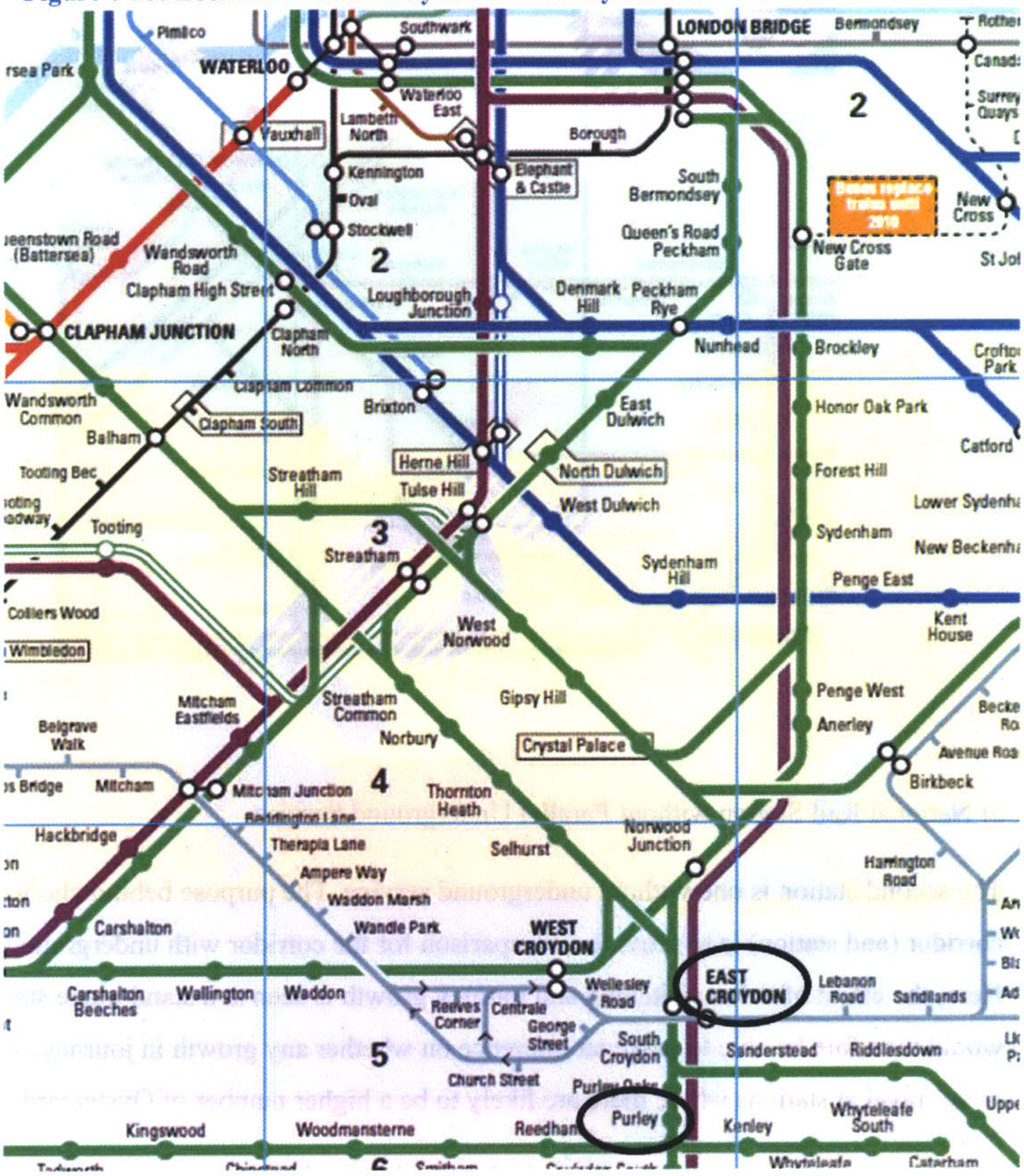


b) National Rail Station without Parallel Underground Service

The second station is one without underground service. The purpose behind choosing such a corridor (and station) is to provide a comparison for the corridor with underground service. Here, the effect of ticket switching and journey growth is seen at a stand-alone station. We would therefore be able to make an inference on whether any growth in journeys is due to more travel at stations where there are likely to be a higher number of Oystercard users.

The station selected is East Croydon which is the busiest NR station in the South. The other chosen station along this corridor is Purley, which is further from Central London and is much less busy. Figure 6-15 shows the location of both stations. Both these stations are served by Southern which provides both peak and off-peak services. There is however, a significant difference between the areas served by these two stations. Croydon is a major commercial center with has retail and service industries. Purley on the other hand is a suburban commuter locality which does not serve as a major transport hub.

Figure 6-15: Location of East Croydon and Purley Stations within Greater London



6.4.2 Station-level Results

This section presents results from the station-level analysis, with the main questions being the same as for the network-wide study, ticket switching and journey growth due to OXNR.

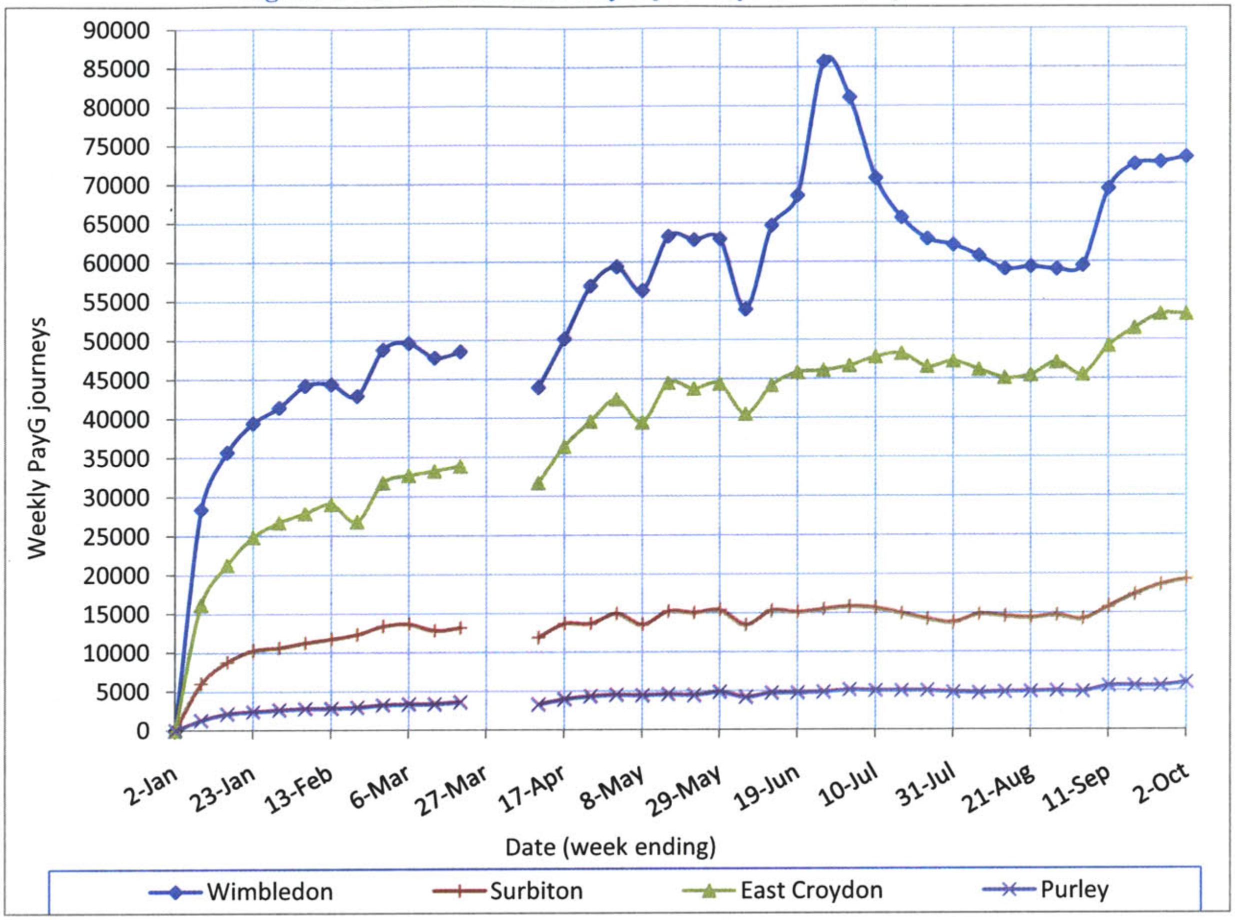
a) Ticket Switching

One of the key questions addressed in the network-wide journeys analysis was the extent of ticket switching due to OXNR. From the selected stations and corridors, it can be seen whether the network-wide ticket switching trends are consistent across stations.

For this analysis, the journey estimation methodology was based on TOC ticket sales at individual stations, with any tickets sold having either origin or destination at the given station. This level of disaggregation does create some inconsistencies, since not all journeys made from (or to) a station will have either origin or destination noted. This problem particularly affects Travelcards since for this ticket type we know only the sale location and the zonal validity. The assumption here is that all the journeys made on a Travelcard are made from (or to) the station at which the Travelcard was bought. While this assumption is clearly not entirely valid since a Travelcard can be used at any station within its zonal validity area, and is likely used in trips involving more than just the retail station, it is necessary to include journeys made on Travelcards as part of our station-level analysis. On the other hand, for journeys made on PayG, both the origin and destination stations are known since they are based on smart-card taps made during each journey. Thus, it is possible that the analysis may be affected by the higher accuracy resulting from the introduction of PayG, especially in the case of switching from Travelcard to PayG. But this is not thought to be a major factor since switching from Travelcards is not as significant as switching from TOC tickets (as shown in the network-wide analysis).

As shown in Fig 6-16, PayG journeys at all chosen stations increase rapidly during the first month of 2010. More than 50% of the journeys made on PayG in the week ending 2 October 2010 were already being made by the end of January, indicating a very significant buildup in the first month. This is clear evidence that OXNR resulted in ticket switching to PayG, and the focus of this section is to identify from which ticket types users switched and whether this was induced by OXNR.

Figure 6-16: National Rail PayG journeys in 2010, by station



For the ticket switching analysis, graphs for each of the chosen stations are shown and the inferences are discussed together at the end. It should be noted that OXNR Phase 2 was introduced on 2 January 2010 (Saturday) and any effect would be seen in the following weeks. Figures 6-17, 6-18, 6-19 and 6-20 show the percentage change in weekly journeys in 2010 from the corresponding week in 2009 for each station by ticket type. Journey percentage change is a relative measure and it is also valuable to see the absolute figures, especially in the case of PayG journeys which were zero in 2009. Figure E-1 to Figure E-20 in Appendix E show the absolute number of estimated journeys for each station.

There were certain issues that affected the journey calculation for East Croydon. East Croydon station belongs to the Croydon BR group of stations, along with West Croydon, and tickets issued are valid at both stations, meaning that LENNON data cannot reveal the exact choice of station. To deal with this, the journeys to (or from) Croydon BR were distributed between East and West Croydon according to the overall share of their journeys based on the 2009 Entries and Exits at each station. This led to allocation of 88% of Croydon BR journeys to East Croydon and the remaining 12% to West Croydon.

Figure 6-17: Weekly Journeys Percentage Change (2010 over 2009), Wimbledon

Figure 6-18: Weekly Journey Percentage Change (2010 over 2009), Surbiton

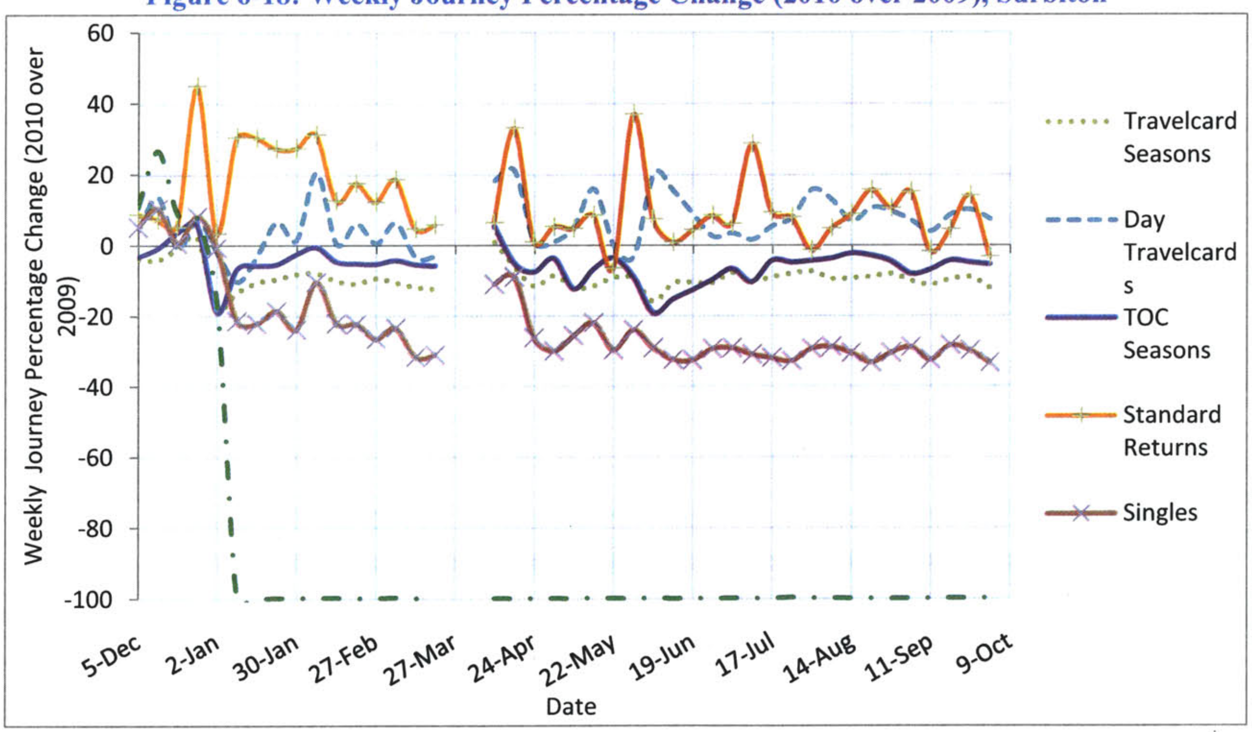


Figure 6-19: Weekly Journey Percentage Change (2010 over 2009), East Croydon

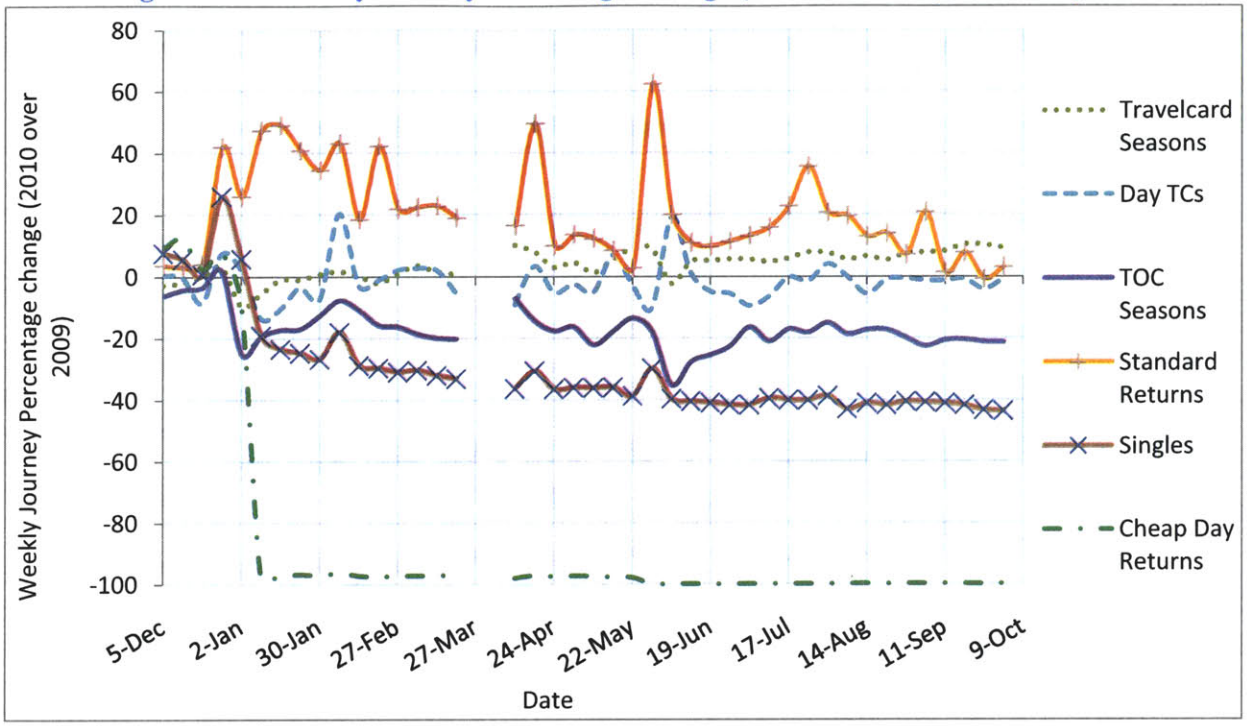
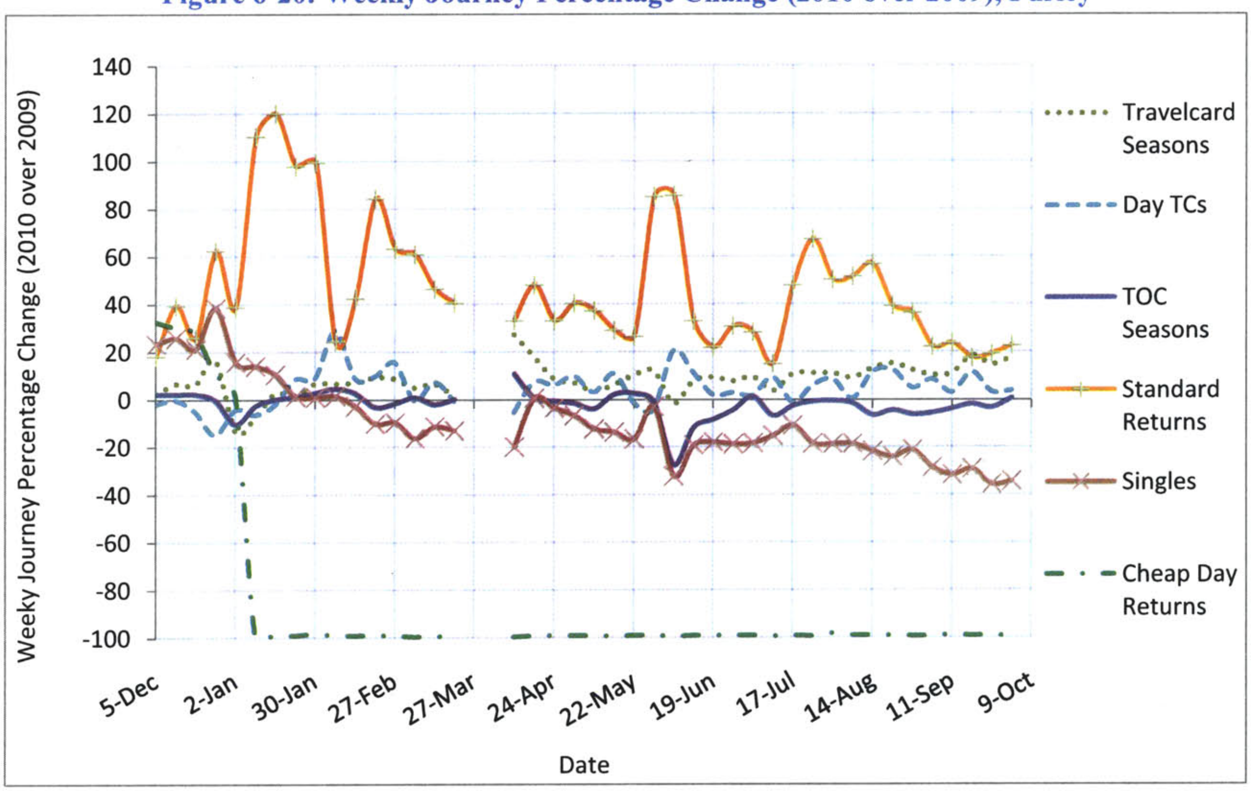


Figure 6-20: Weekly Journey Percentage Change (2010 over 2009), Purley



From the graphs shown, patterns can be identified which suggest ticket switching due to OXNR with the most obvious being the elimination in Cheap Day Returns from 9 Jan 2010.

This is an expected change since these ticket types were no longer sold, and so our focus is then to identify what other switching might have taken place as a result of OXNR. From the journey change graphs a large decrease in Single ticket journeys is apparent from 9 Jan 2010 at Wimbledon, Surbiton, and East Croydon stations. This decreasing trend continues for all stations although for Purley the decrease occurs more slowly but reaches levels equivalent to the other stations (around 40% in October). This change can be attributed to OXNR with a majority of the decrease occurring right after OXNR, and the consistent decreasing trendI indicating that switching from Singles is one of the causes for the continued increase in PayG journeys, accounting for about 30% or less in absolute numbers.

Another interesting observation is the sudden increase in journeys made on Standard Return tickets right after OXNR which would indicate that some of the switching as a result of OXNR was also to Standard Return tickets rather than all of it going to PayG. This is somewhat contrary to our network-wide result which indicated that there was a decrease in journeys on Standard Day Return tickets. This difference between the network-wide and station level result is because single weeks in September / October were being compared, while for the station-level results, the entire period is being observed. This is also indicative that the initial reaction of users might have been to switch from one TOC ticket (Singles or Cheap Day Returns) to another (Standard Day Return) rather than to simply switch to PayG. Over time however, this changed and there seems to have been a gradual switching from Standard Day Returns to PayG.

Journeys made on TOC season tickets also show interesting variation across the stations. For Surbiton and East Croydon there seems to be a decrease in TOC season ticket journeys right after OXNR, and this decrease is maintained throughout 2010, while in the case of Wimbledon and Purley there is no such clear trend with both increases and decreases in journeys over selected weeks. It is therefore hard to state conclusively that OXNR had an impact on TOC season journeys, even though the network-wide study indicated that there was a switching from these ticket types. It is likely that at some stations there was a decrease while at other stations, OXNR had no effect. There might also be other factors affecting this specific change but it is not clear what these might be.

For Travelcards, there is again no clear trend visible. The journey changes vary by station and corridor. For Wimbledon and Surbiton, there is a decrease in Travelcard season journeys right after 2 Jan 2010, and this is maintained for more than 90% of the weeks analysed, which suggests that OXNR might have been the underlying reason. For East Croydon and Purley, there seems to be no change in pattern at the onset of OXNR, even though throughout 2010, there seem to be fewer journeys made on season Travelcards than in 2009. For Day Travelcards, Wimbledon seems to show a fall in journeys made on this ticket type, East Croydon seems to show no real change over the 2 years, while at Surbiton and Purley there seems to be a 6 % average increase on Day Travelcard journeys, but with no clear linkage to OXNR.

Thus, from our ticket switching analysis it appears that most of our previous conclusions from the network-wide analysis remain valid. Much of the switching due to OXNR seems to be out of Single and Cheap Day Return tickets. The switching from Standard Return tickets is however, contrary to the previous result, with an increase in these ticket types initially and a switching out of this ticket type later in the year. It is interesting to note that there is a high degree of variability in journeys made on Day Travelcards and Standard Return tickets. The coefficient of variation for Day Travelcards is greater than 1 for all chosen stations and for Standard Returns this value lies between 0.58 and 0.9. This suggests that users find it easy to switch between these ticket types. A portion of this might simply be users forgetting to carry their Oystercard on a given day and buying a Day Travelcard or Standard Return instead. Another portion could be attributable to irregular travelers who would prefer short-term tickets such as these ticket types. Thus, OXNR has not led to the steady decrease of these ticket types as would have been expected.

b) Journey Growth

The station level analysis is also intended to see whether the journey growth is uniform across stations and corridors or whether it is specific to some stations. As mentioned previously, the method of analysis again utilizes journeys made to (or from) the stations and involves a year-on-year comparison with the control factors estimated using journeys from stations outside London. Total journeys to or from each station are compared, since a breakdown by ticket type is not necessary.

Wimbledon, Surbiton

Figures 6-21 and 6-22 show the total journeys to and from Wimbledon and Surbiton stations for 2009 and 2010, and also show the 2009 figure with the control factor applied, enabling growth calculation. Figure 6.23 shows the percentage change in weekly journeys for both stations together and allows us to compare the two stations.

Figure 6-21: Total journeys to/from Wimbledon

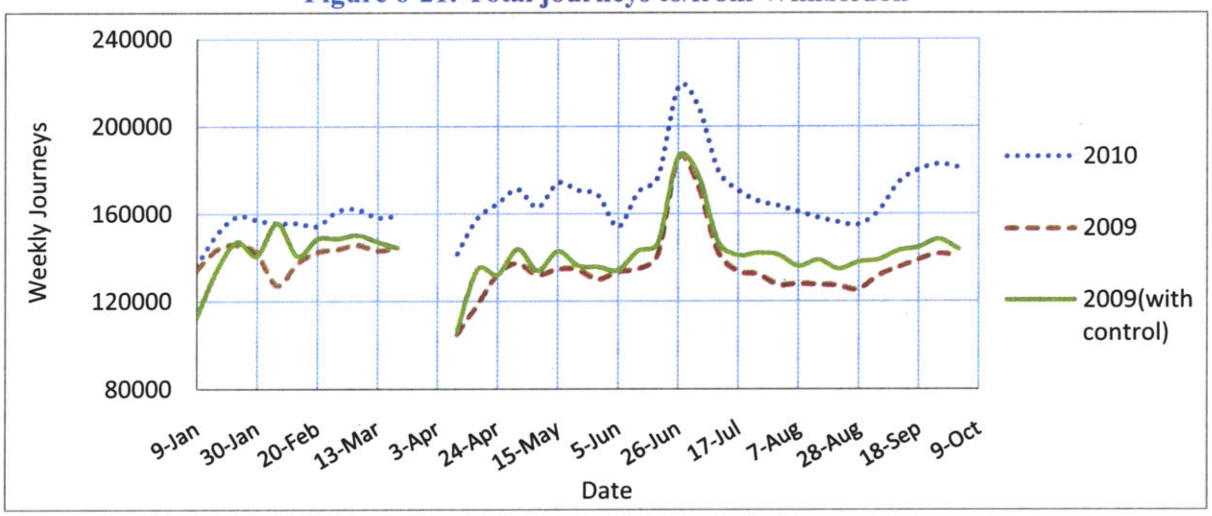


Figure 6-22: Total journeys to/from Surbiton

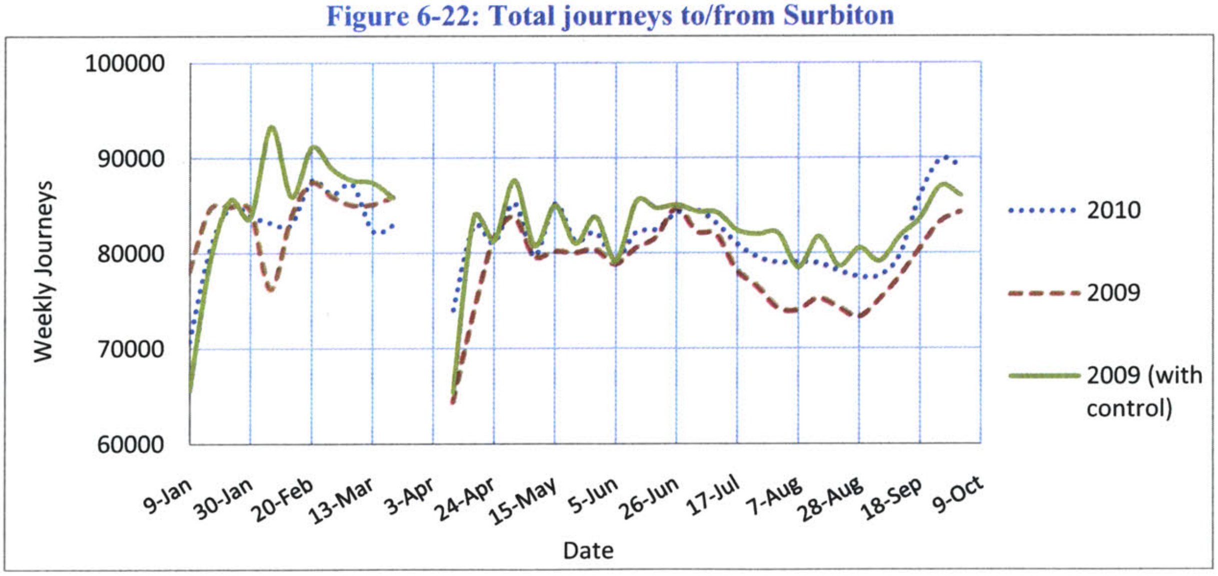
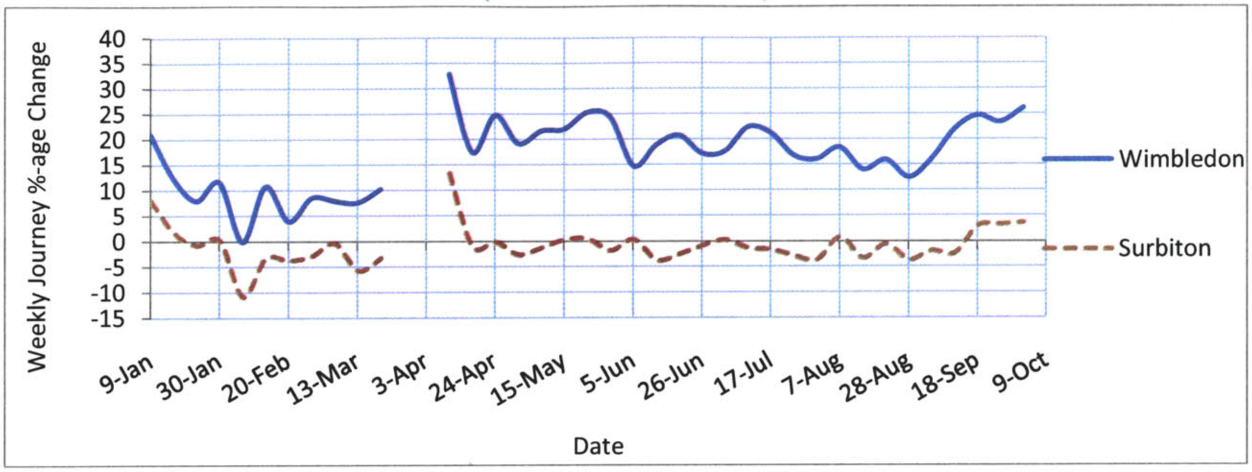


Figure 6-23: Weekly Journeys Percentage Change (2010 over 2009) after applying control (Wimbledon, Surbiton)



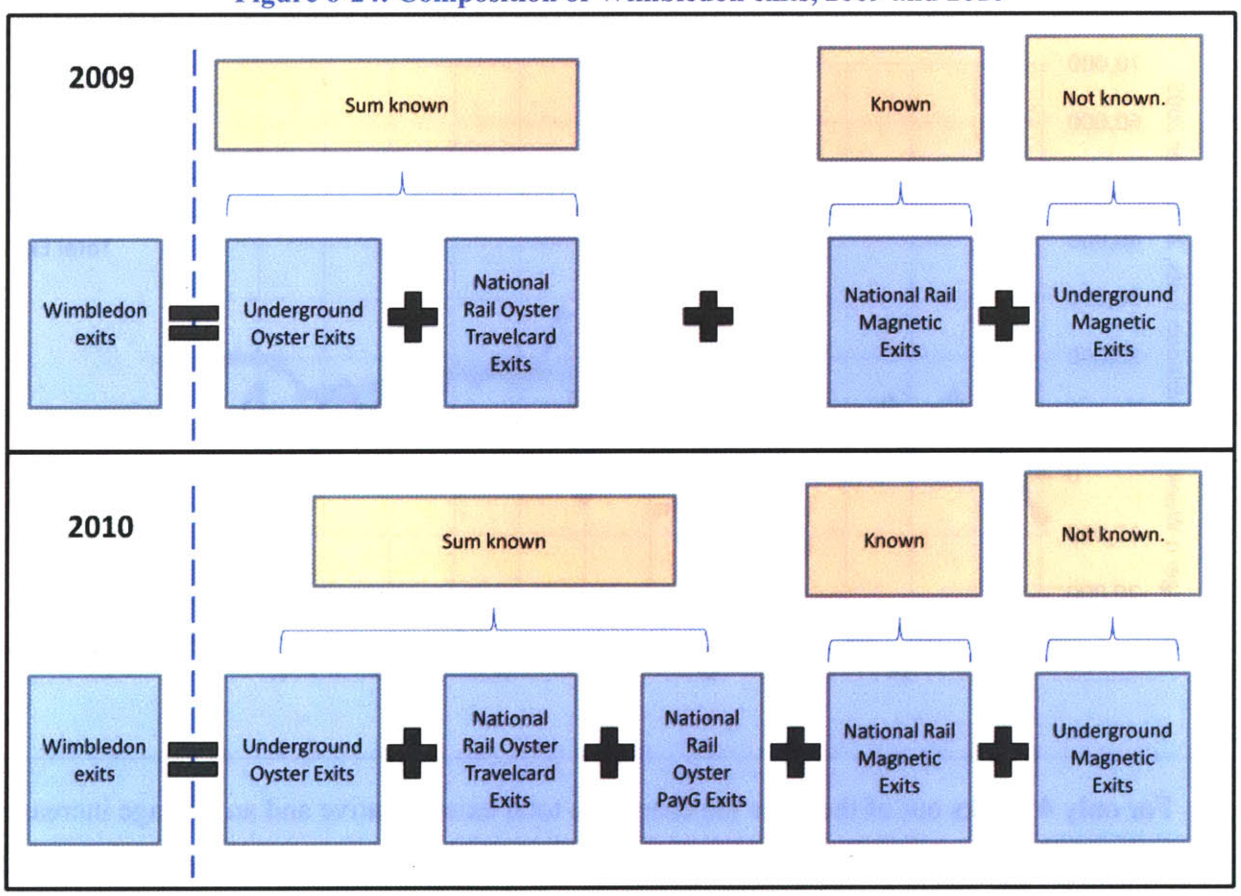
As is evident from Figure 6-21 and 6-23, Wimbledon station shows growth for all weeks in 2010 with average growth over the year of 20.8% without applying control and 16.7 % after applying control. From Figure 6-23, the trend in growth seems to indicate that journey growth was lower in the first few months of 2010, with significant increases being seen starting in April. This might be indicative of the gradual impact of OXNR on journey growth. Surbiton on the other hand seems to show no real growth. There is a 2.5% growth from 2009 to 2010, with the figure dropping to -1.1% after applying our control factors. Surbiton therefore doesn't seem to have been affected by OXNR in terms of journey growth, contrary to the expectation of some growth across all stations.

<u>Underground and National Rail journeys at Wimbledon</u>

Wimbledon station is of the only selected station served by both the Underground and National Rail. Users have the choice between the two modes at the station and when the same ticket type became valid on both, it is likely that there was some switching between modes. Thus, any growth on National Rail witnessed at Wimbledon may include switching from Underground to National Rail. It is important to assess whether OXNR produced only a growth in travel on National Rail or a growth in travel when both National Rail and the Underground are considered.

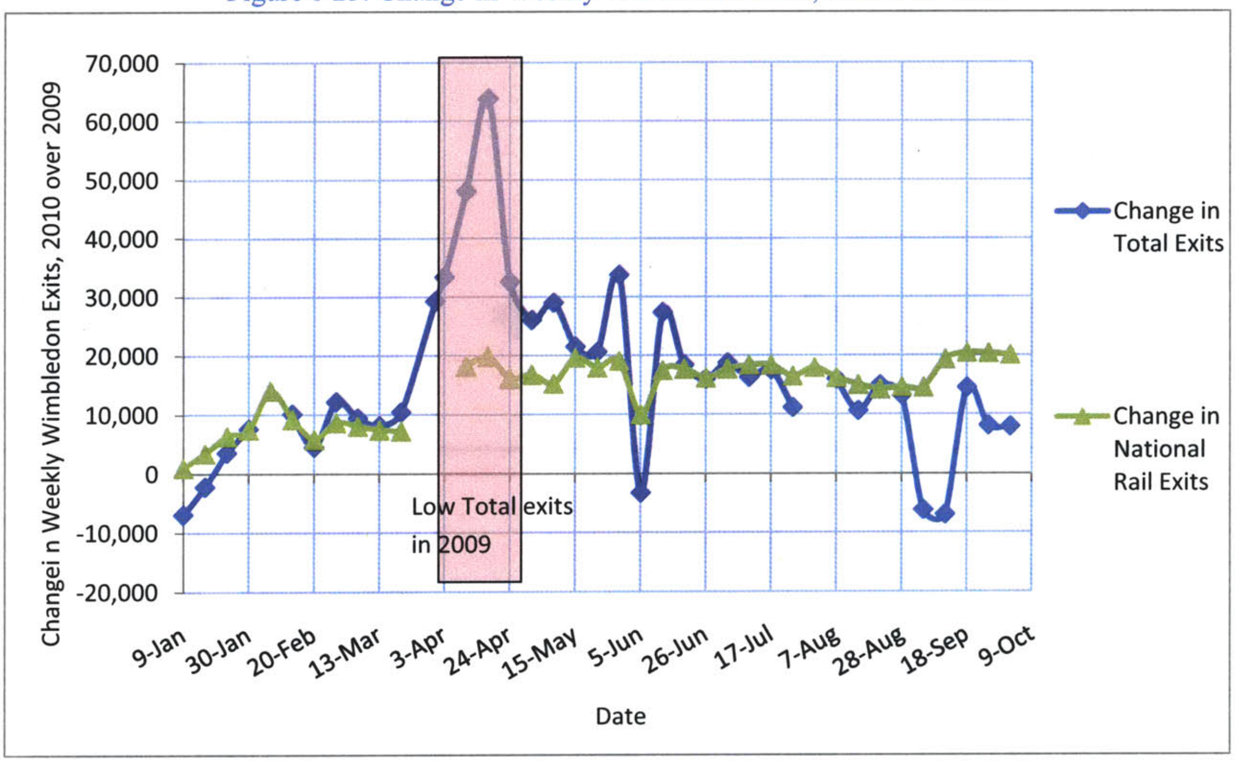
There is no direct data available which indicates the number of journeys to (or from) Wimbledon by Underground in 2009 and 2010. There is however data available on the total Oyster exits at Wimbledon station from the beginning of 2009 to the end of 2010. This data can be combined with the journey estimates of TOC-sold tickets by making certain assumptions. The journey estimates at the station also signify the number of entries and exits at a given station. It is assumed that both of these figures are equivalent and that the journey estimates can be divided by two to obtain the exits during each week. Figure 6-24 shows a breakdown of the various types of exits that occurred at Wimbledon during 2009 and 2010, and which of these components are known or can be estimated from the available data.

Figure 6-24: Composition of Wimbledon exits, 2009 and 2010



As shown in the figure, for both 2009 and 2010 the figures for underground exits using magnetic ticket types are not known. For an estimate from a station close to Wimbledon, Wimbledon Park Underground station was selected with 10% of the exits are made on magnetic tickets. However, since only a combined figure of Oyster and PayG exits is available, (the figure includes both Underground and National Rail exits) it is not possible to estimate this value. The assumption is made that this figure has not changed significantly and can be ignored, a fair assumption considering most Underground users at Wimbledon would likely already be using an Oystercard and those who did not would not be significantly affected by OXNR. Given this assumption, the remaining exit figures are known or can be estimated. A combined estimate of the number of Underground and National Rail exits at Wimbledon can then be made. Once these estimates are made, a yearly change in the number of exits can be estimated. Figure 6-25 shows the results of this analysis, with figures on the change in Total exits, Oyster exits and National Rail exits shown.

Figure 6-25: Change in Weekly Wimbledon Exits, 2010 over 2009



For only 4 weeks out of the 35 is the change in total exits negative and an average increase of 15000 exits per week is observed. For National Rail, the average growth is around 14000 exits per week. This indicates that while there might have been some switching from the Underground to National Rail, there has still been a net increase in journeys. For certain weeks, it is possible that there might have been a significant amount of switching from the Underground to National Rail, and this might be during the weeks where change in Total exits is less than change in National Rail exits. The reason for such an occurrence cannot be directly attributed to OXNR as other factors might have been at play. While some of the increase could be attributable to growth from factors other than OXNR, the total growth is still higher than the estimated control factor of 5%. The analysis thus indicates that OXNR had the effect of increasing travel overall, rather than simply facilitating switching from the Underground to National Rail.

East Croydon, Purley

The analysis of Wimbledon and Surbiton station suggests that OXNR had a significant impact at Wimbledon, but no impact at Surbiton. It is also important to consider the second set of stations along the Southern corridor to further understanding of the effects of OXNR. Figures 6-26 and 6-27 show the total journeys to and from East Croydon and Purley stations for 2009 and 2010, along with the 2009 figure with the control factor applied, which allows calculation of the growth. The control factor applied is the average journey percentage change for the 4 chosen stations outside London, for every week being compared between 2009 and 2010. Figure 6-28 shows the percentage change in weekly journeys for both the stations together. As mentioned previously, journeys for East Croydon contain 88% of journeys belonging to the Croydon BR group of stations.

Figure 6-26: Total journeys to/from East Croydon

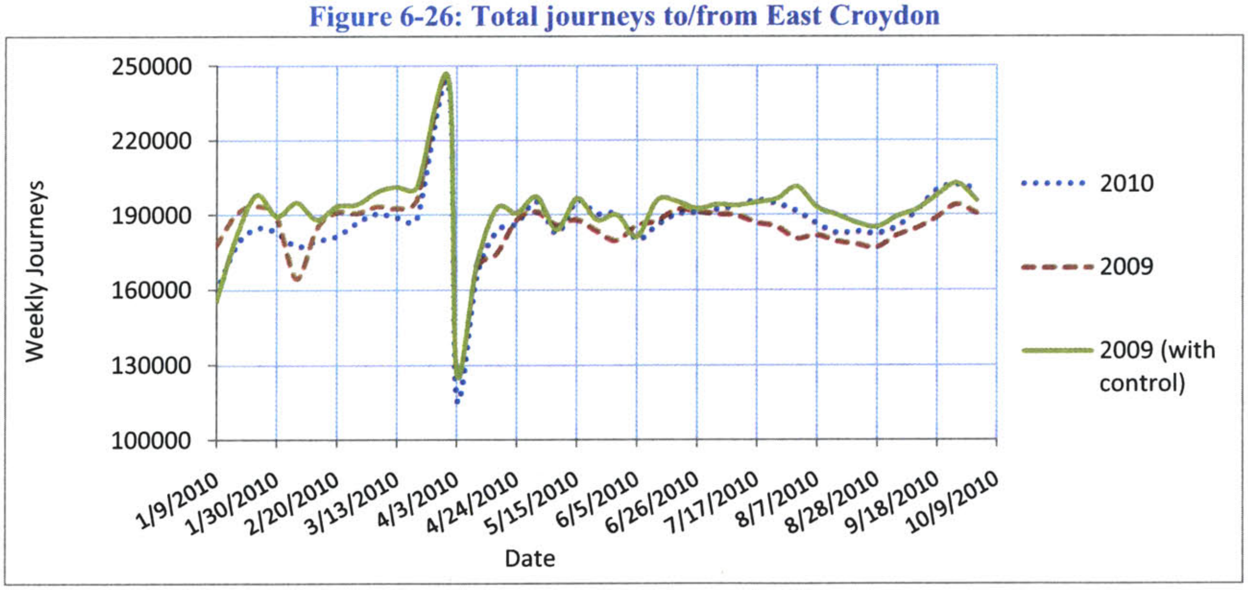


Figure 6-27: Total Journeys to/from Purley

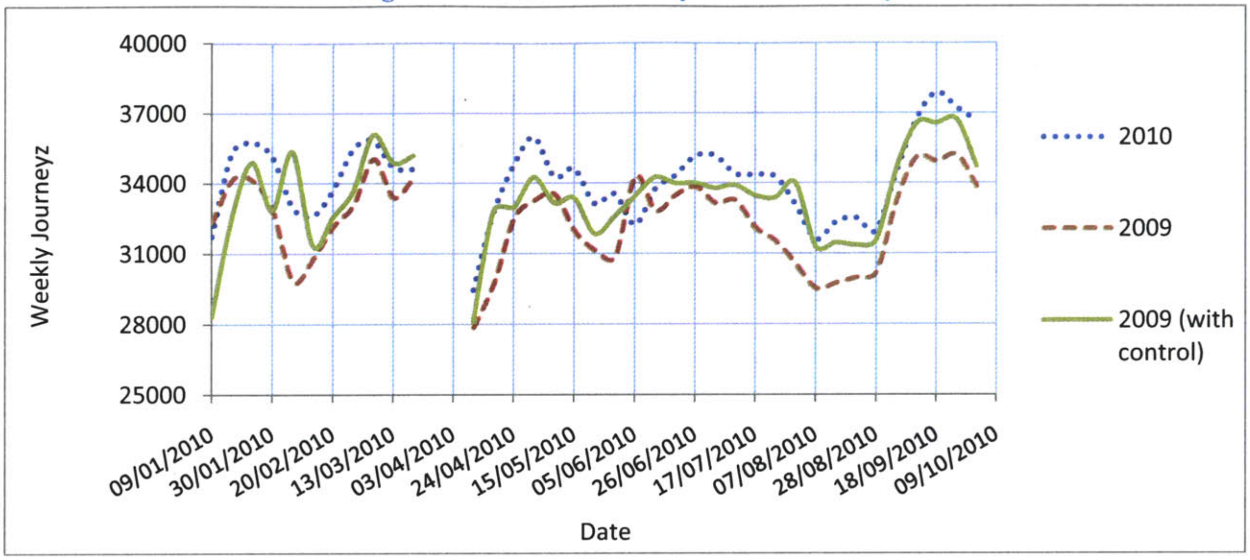
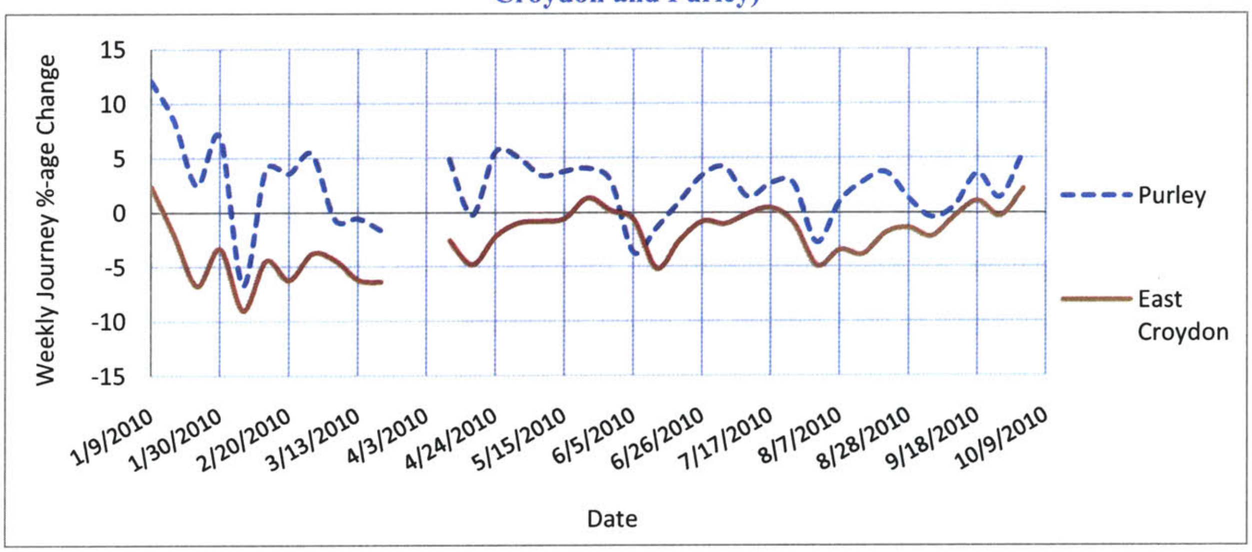


Figure 6-28: Weekly Journeys Percentage Change (2010 over 2009) after applying control (East Croydon and Purley)



From Figure 6-26, it is evident that there has been no growth at East Croydon station. The average growth over the year was 0.4% and -2.5% after applying the control. This indicates that OXNR had no effect on journey growth at East Croydon. A possible shortfall here might be that the control factor used is not a station directly along the same corridor, but rather an average of other stations, but this is not expected to cause a significant change in our conclusions. Purley station, on the other hand shows some growth: 5.4% without applying control factor and 2.3% after applying the control factor.

From these results it appears that OXNR has had no identifiable impact at either of these two stations. While Purley shows some growth and East Croydon shows a decrease in journeys made, these changes are not directly attributable to OXNR.

Comparing the 2 corridors – Wimbledon and Surbiton with East Croydon and Purley – it can be noted that Wimbledon station shows a significant growth in National Rail journeys, while none of the other stations show a similar trend. Surbiton shows no such growth which indicates that this growth is not specific to this corridor, and rather that the existence of the Underground at Wimbledon might have had an effect on the growth due to OXNR. Similarly, at East Croydon and Purley, no significant growth is observed. Similar analyses of journeys at other stations having Underground service, or an Underground station within proximity shows that there seems to be growth due to OXNR. Examples of such stations are Balham, Putney and Richmond whose journey graphs are included in Appendix E. It is possible that the majority of the OXNR-related growth is due to users at joint Underground and National Rail stations making a greater number of journeys. This will be tested in the Oystercard study which is discussed in the next section.

6.5 Oystercard Study

As mentioned in Section 6.2, the aim of the Oystercard journey component is to identify whether there has been any change in journeys made by Oystercard users due to OXNR. The station chosen for analysis was Wimbledon which has both Underground and National Rail services with a common gateline. This meant that Oystercard data was available at Wimbledon even prior to the implementation of OXNR, thus enabling a study of journeys made on Oystercards. Oystercard data was available for the week from the 14^{th} to the 20^{th} of September 2009, prior to OXNR Phase-2, and for 5 weeks after the introduction of OXNR Phase-2, these being 14-20 Mar 2010, 18-24 April 2010, 13-19 June 2010, 15-21 August 2010 and 13-19 September 2010.

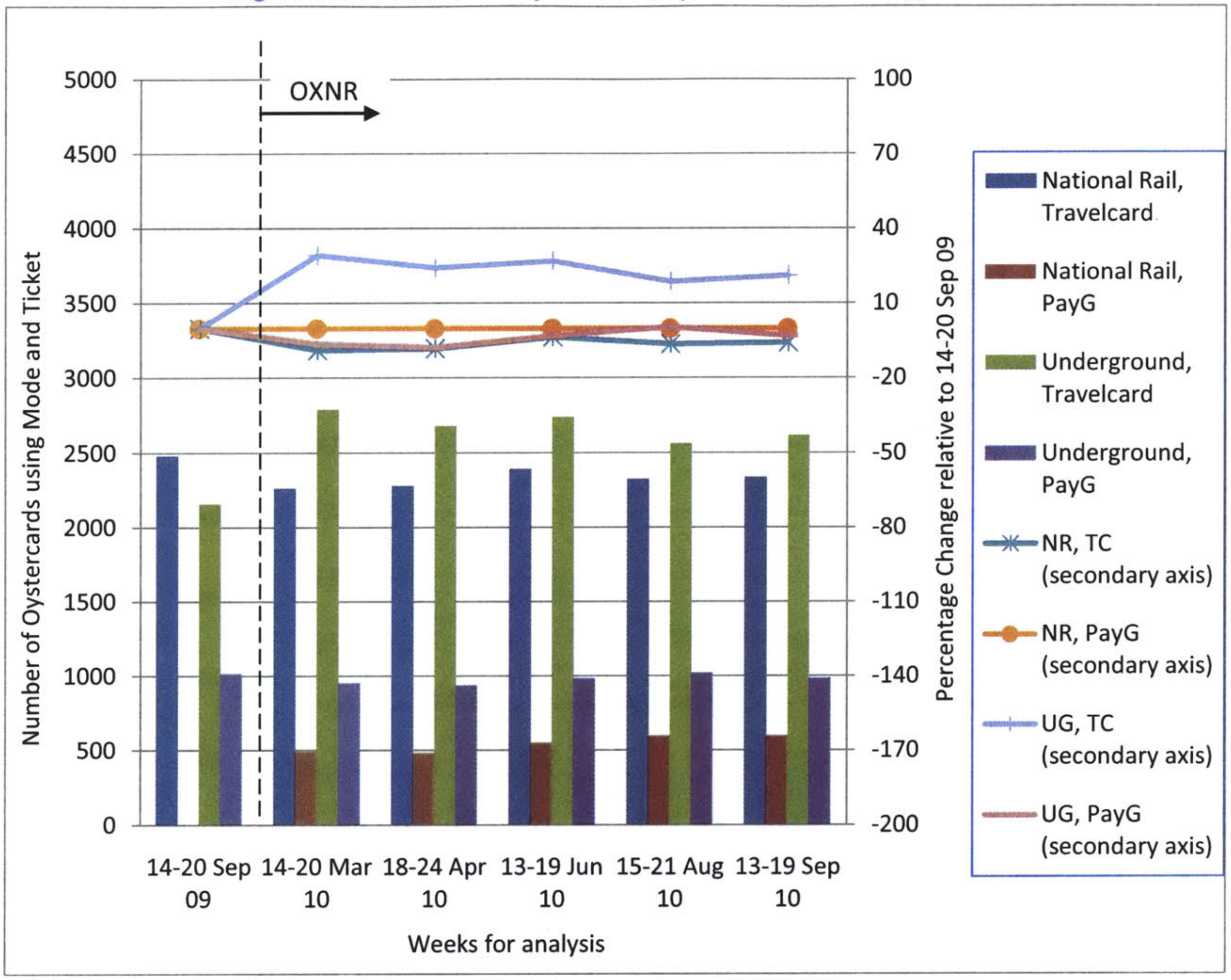
The Oyster card data was queried to obtain a set of Oystercards seen at Wimbledon during all six weeks. This created a balanced panel of 5003 Oystercards, and journeys made by these Oystercards were then analysed, with the focus on ticket used and mode chosen for each trip.

One of the major issues lay with the identification of mode used to make a given journey. While each journey has a subsystem-id associated with it, the subsystem-id is only indicative of possible modes taken to make the journey, rather than specifying a given mode. Within the TfL central data system, each station is assigned one (or more) subsystem-ids based on the modes available at that station. The subsystem-id associated with a given journey is a combination of the subsystem-ids of the origin and destination stations, which means that if a journey was started at a station having underground and rail modes available and ended at a station with only underground mode available the subsystem-id would indicate that the journey was made on the underground. However, when a journey is made from one intermodal station to another intermodal station, the system is unable to identify the mode chosen for the given journey.

In order to obtain the mode for any journey made by the Oystercards within the panel, detailed origin-destination queries were performed. This revealed that subsystem-ids 3 and 263 were seen in the data whenever a journey was made between Wimbledon and another National Rail station, and such a journey was assigned to National Rail mode. Similarly, the subsystem-ids 0, 256 and 261 were seen whenever a journey was made between Wimbledon and an Underground station, and such a journey was assigned as being made on the Underground. These 5 subsystem-ids accounted for over 95% of the journeys and due to the ambiguity in journeys made on other subsystem-ids, they were excluded from this analysis.

Figure 6-29 indicates the increase in the number of Oystercards using PayG on National Rail. While it was not possible to make journeys on National Rail using PayG prior to OXNR, the numbers increased to 499 out of the 5003 Oystercards using PayG at least once during the week of 14-20 March 2010. This number further increased to 597 Oystercards making PayG journeys on National Rail in the week 13-19 September 2010. During the same period of time, number of Oystercards making PayG journeys on the Underground decreased from 1016 (14 -20 September 2009) to a minimum of 938 Oystercards (18-24 April 2010). This might indicate some switching between users from PayG on Underground to PayG on NR.

Figure 6-29: Number of Oystercards, by mode and ticket type used

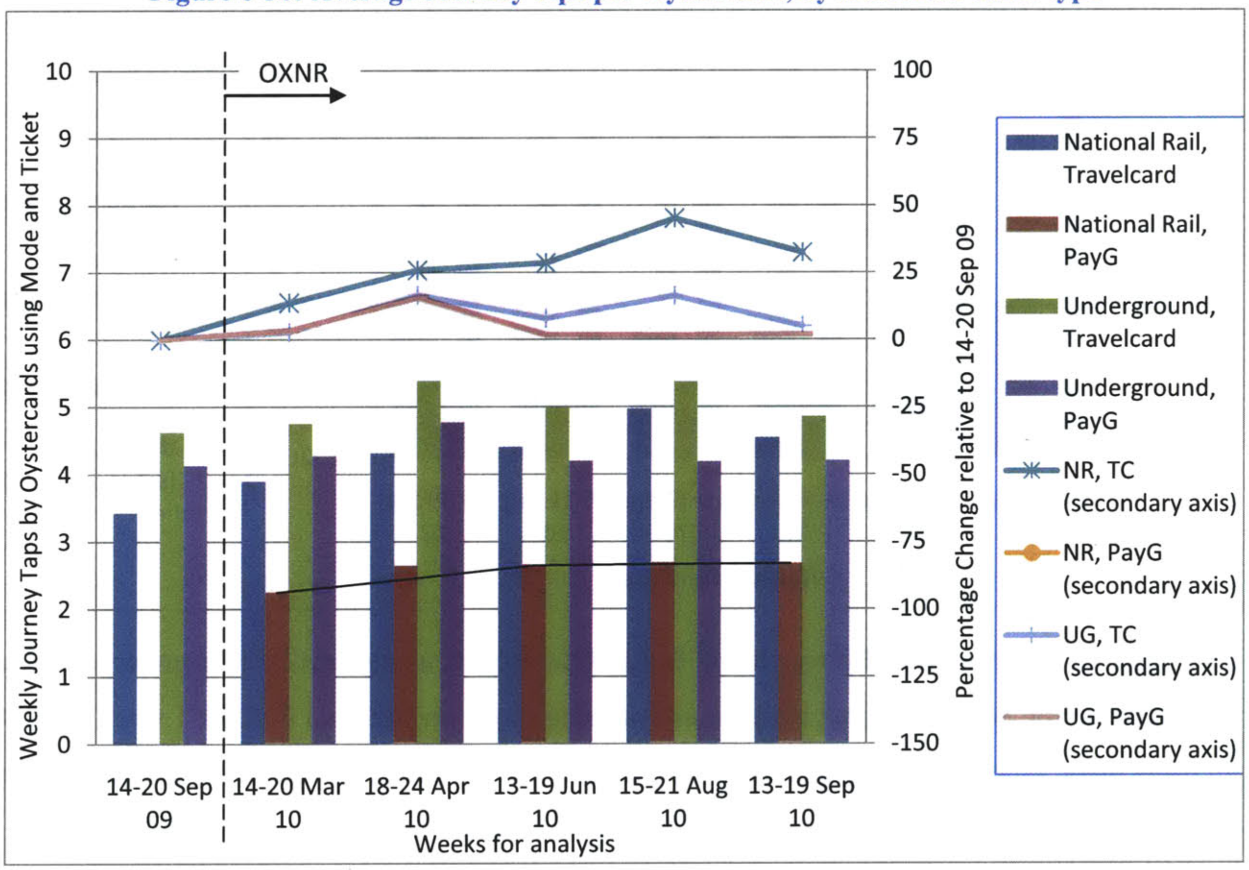


Investigating in further detail it was found that of Oystercards using PayG on the underground in September 2009, 84 Oystercards made journeys using PayG on National Rail for 1 week in 2010, 40 users made journeys during 2 different weeks in 2010, while 28, 10 and 12 Oystercards made journeys during 3,4 and 5 weeks respectively. This indicates that there was some shifting between the two mode-ticket type combinations, accounting for a maximum of 75 out of 597 Oystercards (observed in August 2010) during any given week.

The greatest increase came from users using both a Travelcard (on either National Rail or Underground), as well as PayG on National Rail. They numbered a maximum of 166 Oystercards in March 2010 and 138, 148, 133 and 147 Oystercards during April, June, August and September respectively. These comprised 607 unique Oystercards, 504 of which were only seen during 1 week among the 5 weeks in 2010. This indicates a significant increase in travel by Oysters with a Travelcard, making PayG journeys on National Rail to destinations outside their zonal validity. This is evidence of the increasing use of the Oyster extension permit system which allows users to travel to zones outside their Travelcard validity.

There is also the additional question of whether journeys on the Underground are decreasing and those on National Rail are increasing. This question can be answered by taking into account the average journey taps made per Oystercard. Figure 6-30 illustrates this change for the four major ticket-mode combinations.

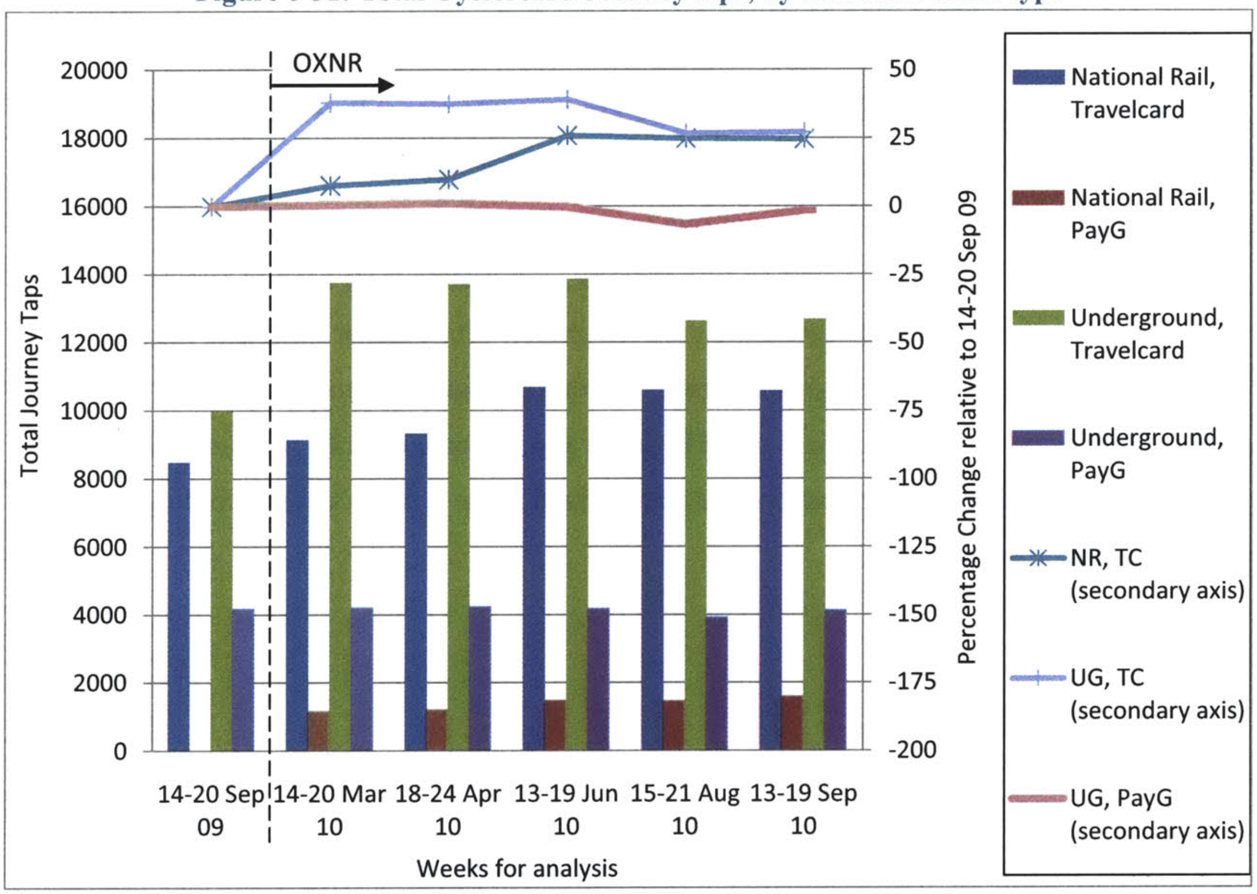
Figure 6-30: Average Journey taps per Oystercard, by mode and ticket type



A somewhat surprising result is the significant increase for Travelcard journeys on National Rail. One explanation for such a change might be the improvement in capture of validations due to the gating of the station. For both ticket types on the Underground there seems to be minimal change, but no decrease was seen during any period. While there was no option to make PayG journeys on National Rail prior to 2010, there seems to be a significant increase in journey taps per Oyster with the number undergoing a steady increase to 2.3 journeys per Oystercard in March and to 2.79 journeys per Oystercard in September.

Overall, there seems to be an increase in the number of Oystercards using PayG on National Rail with about 10% of sample being seen with this ticket and mode in September 2010, leading to a large increase in the number of journey taps on average. Some of this initially seems to stem from a decrease in Oystercards using PayG on the Underground but by October this number is back to September 2009 levels. The per Oystercard PayG journey taps on the Underground also do not undergo a significant decrease, indicating that there is an overall increase in PayG journeys by existing users at Wimbledon. Figure 6-31 shows the total journey taps for our chosen group of Oystercards

Figure 6-31: Total Oystercard Journey taps, by mode and ticket type



The total journey taps using PayG on the Underground seems to show no change till August 2010, when there is a small decrease likely caused by the holiday period. The total number of PayG journeys on the Underground seems to remain constant at around four thousand. Compared to this, PayG journey taps on National Rail increase by a thousand in March and this figure reaches 1700 by September, following the same steady increasing curve as was found in the station-level analysis. The large increases in Travelcard journeys might be attributed to the installation of a gate at Wimbledon, with users now having to tap their Oystercard to exit the system. Thus, it seems that there has been no growth of PayG journeys on the Underground, and all the growth has come from National Rail, a scenario which is quite plausible since users would have continued to make the same number of journeys on the Underground, except for some natural growth from 2009 to 2010.

6.6 Summary and Fare Policy Conclusions

Oyster on National Rail (Phase-2) represented the introduction of TfL's electronic smart card system across the National Rail network in London, in terms of both fare retail and fare validation. With this introduction, the fare structure across National Rail and Underground modes was also integrated resulting in a common zonal fare structure with the Underground, though with different levels of fare according to modes used during a trip. Users now also had the option to use a stored value card on this network, eliminating their need to purchase a ticket every time they want to travel, increasing their flexibility. This chapter described the methodology and results of studying the impact of this system on journeys made on National Rail, as well as on the ticket choices made by users and presented results for this analysis, and the results and fare policy implications are summarized in the next sections according to the questions they answer.

6.6.1 Journey Growth

The first aim of this case study was to assess journey growth due to this fare policy change, both at a Greater London network-wide level and at a corridor and station-specific level. The network-wide journeys analysis proceeded through multiple stages, first comparing journeys as they actually existed, then controlling for growth due to yearly change and finally controlling for the other major change: the increase in service due to the East London Line extension reopening. The impact of OXNR was estimated to be an increase of around 275,000 to 350,000 journeys, equivalent to 2.9% - 3.8% journey growth, by the month of October 2010. This growth was not uniform across the corridors and stations with Wimbledon along the South West Trains corridor showing significant growth while Surbiton did not seem affected, and both East Croydon and Purley on the Southern corridor showing no growth. The Oystercard study suggested that some of the growth at Wimbledon could be attributed to an increase in travel on National Rail by existing users. This increase was not at the expense of Underground journeys, with previous users continuing to travel the same number of journeys on average. Thus, there would seem to have been a positive influence of OXNR on travel.

The evidence from this case study suggests that the introduction of an electronic ticketing system and fare integration in a transit system would have the effect of increasing journeys made by users. This growth however seems to be restricted to stations where users have access to both the National Rail and Underground modes, and some amount of the growth is attributed to increase travel by users already having an Oystercard but using it on the Underground. This would indicate that one of the advantages of using a stored value smartcard valid on both modes is the ease of travel on multiple modes. While it is not possible to separate the effect of the smart card ticketing option and fare structure integration, it is likely that both of these had a positive influence on growth.

6.6.2 Ticket Switching

Ticket switching was investigated at a network-wide, corridor and station level. It was found that PayG use increased rapidly in the first month of January 2010 to nearly 50% of the levels of October, and about 30% of this increase was attributable to shifting from Cheap Day Return tickets which were withdrawn as part of OXNR. The rest of the switching was attributable to shifting from Standard Singles and TOC seasons, both of which decreased with OXNR. Standard Return tickets saw a growth in the initial months of January, most likely due to switching from other TOC ticket types, but by October, journeys on this ticket type were back to 2009 levels with a trend of switching away from Standard Return tickets, likely to PayG which showed a further increasing trend. There was no real change in journeys made on Day Travelcards, and for Season Travelcards while there was some evidence of shifting from TfL outlets to National Rail outlets, no significant evidence was seen suggesting an increase due to OXNR.

In terms of fare media, this suggests that stored value smart cards may have an advantage over standard paper or magnetic tickets. Differential pricing and a restriction of available fare types encourages users to shift towards smart cards, and the majority of switching is from equivalent fare types but switching from other ticket types, (for example, from Season tickets to PayG) is also likely. Stored value tickets may also have the advantage over equivalent paper/magnetic tickets where no price differential exists, but users are more likely to switch over some period of time rather than instantly, as in the case where price differentials exist.

6.6.3 Mode Switching

The mode switching analysis was carried out on a panel of pre-existing Oystercard users and was restricted to switching between the Underground and National Rail, the two modes most likely to be affected by Phase-2 of OXNR. The evidence from this case study suggests that some mode switching took place, with about a 5% decrease in Oystercards using PayG seen on the Underground and a large increase of PayG Oystercards on National Rail. This switching was however not sustained with the Underground recapturing users over time, while growth of Oystercards on National Rail was steady. Further, in terms of total growth of journeys, there seems to have been minimal impact on the Underground and significant growth on National Rail.

The mode switching patterns indicate that users are not likely to change their modes of travel drastically on the basis of a fare structure and technology change. While there might be small changes over the course of time, it is more likely that providing users with a fare media allowing uninterrupted travel (due to ticket purchase) on multiple modes will choose to travel more, likely due to the increased convenience in travel.

Chapter 7 Summary and Future Research

This thesis analyzed the impacts of fare policy changes (changes in the fare structure, fare payment and collection technology) on travel demand and behavior. Specifically, Greater London was chosen as the case study because of the major changes in fare technology (and associated changes in fare structure) in the last decade as well as the multiplicity of modes, complex fare structure and high levels of public transport use. This chapter summarizes the research and analysis presented in this thesis. Section 7.1 presents the findings in response to the questions that were asked in the first chapter. Section 7.2 discusses the fare policy implications stemming from these results and Section 7.3 presents the limitations of the work and suggests future research areas follow up.

7.1 Findings

In this section, the findings from the thesis are divided according to the questions posed in the first chapter.

The first question asked was whether there had been any change in fare elasticity values from previous studies. The results from our case study suggest that there has been no significant change in the fare sensitivity of Underground users, with own fare elasticity in the order of -0.43, similar to the value found in the previous study carried out in 2002. For buses, the own fare elasticity estimate has decreased, with an own fare elasticity value of -0.63 from this case study compared to -0.70 as of 2000, but these values are similar given the 95% confidence limits. This would suggest that elasticity has not changed significantly over the past decade.

The second question focused on the impact of recent fare policy changes, i.e. the introduction of the electronic ticketing system, Oyster PayG on buses and the Underground, and the introduction of free travel for under-16 year olds. On buses, it was found that, within 95% confidence limits, the model could not conclusively determine whether Oyster PayG had any discernible impact on increasing travel, but within 90% confidence limits the growth predicted is around 3%. There was however growth of around 5% due to fare simplification in 2004, and this estimate might have captured some of the initial growth due to PayG. Some of the impact of Oyster PayG might also have been confounded by the introduction of free travel for under-16s, the other major change that happened a year later. This reduced revenue demand by 6%, while TfL estimates suggest that by the end of 2009 these users account for 19% for all bus journeys. This difference might be explained by growth in travel for these users (because they experience no monetary cost of travel) but it is also possible that the model was not robust enough or had too few data points to separate the impact of increase due to Oyster PayG from the decrease (in revenue demand) due to the free child policy. For the underground, the model was able to estimate the impact of PayG at 4.7% growth by 2009 suggesting that if Pay-as-you-Go had not been introduced, the Underground demand at the end of 2009 would have been 4.7% lower. The large cash fare increases in 2006 were predicted to decrease demand by 4.2%. While the impact of this cash fare increase should have been captured by the fare variable in the model, the variable used as a proxy for fare has the limitation that it does not adequately take into account the effect of ticket switching. Due to this, it is possible that the fare index value for 2006 is erroneous, with the effect of the error captured by the dummy variable.

The third question was on changes in fare media use patterns which were analysed in the second case study on the impact of Oyster PayG on National Rail on travel behavior. This study indicated that there was a near tripling of journeys on National Rail made using PayG, the stored value fare media. This growth came primarily from the elimination of the Cheap Day Returns, while there was also switching from other similar ticket types, primarily Standard Singles. There was also switching from season tickets sold by the TOCs allowing travel only on National Rail, suggesting that users prefer to buy tickets which enable them to travel on multiple modes. Overall, the case study suggested that electronic ticketing use increased rapidly on the National Rail network, at the expense of magnetic tickets.

The fourth question was the impact of an electronic ticketing system on travel. This was again analyzed through the second case study and results suggested growth of 0.3 million journeys per week, or about 3%, on National Rail. This growth was not uniform across stations and corridors, with large growth at stations serving both National Rail and the Underground, but minimal or even no growth at other stations. This suggests that growth might be due to an increase in travel across modes due to the increased flexibility provided by the integrated system. Significant growth was also seen by users owning Oystercards prior to the fare policy change, suggesting that they might be contributing to a large chunk of the growth.

The fifth and final question, linked to the fourth question, asked whether there was significant change in travel mode choice. Findings from the case study suggest that while there is evidence of some switching, there is an overall increase in travel on both modes.

7.2 Fare Policy Implications

While the results from this thesis are particular to the London region, answers to the questions asked in this thesis have implications for fare policy-makers in public transport systems across the world. The finding that there has been no change in fare elasticity suggests that user's elasticity to price does not change significantly with the introduction of an electronic ticketing system with post paid capability. This means that while technology allows greater flexibility in fare policy design and implementation, people's fundamental responses to price are not significantly altered. In terms of transit agency planning practices, this suggests that even when further technological changes are implemented in transit fare systems, the elasticity values used for fare modeling may continue to be based upon this and prior literature, relevant to a given location.

While behavioural responses to price may not change, transit agencies need to take into account the other findings as well. The finding that there has been an increase in travel on buses from the move to a flat fare structure across the bus network has interesting implications. The case for a differentiated fare structure is based on payment according to the distance of travel and is therefore strengthened by equitability justifications. However, a case could be made for simplification of the fare structure since it increases the ease in understanding the system, and leads to an increase in travel. To balance the social, political and financial concerns, policy makers need to take into account both of these criteria, and attempt to create a fare structure which is equitable and yet simple.

Another interesting finding is the increase in travel on the Underground and National Rail due to the electronic smartcard ticketing system. The experience of London would suggest that a stored credit smartcard that can be loaded with other ticket types provides significant user benefits, and results in increases in travel demand. This growth depends upon many factors that need to be considered, such as the smart card capabilities, fare structure, ease of purchase and method of use, among others, and these need to be considered when electronic ticketing systems are being planned. The scale and rapidity of the growth in the National Rail case as compared to the Underground would be expected as the system was first introduced on the other major public transport modes. The prior experience of users with the system would account for the rapidity of the increase, as would also be suggested by the high increase by previously existing users (as found in the Oystercard panel component). It is important to note that the last implementation brought the whole system under a common structure and this would have a significant influence as well and needs to considered by agencies operating in multi-operator multi-modal transit systems.

This case study also indicates that eliminating certain ticket types as well as keeping a price differential[33] encourages users to switch to smart cards, and also that the usage of season tickets decreases with users being likely to switch to smart cards (with post paid as well as seasonal travel capability). Also, ticket types having the capability for use on multiple modes are likely to encourage use of the different modes, but this need not result only from a decrease in travel on one mode. While it might be imperative to initially incentivize users to take-up smart cards, through means such as price differentials[33], elimination of equivalent, competing ticket types[34] and value propositions such as daily capping, in the longer term this would increase demand as users get familiar with the smart card and make a greater number of trips, on average.

The results from the policy of providing free travel for children suggest that such policies do promote travel by them. It could be argued that the increase in journeys is a reflection of an increase in user accessibility, although it might also reflect an increase in non-essential travel, such as very short trips made by children on public transport. Policy makers need to carefully consider the impact of such policies on the travel behaviour of groups afforded such concessions, and only provide subsidies to those that require them and will benefit the most, since such

[33] Price differentials here refer to higher prices for magnetic or cash fares relative to smart card options
[34] Such as Cheap Day Return tickets and PayG

policies will not only affect transit agency revenue streams adversely but might also affect the experience of travelers who pay full fares.

Thus, the main implications for fare policy seem to be that smart card ticketing systems encourage increases in travel from more traditional paper or magnetic ticketing systems, but with the caveat that certain features must be available on smart cards, such as post payment, uniform fare structure through regional integration, availability of multiple fare types on the same smart card system. While it is possible that there would be an increase in travel even without such features, it cannot be predicted based on the evidence from this thesis.

7.3 Limitations and Future Research

This section addresses the limitations of the current work and possibility of further research to improve the analysis on the two case studies as well as aid in understanding the impact of changes in fare policy, fare structure and fare payment and collection technology in more general terms. The possible options for future research are divided according to the case study to which they are related.

7.3.1 Elasticity Analysis

Elasticity modeling is a vital component of fare policy analysis, as discussed in Chapter 3. The base demand model in the first case study estimating elasticity factors in London was developed in the 1980s. The model provides elasticity estimates of fares, service changes, socio-economic demand drivers and other factors, and the use of these factors is vital in transit planning and forecasting. While the model still provides a good model fit over a 40-year time period lending credibility to the elasticity estimates, there are certain inefficiencies in the model. The dependent variable uses revenue data, which is traditionally more accurate than journey data, to create a proxy for journeys. It relies on fare data from the 1980s when large fare changes occurred and influenced travel demand greatly. The gross yield index, a proxy for fares, does not accurately account for ticket switching. Most importantly, the elasticity estimate is an aggregate estimate which provides a single elasticity measure each for the Underground and Bus networks. To improve planning in the future, disaggregated elasticity measures, by user groups, time of travel, location of travel etc are required, and this will only be possible through the formulation of a new demand model.

There have been major improvements in the availability of data with the increasing use of smart cards (which now account for over 75% of all TfL journeys). Smart card data collection ensures that vast amounts of data are available for study and could be used for more accurately estimating demand elasticities, at different levels of aggregation. With the increasing use of smart cards and improvement in data collection through gating and other measures, journey data is becoming more reliable. While it was not found possible to use available journey data for this study, it may be possible to use either gatecount data or Automatic Fare Collection (AFC) data in the future. The formulation of other variables might also be investigated further, such as the use of the gross yield index, a proxy for fares, which does not accurately account for ticket switching and is a very aggregate measure of fare. AFC data could be used for the estimation of the effect of fares, by each fare type.

While Zureiqat (2008) has done a significant amount of work in this direction and laid out the basis for a possible model, there are certain flaws in his model which prevent its immediate application. His model does not explicitly account for the effects of service changes, socio-economic demand drivers and major events. These are assumed to be part of the user behavior represented by the AFC data. In order to be of value to transit agencies, any model needs to explicitly account for the other factors, and the estimates need to be comparable to prior literature or values used in industry. This might become possible as smart cards get linked to post code or socio-economic data, or as credit cards are implemented on transit systems. Origin-destination inference studies (Zhao (2004), Seaborn (2008), Wang (2010)) may also allow the geo-coding of smartcard users home and work locations which would provide some socio-economic data and enable disaggregate elasticity estimation. Thus, there is both a great need for a new demand model and also the scope of using vast amounts of data to formulate such a model.

There are also certain other avenues of research which are presented below:

- Separating impact of Oyster PayG and Free Child Travel policies on demand for buses – Oyster PayG, Free Child Travel and the London Tube terror attacks all happened within 16 months of each other. The current model is not able to identify the separate effects of these major changes on demand and further work could be done in this area.

- Impact of PayG on Underground and Buses – This case study analysed the impact of the stored value payment system, Oyster PayG, on the Underground and Buses as part of the larger elasticity modeling framework allowing the impact of other factors to improve the estimate. Further improvement is possible in this area through means of more advanced modeling techniques and the analysis of disaggregate data. Similar to the work done in the Oyster on National Rail case study, it might be possible to model use patterns of Oyster users using archived Oystercard data. A complicating factor in such a study would be accounting for other events that had an impact, such as the July 2005 terror attacks, but using the estimates provided in this study as well as previous work done by Samad (2006) their effects could be controlled.

7.3.2 Oyster on National Rail Case Study

There is also scope for further study of Oyster on National Rail. The possible changes have been divided into system-related studies and user-related studies, though the focus of both would be the impact on user behavior.

- Capture of fare level effects – This thesis focused on changes due to the new ticketing system and fare structure, but it might also be possible to capture the effect of fare level changes. Work could be done in this area to further estimate the effects purely due to the introduction of the new ticketing system.
- Further monitoring of OXNR – This thesis explores the changes that occurred within the first 9 months of implementation and it is likely that further changes in travel behavior will continue to have taken place after this period. Extending this analysis until PayG usage reaches a stable level would capture these changes.

- Use of Demand Model – This study used a before and after journey comparison approach to estimate the impact of OXNR. This method relies on estimation of control factors and is not as rigorous as we would like. It might be possible to model the impact of OXNR by capturing changes in the other factors affecting travel during this period. Such a study would be able to utilize journeys as estimated in this case study within a demand model also capturing other effects.
- Growth categorization by station characteristics – This study relied on the evidence of journeys to/from four main National Rail stations, along with an analysis of journeys at 6 other stations. Individual stations along corridors could be studied in more detail to identify which factors are most influential in changing user behavior. This could involve categorization of stations on factors thought to influence travel behavior, such as distance/time from London, location of station and surrounding land-use, ease of access, availability of modes etc.
- Further analysis of user panel – This thesis focused on broad changes in user panel behavior due to OXNR. While there is no Oyster data available prior to OXNR for users making journeys on National Rail, for the period after there is an increasing wealth of data. Change in user behavior over time could be modeled on attributes of time and cost, among other factors. This would however not be easy to do strictly for Oyster on National Rail since there were no Oystercards using PayG before OXNR and there is no before data.
- Linking intermodal journey segments – It might be possible to assess the impact of OXNR on actual trips rather than journey segments using available Oyster data since there are more likely to change over time rather than instantly. There is an increasing amount of literature in the area of inferring actual origin and destination using trip-linking methods and previous work or analysis can be found in Zhao (2004), Seaborn (2008), Wang (2010), Ng (2011). Research is possible on how trip patterns have changed and whether travelers have changed their mode usage and corresponding travel patterns to take advantage of the greater flexibility of PayG.

There is a lack of literature accurately estimating the impact of major fare policy changes such as electronic ticketing systems on demand and journey patterns using journey data available post the implementation. Most studies focus on user surveys which indicate whether users feel there has been an improvement in their ease of travel. While this is a valuable exercise since it is likely that users finding an improvement in their travel experience will increase travel, it is not certain and there is requirement for validation of results from stated preference surveys with revealed preference results. Thus, there is great scope for further studies on the effects of fare policy changes using both aggregate and disaggregate sources of data to estimate the impact on actual user behavior and on system-wide changes in travel.

Appendix A: Current Fare Levels

Figure A-1: Sample Adult Bus Fares (snapshot from TfL website, http://www.tfl.gov.uk/)

Adult

Cash Single	Oyster pay as you go		Bus and Tram Passes		
	Pay as you go	Daily Price Cap	7 Day	Monthly	Annual
£2.20	£1.30	£4.00	£17.80	£68.40	£712

Figure A-2: Sample Adult Underground Fares (snapshot from TfL website, http://www.tfl.gov.uk/)

Adult

Zone	Cash	Oyster pay as you go				Travelcards				
		Peak single	Off-peak single	Peak price cap	Off-peak price cap	Day Anytime	Day Off-peak	7 Day	Monthly	Annual
Zone 1 only	£4.00	£1.90	£1.90	£8.00	£6.60	£8.00	£6.60	£27.60	£106.00	£1,104
Zones 1-2	£4.00	£2.50	£1.90	£8.00	£6.60	£8.00	£6.60	£27.60	£106.00	£1,104
Euston - Zone 2*	£4.00	£2.00	£1.90	£8.00	£6.60	£8.00	£6.60	£27.60	£106.00	£1,104
Zones 1-3	£4.00	£2.90	£2.50	£10.00	£7.30	£10.00	£7.30	£32.20	£123.70	£1,288
Euston - Zone 3*	£4.00	£2.70	£2.50	£10.00	£7.30	£10.00	£7.30	£32.20	£123.70	£1,288
Zones 1-4	£5.00	£3.40	£2.50	£10.00	£7.30	£10.00	£7.30	£39.40	£151.30	£1,576
Euston - Zone 4*	£5.00	£3.10	£2.50	£10.00	£7.30	£10.00	£7.30	£39.40	£151.30	£1,576
Zones 1-5	£5.00	£4.10	£2.70	£15.00	£8.00	£15.00	£8.00	£47.00	£180.50	£1,880
Euston - Zone 5*	£5.00	£3.80	£2.70	£15.00	£8.00	£15.00	£8.00	£47.00	£180.50	£1,880
Zones 1-6	£5.00	£4.50	£2.70	£15.00	£8.00	£15.00	£8.00	£50.40	£193.60	£2,016

Figure A-3: Sample Adult National Rail only Fares (snapshot from TfL website, http://www.tfl.gov.uk/)

Adult National Rail only fares

Zone	Cash	Oyster pay as you go	
		Peak single	Off-peak single
Zone 1 only	£2.20	£2.00	£1.50
Zones 1-2	£2.60	£2.20	£1.70
Zones 1-3	£3.40	£2.80	£2.00
Zones 1-4	£4.00	£3.30	£2.30
Zones 1-5	£4.80	£4.20	£2.60
Zones 1-6	£5.50	£5.20	£3.20
Zones 1-7		£5.20	£3.20
Zones 1-8		£6.00	£3.20
Zones 1-9		£6.00	£3.20
Zones 1-9 + Watford Junction		£6.90	£4.10
Zones 1-9 + Grays		£4.90	£4.10
Zone 2 only	£1.80	£1.50	£1.30
Zones 2-3	£2.30	£1.90	£1.50

Figure A-4: Sample Adult National Rail through fares (snapshot from TfL website, http://www.tfl.gov.uk/)

Adult National Rail through fares

Zone	Cash	Oyster pay as you go				Travelcards				
		Peak single	Off-peak single	Peak price cap	Off-peak price cap	1 Day Anytime	1 Day Off-peak	7 day	Monthly	Annual
Zone 1 only	£5.00	£3.30	£2.70	£8.00	£6.60	£8.00	£6.60	£27.60	£106.00	£1,104
Zones 1-2	£5.00	£3.50	£2.90	£8.00	£6.60	£8.00	£6.60	£27.60	£106.00	£1,104
Zones 1-3	£6.00	£4.10	£3.20	£10.00	£7.30	£10.00	£7.30	£32.20	£123.70	£1,288
Zones 1-4	£6.00	£4.60	£3.50	£10.00	£7.30	£10.00	£7.30	£39.40	£151.30	£1,576
Zones 1-5	£7.00	£5.50	£3.80	£15.00	£8.00	£15.00	£8.00	£47.00	£180.50	£1,880
Zones 1-6	£8.00	£6.50	£4.40	£15.00	£8.00	£15.00	£8.00	£50.40	£193.60	£2,016

Appendix B: Terror Attack Modeling

Previous modeling work done within the London Underground on the impact of the July 2005 attacks on Underground revenue suggested the range of estimates shown in Table B-1 and Table B-2. This study further suggested that the impact of the terror attacks on buses was in the range of 0.5% decrease in revenue of 2005 over 2004.

Table B-1: Estimate of Underground revenue lost from 7/7/2005 (Reproduced from Samad (2006))

Period End Date		Actual total revenue, £m	Forecast lost Revenue based on modelling, £m	Lost revenue as a proportion of total actual revenue
7/23/2005	0506P4	95.2	11.0	11.5%
8/20/2005	0506P5	84.6	15.8	18.6%
9/17/2005	0506P6	91.7	9.5	10.4%
10/15/2005	0506P7	103.7	5.6	5.4%
11/12/2005	0506P8	105.8	4.3	4.1%
12/10/2005	0506P9	109.1	3.1	2.8%
1/7/2006	0506P10	88.8	1.7	1.9%
2/4/2006	0506P11	103.7	1.3	1.3%
3/4/2006	0506P12	107.4	0.9	0.8%
3/31/2006	0506P13	105.1	0.4	0.4%
	Total	995.0	53.6	5.7%

Table B-2: Estimate of Lost Underground journeys and revenue from 7/7/2005 (Reproduced from Samad (2006))

Period End Date		Actual passenger journeys, m	Y on Y % change	Av. Y on Y growth before and after	Forecast PJs assuming past growth, m	Lost journeys, m	Lost Revenue given av. revenue per pj of £1.34 as before 7/7, £m
4/30/2005	0506P1	76.3	4.6%				
5/28/2005	0506P2	77.6	4.3%	4.2%			
6/25/2005	0506P3	76.3	3.8%				
7/23/2005	0506P4	71.6	-4.1%		77.8	-6.2	-8.3
8/20/2005	0506P5	64.1	-10.1%		74.4	-10.2	-13.7
9/17/2005	0506P6	68.7	-5.1%		75.4	-6.7	-9.0
10/15/2005	0506P7	76.5	-1.0%		80.5	-4.1	-5.4
11/12/2005	0506P8	78.9	-1.6%	-2.7%	83.6	-4.7	-6.3
12/10/2005	0506P9	80.6	-0.5%		84.4	-3.8	-5.1
1/7/2006	0506P10	65.6	-0.9%		69.0	-3.4	-4.6
2/4/2006	0506P11	74.4	-1.4%		78.7	-4.2	-5.7
3/4/2006	0506P12	77.7	-0.1%		81.1	-3.3	-4.5
3/31/2006	0506P13	80.1	4.8%		79.7	0.5	
	Total						-62.6

Based on these estimates, a dummy variable was created on both the underground and buses. The underground model followed the above estimates while for the bus model it was assumed that the terror attack effect initially followed the same pattern but demand recovered sooner.

Figure B-1: Terror Attack Variable on Underground

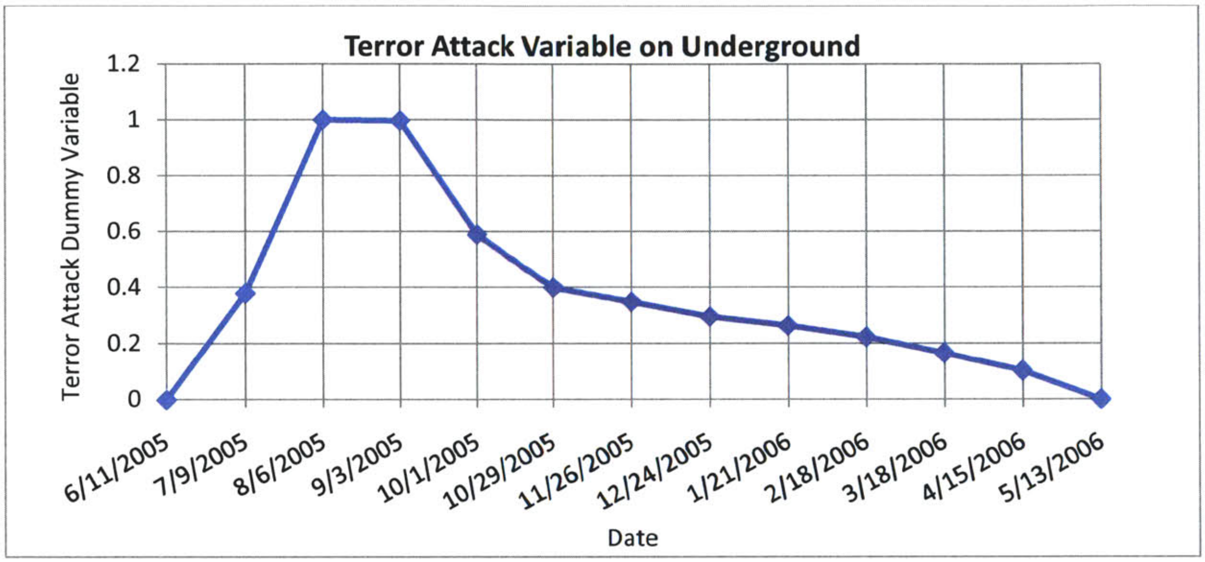
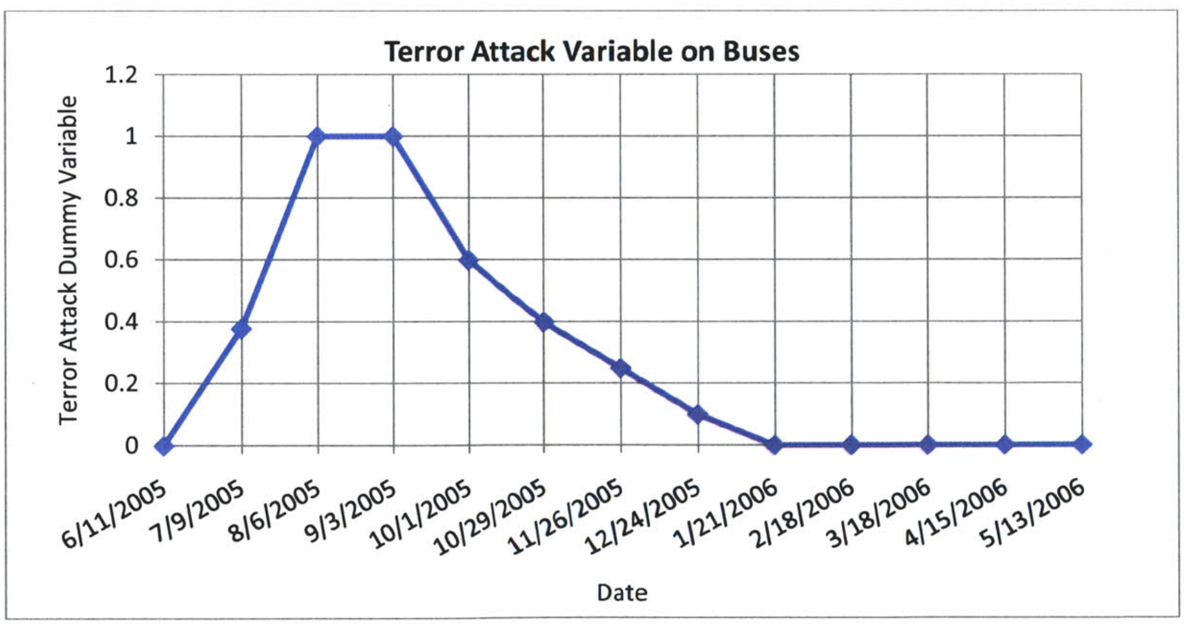


Figure B-2: Terror Attack Variable on Buses



Appendix C: Bus Model Results

Table C-1: Demand Elasticity Estimates for 1970-2009 (Effect on Demand of Increase in Factor)

Year on year trend (%)	Estimate	Std Error	t-value	95% -	95% +
PRICE RELATED VARIABLES, ADJUSTED TO 2009 FARE LEVELS					
Impact Fare Elasticity a	-0.35	0.01	-25.88	-0.37	-0.32
Smoothed Fare Elasticity b	-0.17	0.05	-3.76	-0.26	-0.08
Elasticity with Respect to Underground c	-0.12	0.03	-3.56	-0.18	-0.05
Impact effect of BR fare change d	0.17	0.03	4.97	0.10	0.23
Own Price Elasticity (a+b+c)	-0.63				
Conditional Price Elasticity (a+b+d)	-0.35				
SERVICE VARIABLES					
Smoothed Bus Miles Elasticity (1970-77)	0.28	0.10	2.83	0.09	0.47
Smoothed Bus Miles Elasticity (1977-79)	1.18	0.10	11.73	0.98	1.38
Smoothed Bus Miles Elasticity (1980-86)	0.28	0.09	3.01	0.10	0.46
Smoothed Bus Miles Elasticity (1987-94)	-0.07	0.08	-0.84	-0.22	0.09
Smoothed Bus Miles Elasticity (1995-2002)	0.63	0.13	4.75	0.37	0.89
Smoothed Bus Miles Elasticity (2003+)	0.43	0.08	5.50	0.27	0.58
DEMAND DRIVERS					
Effect of 10% increase in real Retail Sales	0.86	0.40	2.17	0.08	1.65
Effect of 10% rise in Greater London Unemployment (%)	-0.49	0.07	-6.70	-0.64	-0.35
Effect of 10% increase in Inner London road speeds (%)	1.51	0.57	2.64	0.39	2.64
Effect of 10% increase dedicated bus lane kilometres (%)	1.67	0.59	2.82	0.51	2.83
Effect of 10% rise in Cars per Head in GL (1970 - 1990)	-8.77	1.27	-6.93	-11.25	-6.29
IMPACT OF CHANGES IN TICKETING STRUCTURE					
Effect of Travelcards Being Introduced (ends 5/84) (%)	2.53	0.79	3.21	0.99	4.07
OTHER VARIABLES					
Effect of Bank Holiday on Demand (%)	-2.29	0.20	-11.54	-2.68	-1.90
Effect of Full BR Service Day Lost (%)	0.41	0.08	5.19	0.26	0.57
Effect of 10% increase in Temperature (%)	-0.03	0.06	-0.55	-0.16	0.09
Effect of 10% increase in Rainfall (%)	-0.06	0.02	-3.50	-0.10	-0.03
DUMMY VARIABLES					
Effect of 1975 fares revision (recouped 1 year later) (%)	2.61	0.96	2.72	0.73	4.49
Effect of free travel for the elderly (%)	-6.21	1.63	-3.81	-9.41	-3.01
Effect of 1981 series change/recession (%)	-8.77	1.27	-6.93	-11.25	-6.29
Effect of 1982 bus rescheduling (%)	-0.07	0.08	-0.84	-0.22	0.09
Effect of 1986 sevice interruptions (%)	-1.77	0.85	-2.07	-3.44	-0.09
Effect of 2000 Fuel Crisis (%)	2.61	0.96	2.72	0.73	4.49
Pay as you Go effect in 2004 (%)	0.05	0.08	1.59	-0.03	0.30

Pay as you Go effect in 2005 (%)	0.27	0.33	1.59	-0.12	1.16
Pay as you Go effect in 2006 (%)	0.96	0.85	1.59	-0.32	3.03
Pay as you Go effect in 2007 (%)	0.86	0.71	1.59	-0.26	2.50
Pay as you Go effect in 2008 (%)	0.54	0.27	1.59	-0.10	0.97
Pay as you Go effect in 2009 (%)	0.29	0.04	1.59	-0.01	0.13
Free Child and Student Travel effect in 2005 (%)	-0.91	0.30	3.19	0.37	1.56
Free Child and Student Travel effect in 2006 (%)	-3.57	1.19	3.19	1.46	6.13
Free Child and Student Travel effect in 2007 (%)	-1.40	0.47	3.19	0.57	2.41
Free Child and Student Travel effect in 2008 (%)	-0.27	0.09	3.19	0.11	0.47
Free Child and Student Travel effect in 2009 (%)	-0.03	0.01	3.19	0.01	0.05
Effect of 2004 Fares Revision (%)	5.38	0.62	8.69	4.17	6.60
Effect of 2007 October Fares Revision (%)	-2.88	0.63	-4.65	-4.11	-1.64
2005 Terror Attack effect in 2005 (%)	-0.50	0.24	-2.07	-0.98	-0.01
2005 Terror Attack effect in 2006 (%)	0.50	-0.25	-2.07	0.02	0.99
2005 Terror Attack effect in 2007 (%)	0.01	0.00	-2.07	0.00	0.00
OTHER INFORMATION					
Observations	440				
R-Squared (%)	0.8922				

Table C-2: Bus Service Elasticities Comparison

Service Elasticities	1970-2000 Model		1970-2009 Model	
	Estimate	t-stat	Estimate	t-stat
Smoothed Bus Miles Elasticity (1970-77)	0.14	1.40	0.28	2.83
Smoothed Bus Miles Elasticity (1977-79)	1.15	10.80	1.18	11.73
Smoothed Bus Miles Elasticity (1980-86)	0.33	3.50	0.28	3.01
Smoothed Bus Miles Elasticity (1987-94)	-0.03	-0.3	-0.07	-0.84
Smoothed Bus Miles Elasticity (1995-2000)	0.65	4.1		
Smoothed Bus Miles Elasticity (1995-2002)			0.63	4.75
Smoothed Bus Miles Elasticity (2003+)			0.43	5.50

Table C-3: Bus Demand Driver Elasticities Comparison

Demand Driver Elasticities	1970-2000 Model		1970-2009 Model	
	Estimate	t-stat	Estimate	t-stat
Effect of 10% increase in real Retail Sales	0.78	1.70	0.86	2.17
Effect of 10% rise in Greater London Unemployment (%)	-0.42	-5.80	-0.49	-6.70
Effect of 10% increase in Inner London road speeds (%)			1.51	2.64
Effect of 10% increase dedicated bus lane kilometres (%)			1.67	2.82
Effect of 10% rise in Cars per Head in GL (1970 - 1990)	-8.51	-6.60	-8.77	-6.93

Appendix D: Underground Model Results

Table D-1: Demand Elasticity Estimates for 1970-2009 (Effect on Demand of Increase in Factor)

Year on year trend (%)		Estimate	Std Error	t-value	95% -	95% +
PRICE RELATED VARIABLES, ADJUSTED TO 2009 FARE LEVELS						
Impact Fare Elasticity	a	-0.26	0.01	-20.20	-0.29	-0.24
Smoothed Fare Elasticity	b	-0.04	0.04	-0.90	-0.13	0.05
Elasticity with Respect to Bus	c	-0.13	0.04	-3.76	-0.20	-0.06
Impact effect of BR fare change	d	0.11	0.03	3.13	0.04	0.17
Own Price Elasticity	(a+b+c)	-0.43				
Conditional Price Elasticity	(a+b+d)	-0.19				
SERVICE VARIABLES						
Underground Miles		0.04	0.03	1.54	-0.01	0.09
Smoothed Bus Miles Elasticity (general)		-0.15	0.05	-3.05	-0.24	-0.05
Smoothed Bus Miles Elasticity (1978-80)		-0.34	0.10	-3.22	-0.53	-0.12
DEMAND DRIVERS						
Effect of 10% increase in real Retail Sales		0.70	0.47	1.49	-0.22	1.62
Effect of 10% rise in Greater London Employment (%)		6.12	0.66	9.13	4.82	7.41
Effect of 10% rise in Tourism (%)		0.40	0.09	4.36	0.22	0.58
Effect of 10% rise in Cars per Head in GL (1970 - 1990)		-4.09	1.10	-3.74	-6.24	-1.94
IMPACT OF CHANGES IN TICKETING STRUCTURE						
Additional 100,000 Valid Bus Passes (%)		-5.35	0.86	-6.21	-7.04	-3.66
Additional 100,000 Valid Travelcards (%)		8.56	0.90	9.52	6.79	10.32
Additional 100,000 Valid Capitalcards (%)		5.06	1.29	3.94	2.54	7.58
OTHER VARIABLES						
Effect of Bank Holiday on Demand (%)		-2.76	0.24	-11.59	-3.23	-2.29
Effect of Christmas Day Shutdown on Demand (%)		-3.27	0.73	-4.48	-4.70	-1.84
Effect of 10% increase in Temperature (%)		0.02	0.05	0.46	-0.08	0.12
Effect of 10% increase in Rainfall (%)		-0.04	0.02	-2.38	-0.08	-0.01
Effect of Full BR Service Day Lost (%)		0.27	0.09	3.02	0.09	0.44
DUMMY VARIABLES						
Effect of 1972 Fares Revision (%)		6.40	0.83	7.74	4.78	8.02
Effect of Heathrow Extension (%)		2.76	0.74	3.73	1.31	4.21
Effect of Victoria Line Extension (%)		4.25	0.76	5.58	2.76	5.75
Effect of Jubilee Line Extension (%)		1.50	1.06	1.41	-0.59	3.58
Unemployment dummy (1980-81) (%)		-1.85	0.68	-2.73	-3.17	-0.52
Effect of 1981 series changes/recession (%)		-7.45	0.92	-8.08	-9.26	-5.64
Kings Cross Fire effect in 1987 (%)		-0.20	0.03	-6.38	-0.26	-0.14
Kings Cross Fire effect in 1988 (%)		-4.88	0.77	-6.38	-6.38	-3.38

Kings Cross Fire effect in 1989 (%)	1.67	0.26	-6.38	1.16	2.18
Kings Cross Fire effect in 1990 (%)	2.76	0.43	-6.38	1.91	3.61
Kings Cross Fire effect in 1991 (%)	0.44	0.07	-6.38	0.31	0.58
UTS Gate effect in 1989 (%)	4.68	4.29	1.09	-3.72	13.08
UTS Gate effect in 1990 (%)	0.15	0.14	1.09	-0.12	0.43
UTS Gate effect in 1991 (%)	1.91	1.75	1.09	-1.52	5.33
Effect of Waterloo & City acquisition/penalty fares (%)	3.81	0.72	5.31	2.41	5.22
Peak Effect of Chancery Lane Derailment, 2003 (%)	-3.78	0.91	-4.14	-5.57	-1.99
Peak Effect of Northern Line Derailment, 2003 (%)	-3.26	1.36	-2.40	-5.92	-0.59
Pay as you Go effect in 2004 (%)	0.27	0.12	2.29	0.04	0.51
Pay as you Go effect in 2005 (%)	0.43	0.19	2.29	0.06	0.81
Pay as you Go effect in 2006 (%)	1.59	0.69	2.29	0.23	2.95
Pay as you Go effect in 2007 (%)	1.24	0.54	2.29	0.18	2.31
Pay as you Go effect in 2008 (%)	0.82	0.36	2.29	0.12	1.52
Pay as you Go effect in 2009 (%)	0.37	0.16	2.29	0.05	0.68
Effect of 2006 Fares Revision (%)	-4.21	0.89	-4.73	-5.87	-2.38
2005 Terror Attack effect in 2005 (%)	-3.47	0.30	-11.7	-4.06	-2.89
2005 Terror Attack effect in 2006 (%)	3.00	-0.26	-11.7	2.49	3.50
2005 Terror Attack effect in 2007 (%)	0.66	-0.06	-11.7	0.77	0.55
OTHER INFORMATION					
Observations	441				
R-Squared (%)	0.9077				

Table D-2: Underground Service Elasticities Comparison

Service Elasticities	1970-2000 Model		1970-2009 Model	
	Estimate	t-stat	Estimate	t-stat
Underground Miles	0.08	2.60	0.04	1.54
Smoothed Bus Miles Elasticity (general)	-0.19	-3.00	-0.15	-3.05
Smoothed Bus Miles Elasticity (1978-80)	-0.28	-2.60	-0.34	-3.22

Table D-3: Underground Demand Driver Elasticities Comparison

Demand Driver Elasticities	1970-2000 Model		1970-2009 Model	
	Estimate	t-stat	Estimate	t-stat
Effect of 10% increase in real Retail Sales	1.80	3.40	0.70	1.49
Effect of 10% rise in Greater London Employment (%)	7.14	11.40	6.12	9.13
Effect of 10% rise in Tourism (%)	0.55	4.60	0.40	4.36
Effect of 10% rise in Cars per Head in GL (1970 - 1990)	-5.26	-4.30	-4.09	-3.74

Appendix E – Journey graphs at station level

Figure E-1: Journeys by ticket type – Wimbledon 1

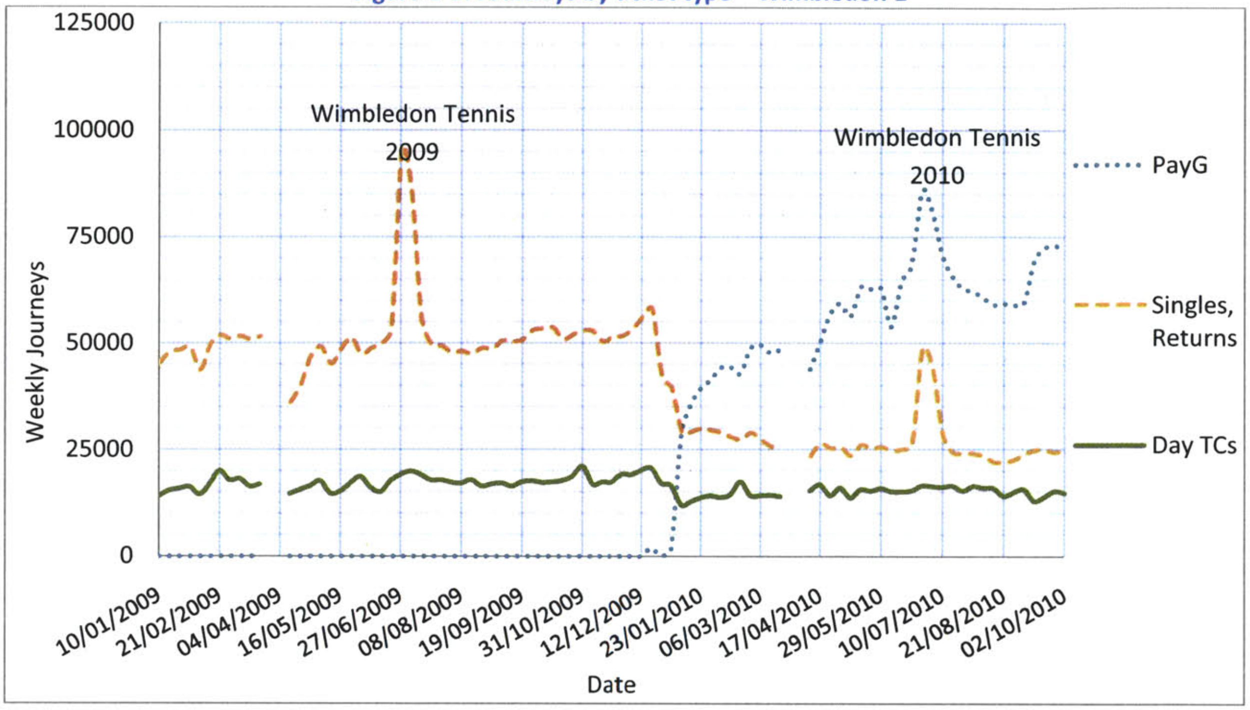


Figure E-2: Journeys by ticket type – Wimbledon 2

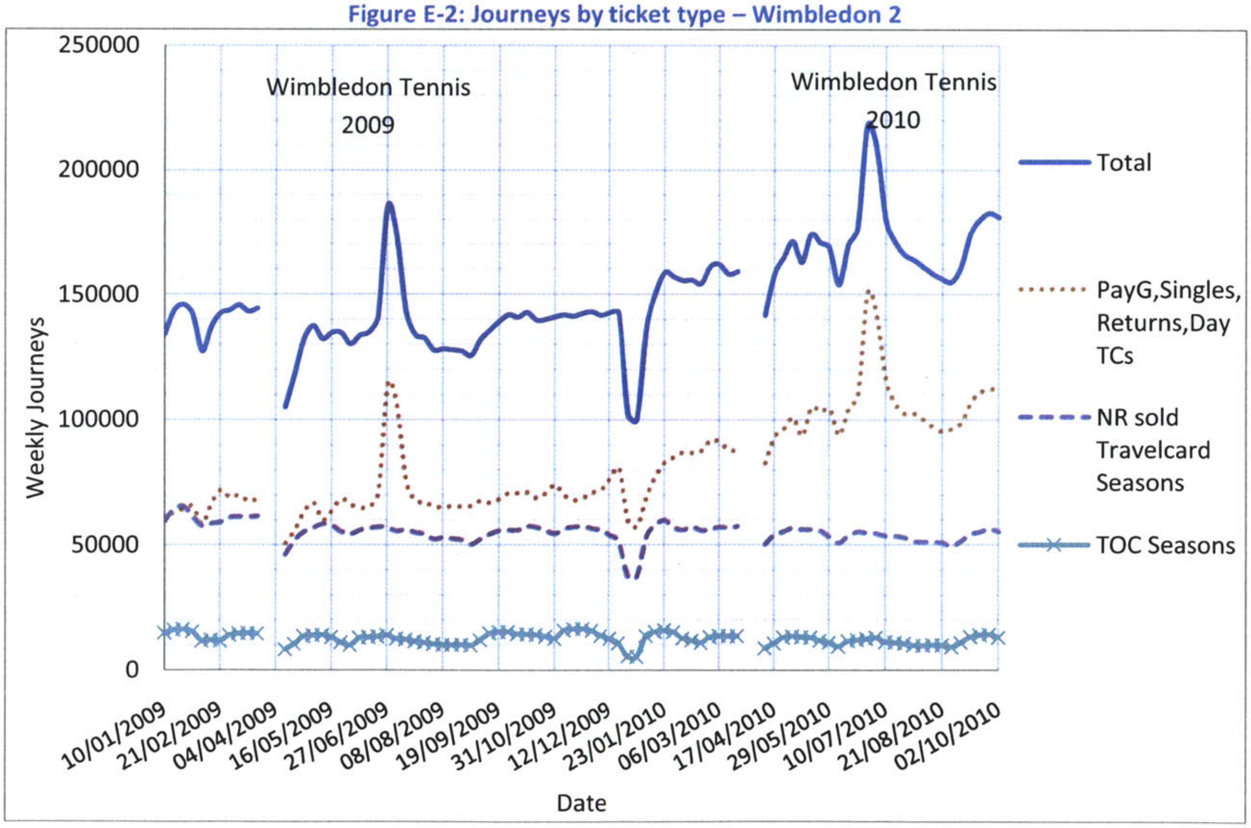


Figure E-3: Journeys by ticket type – Surbiton 1

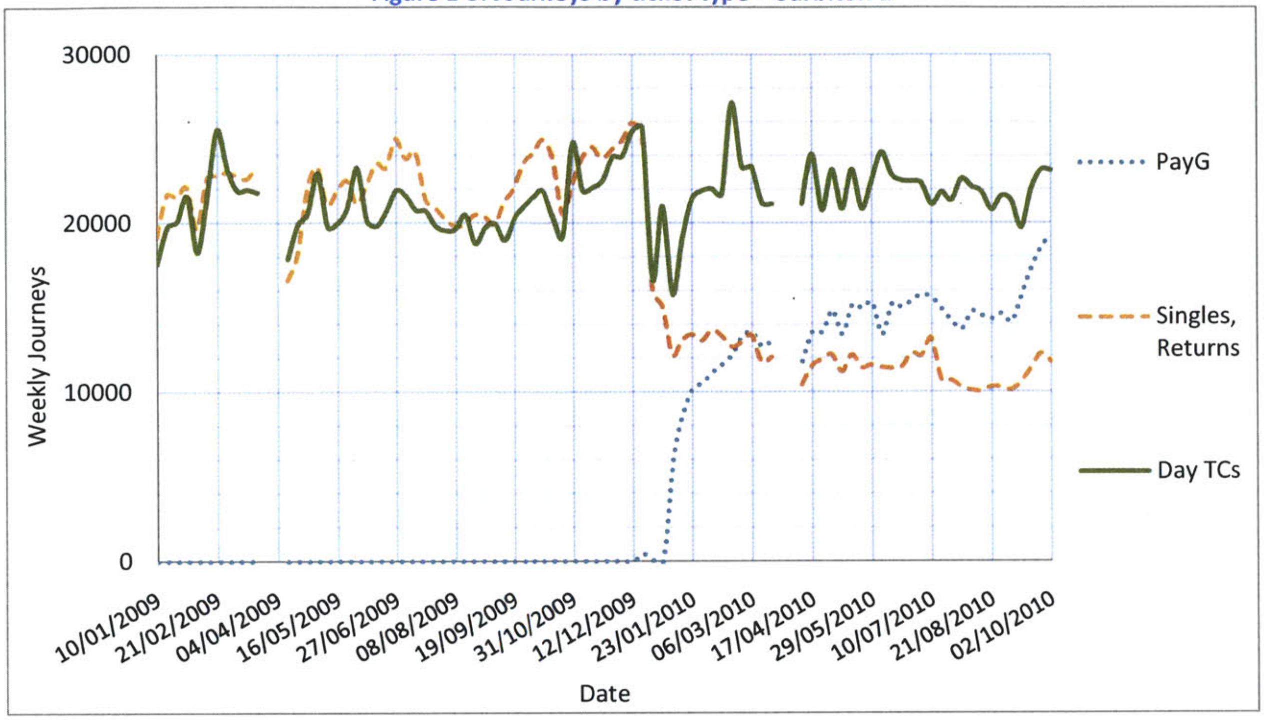


Figure E-4: Journeys by ticket type – Surbiton 2

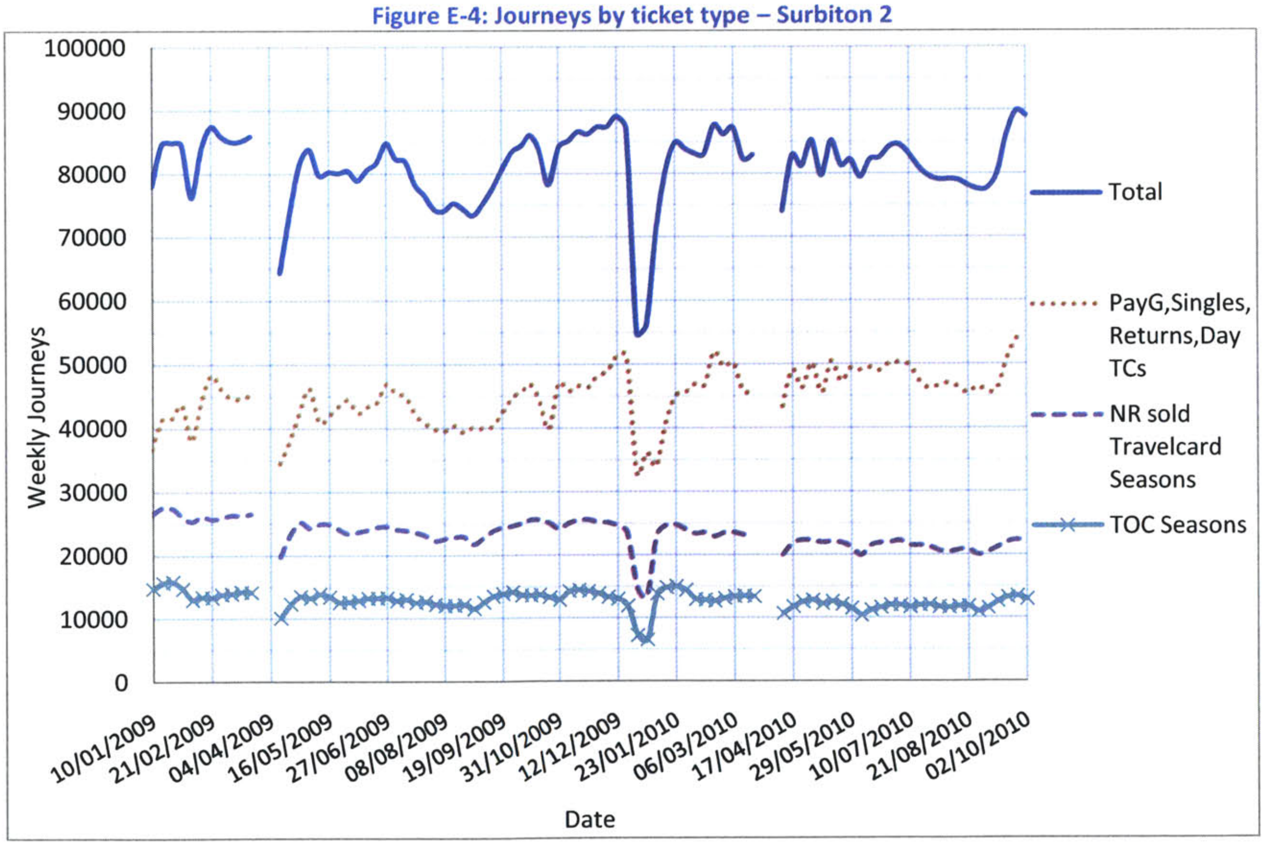


Figure E-5: Journeys by ticket type – East Croydon 1

Figure E-6: Journeys by ticket type – East Croydon 2

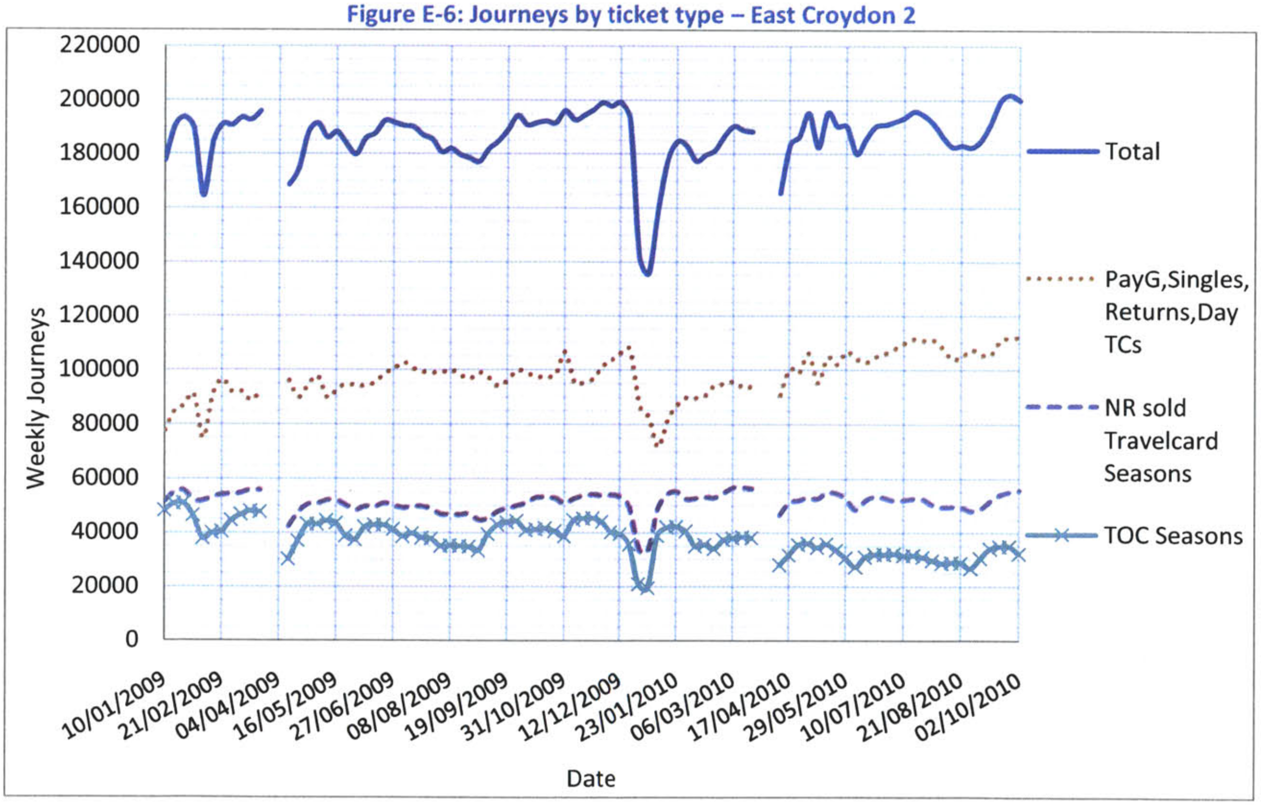


Figure E-7: Journeys by ticket type – Purley 1

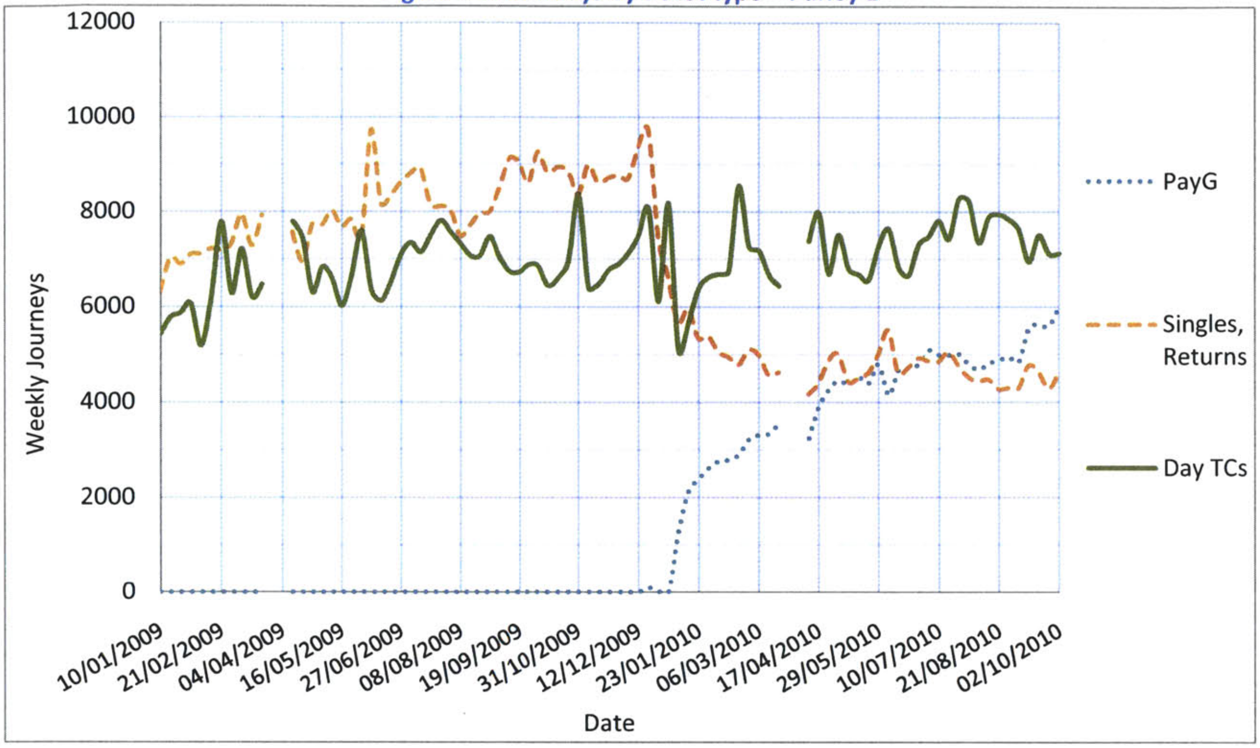


Figure E-8: Journeys by ticket type – Purley 2

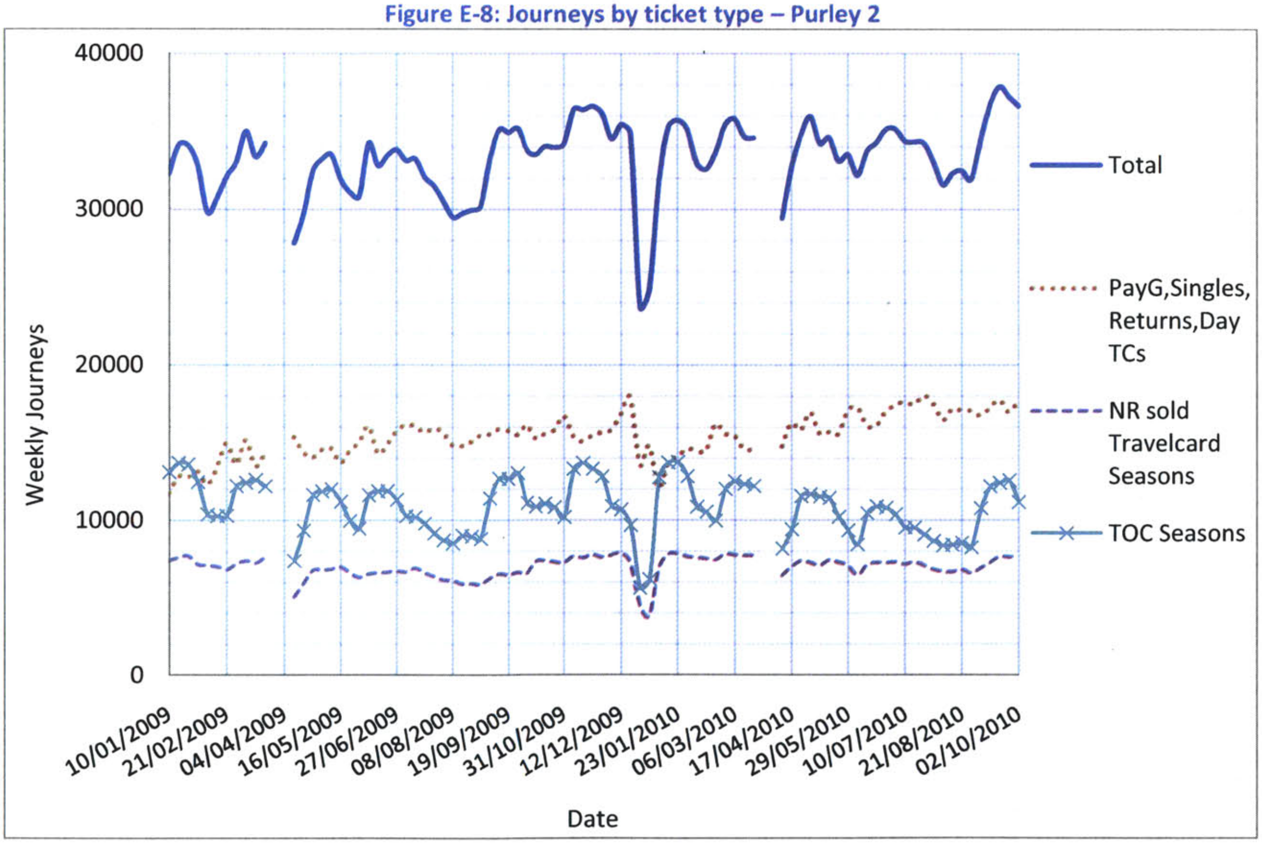


Figure E-9: Journeys by ticket type – Balham 1

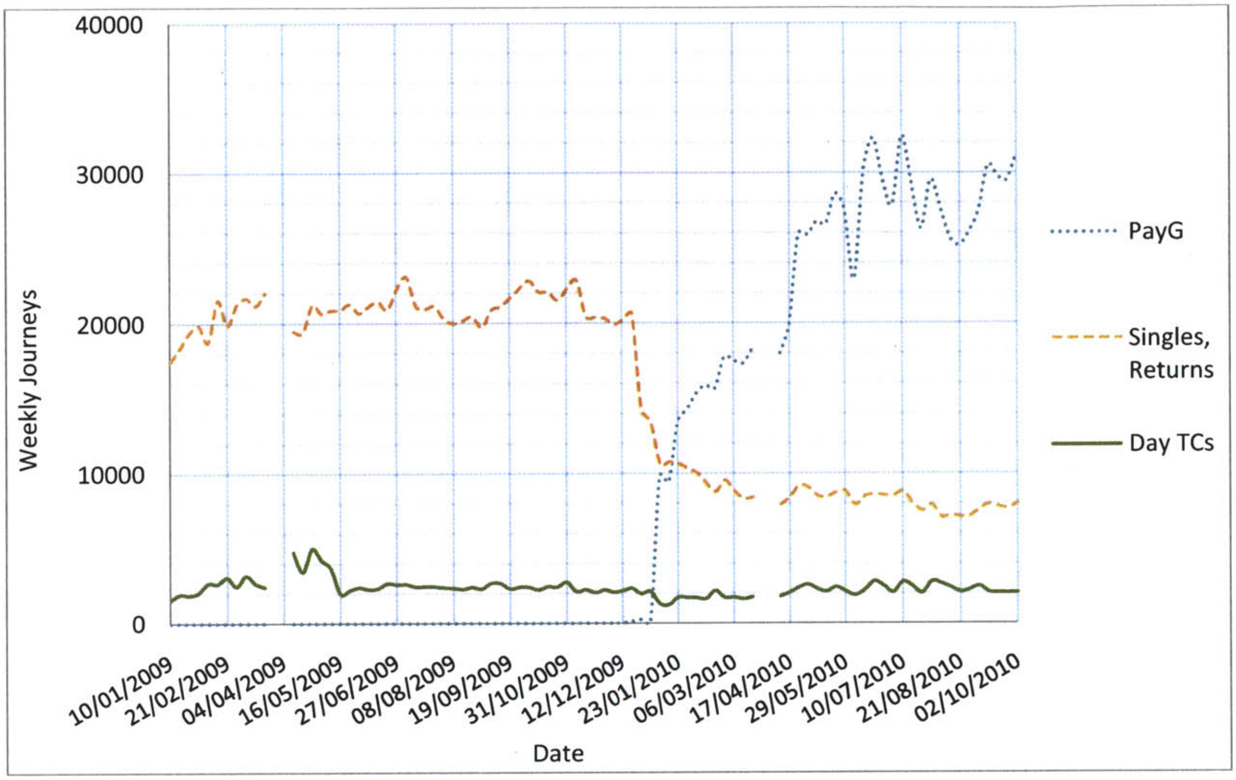


Figure E-10: Journeys by ticket type – Balham 2

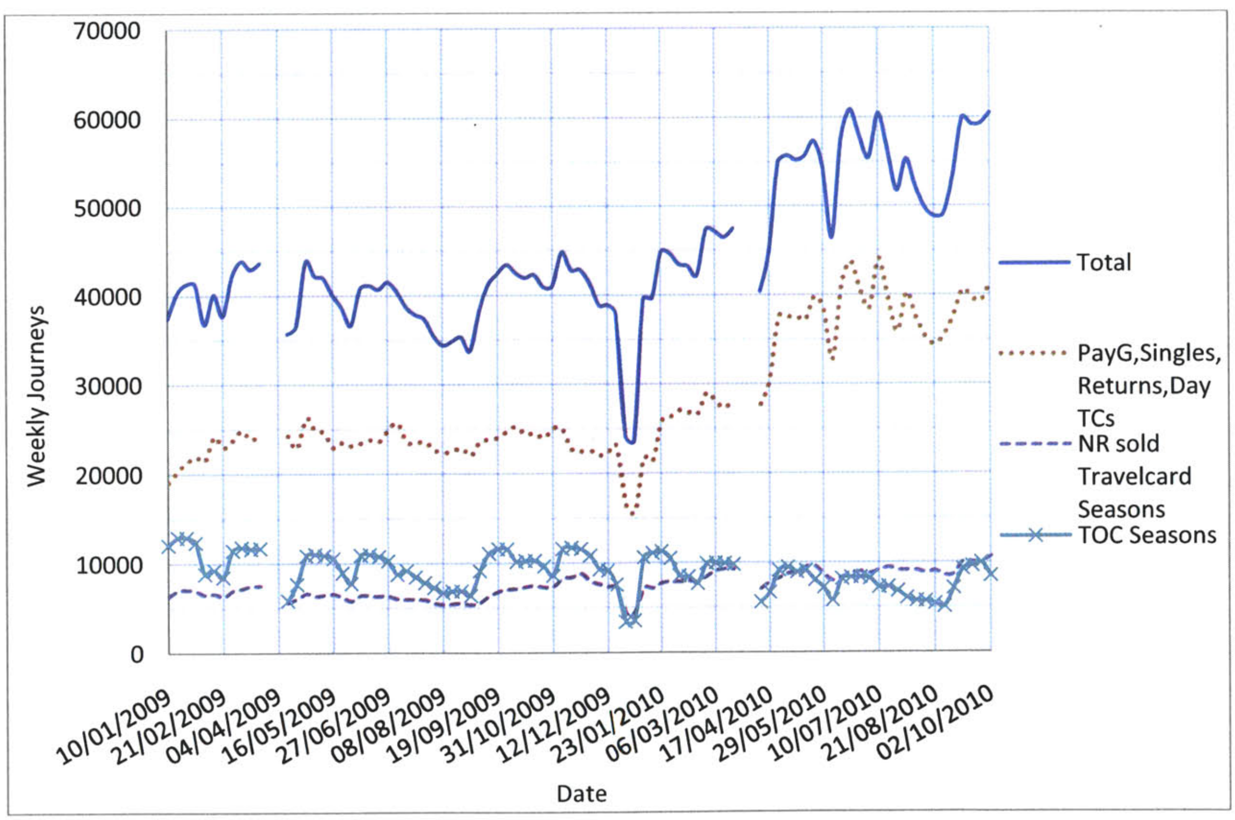


Figure E-11: Journeys by ticket type – Bexleyheath 1

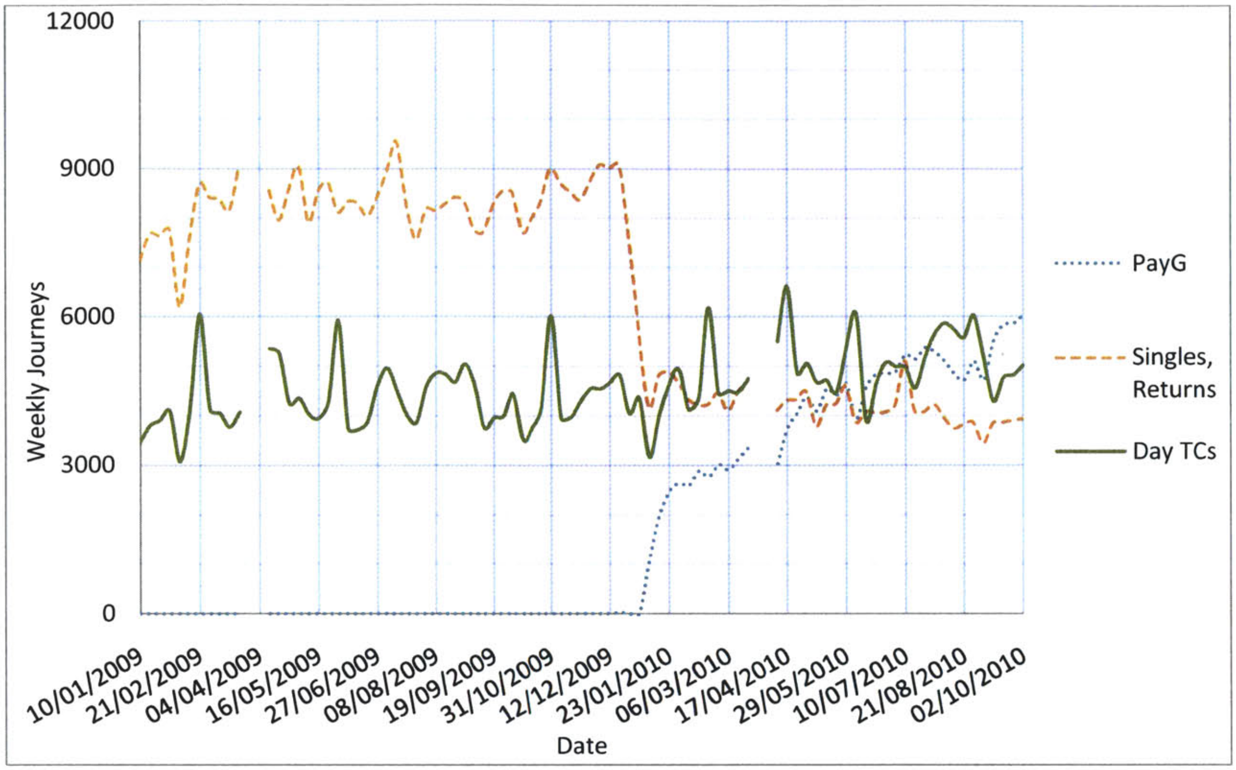


Figure E-12: Journeys by ticket type – Bexleyheath 2

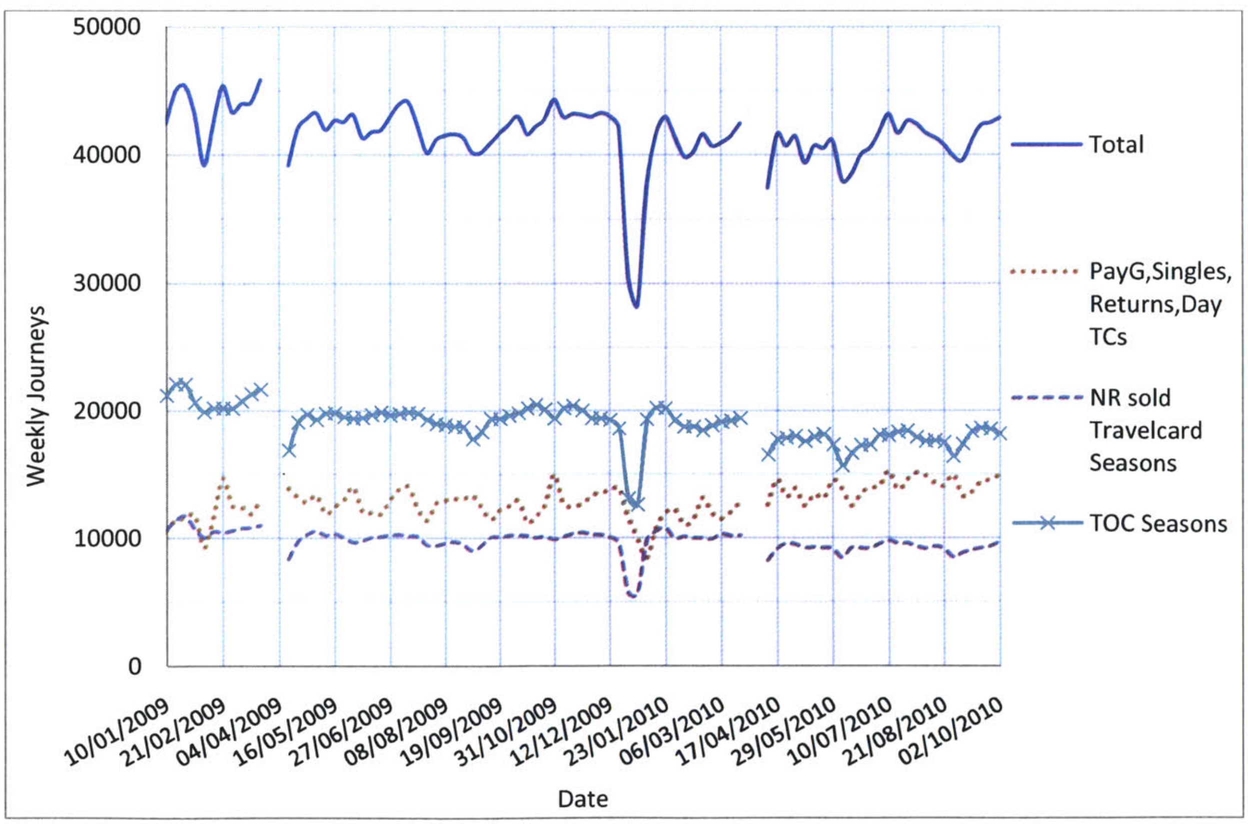


Figure E-13: Journeys by ticket type – Bromley South 1

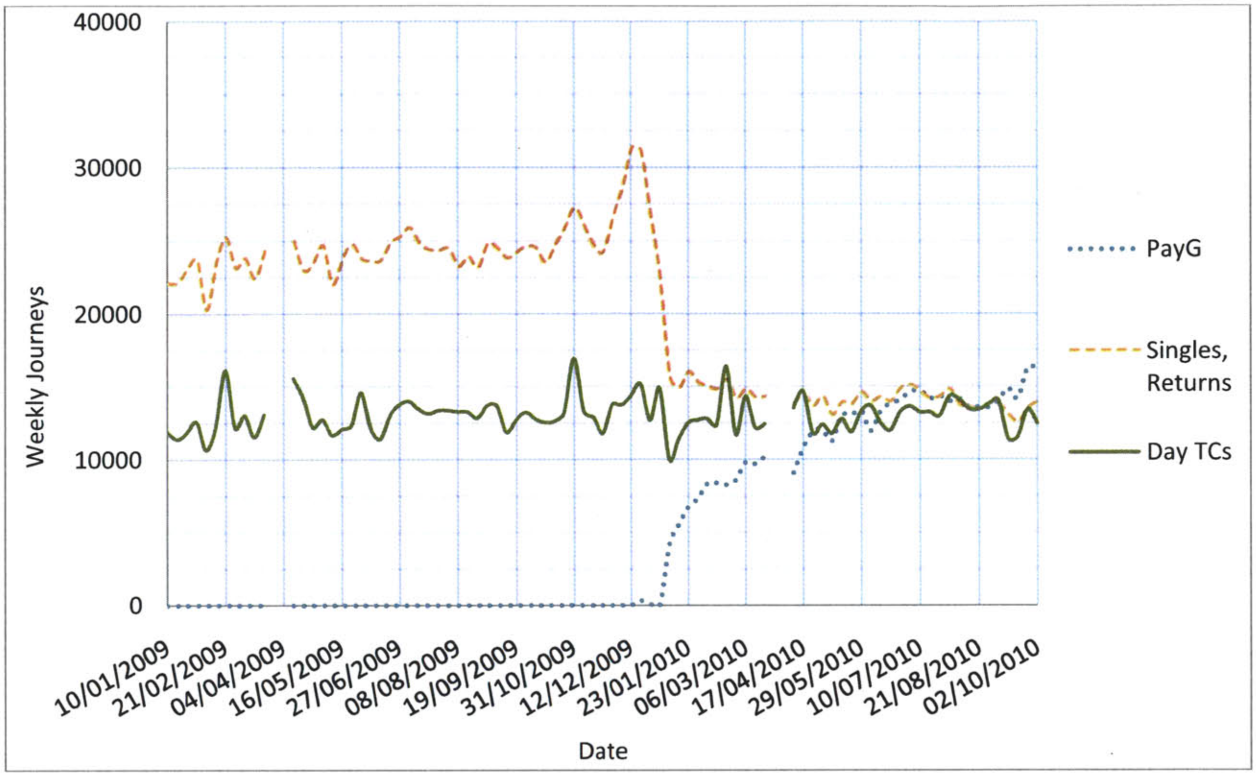


Figure E-14: Journeys by ticket type – Bromley South 2

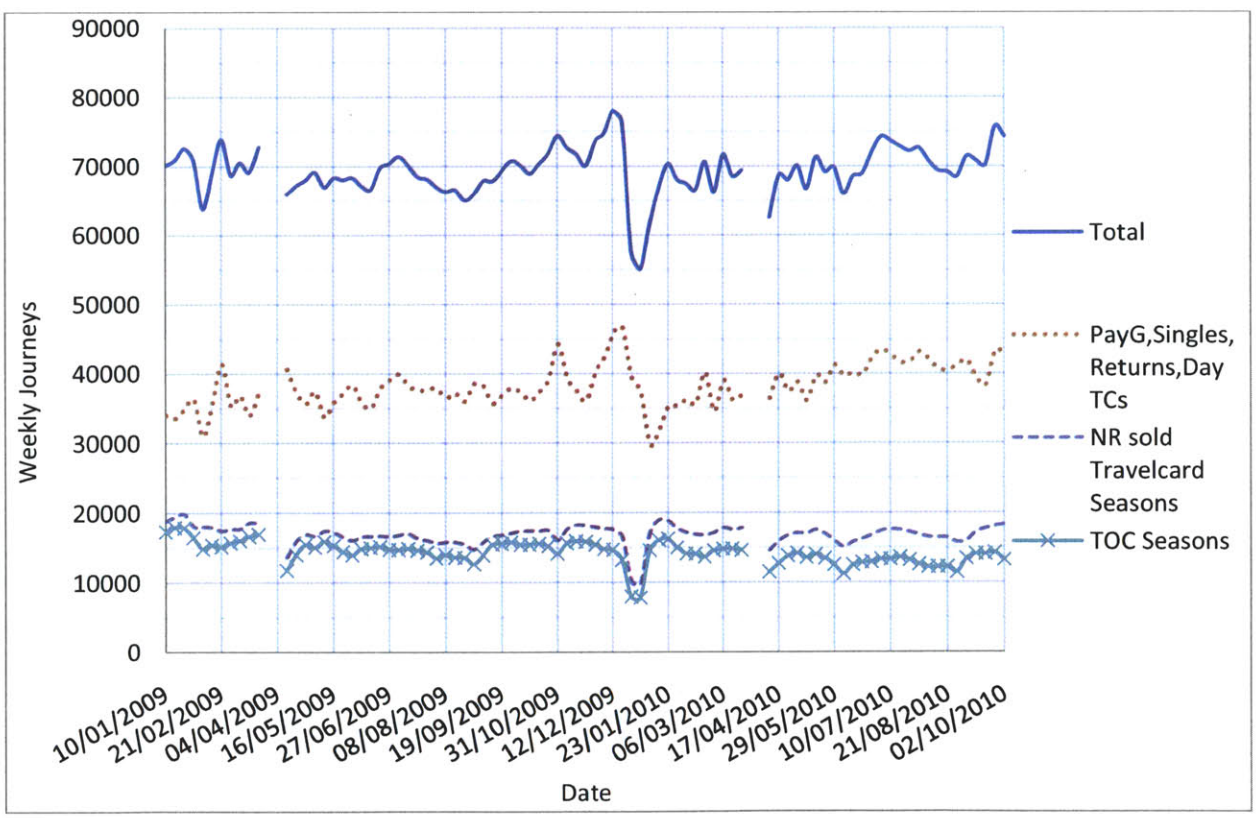


Figure E-15: Journeys by ticket type – Orpington 1

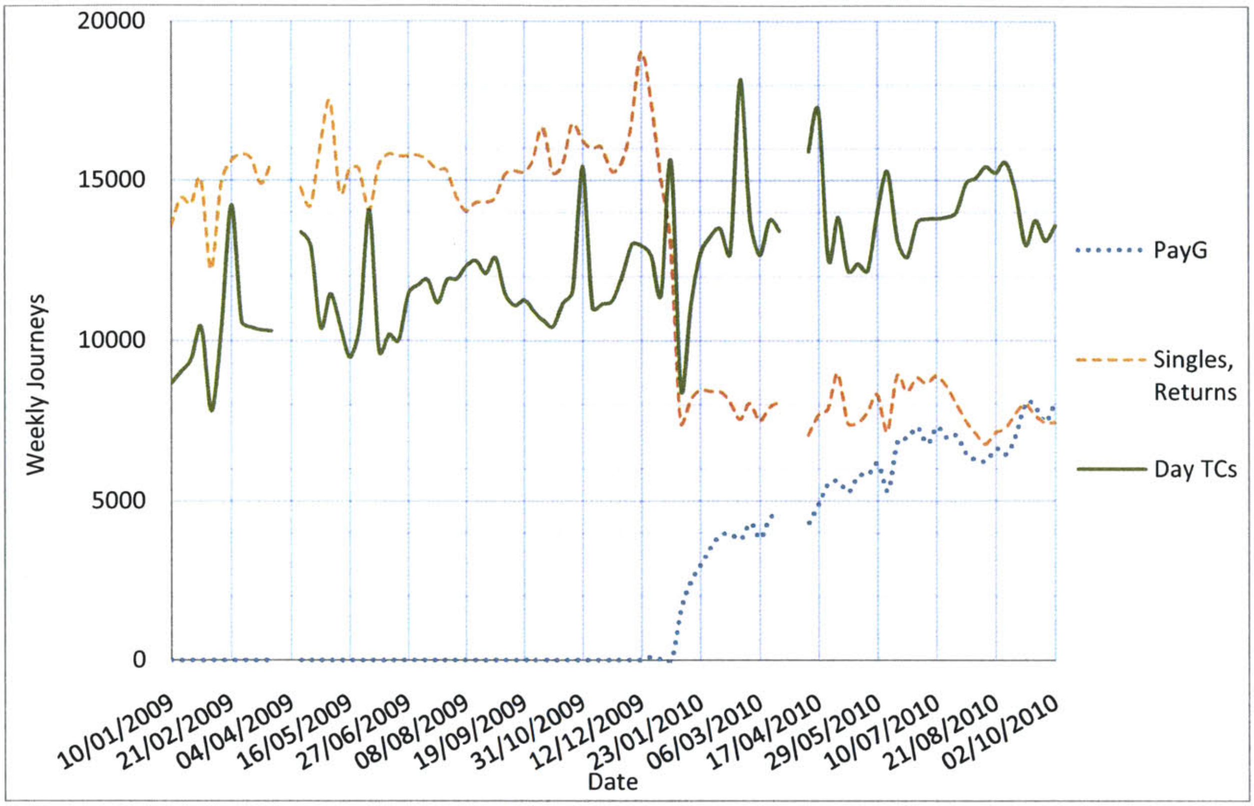


Figure E-16: Journeys by ticket type – Orpington 2

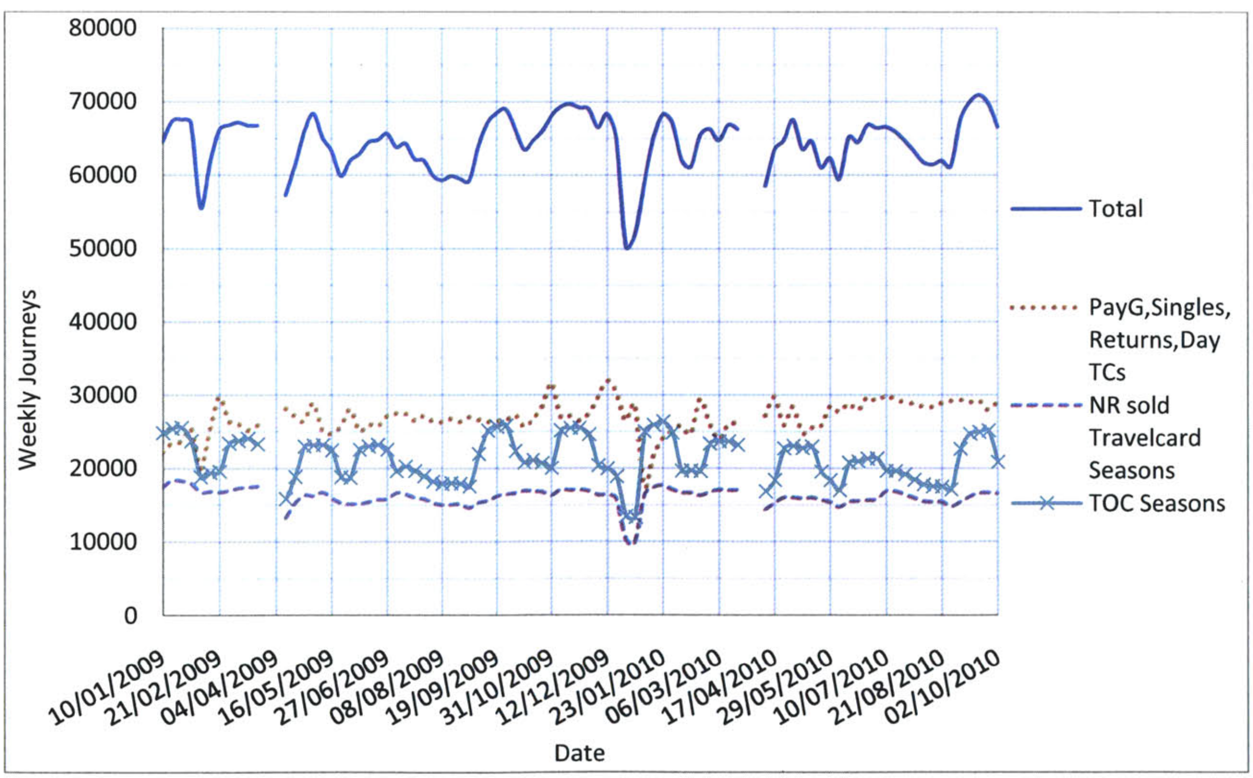


Figure E-17: Journeys by ticket type – Putney 1

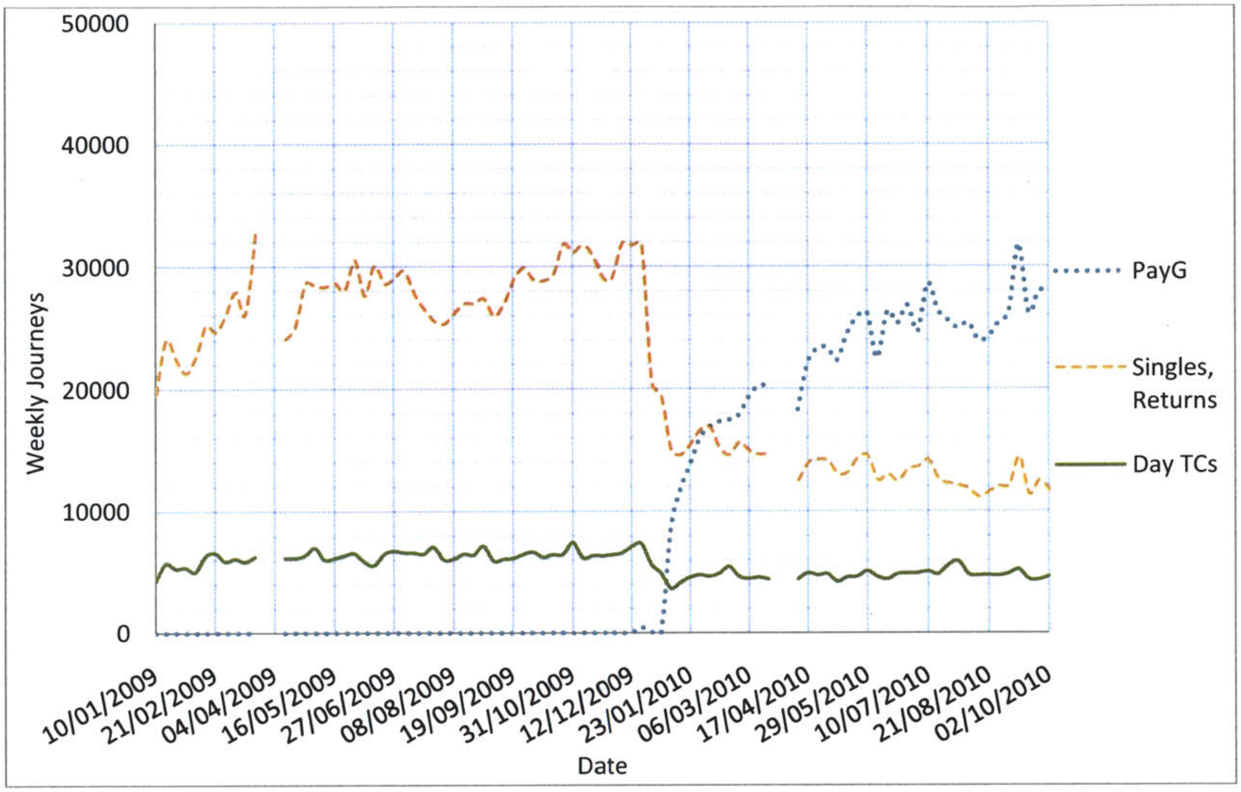


Figure E-18: Journeys by ticket type – Putney 2

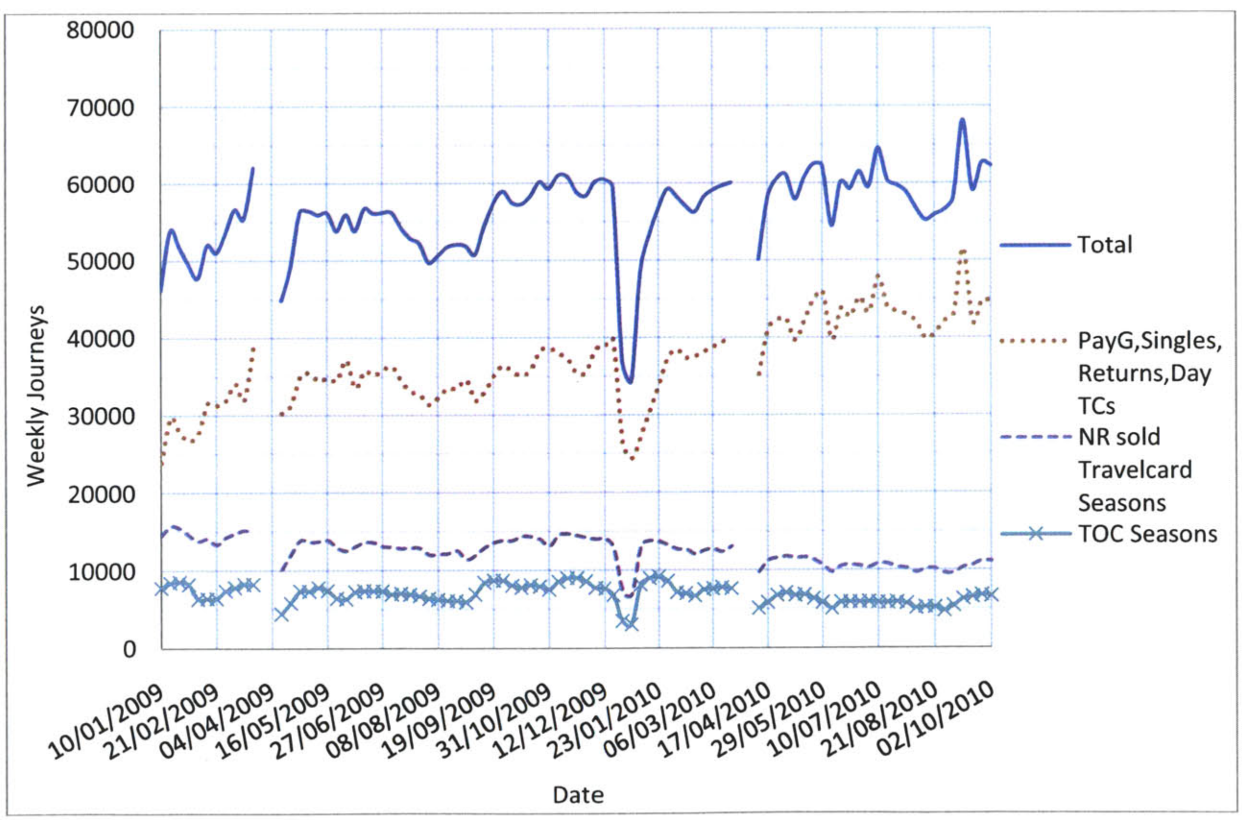


Figure E-19: Journeys by ticket type – Richmond 1

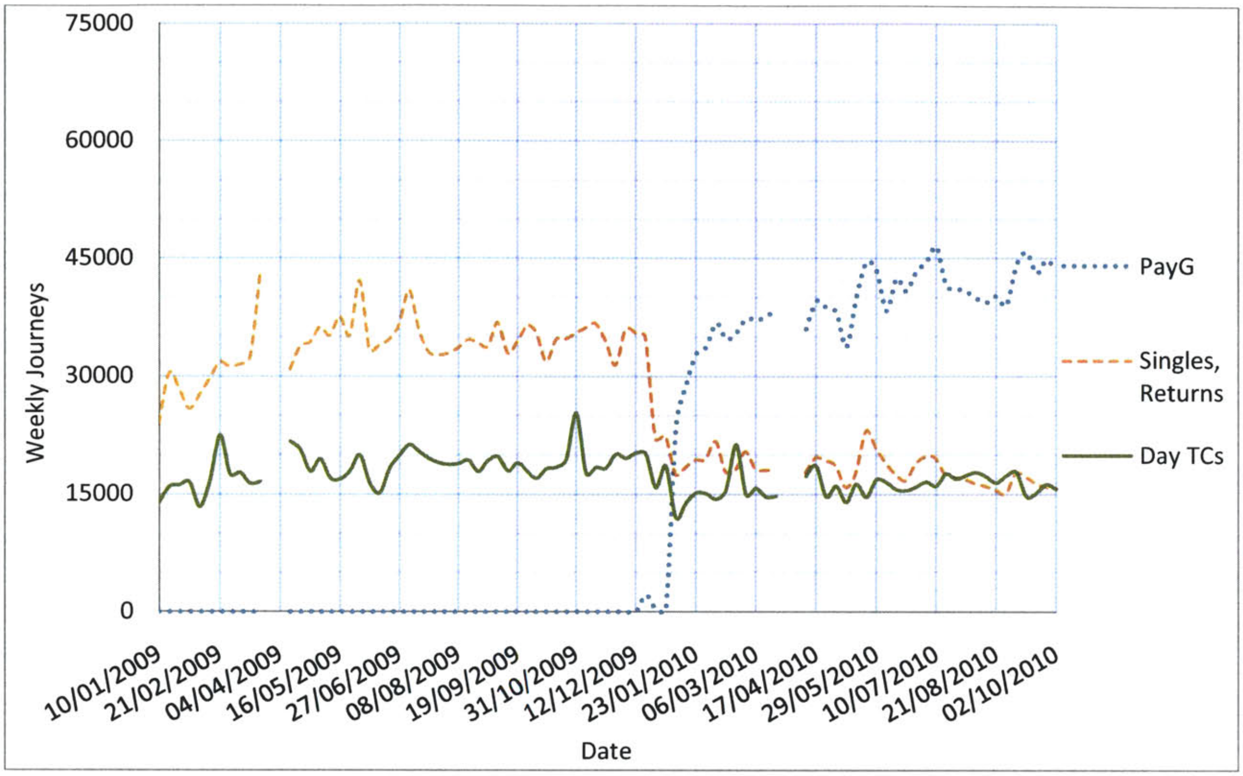
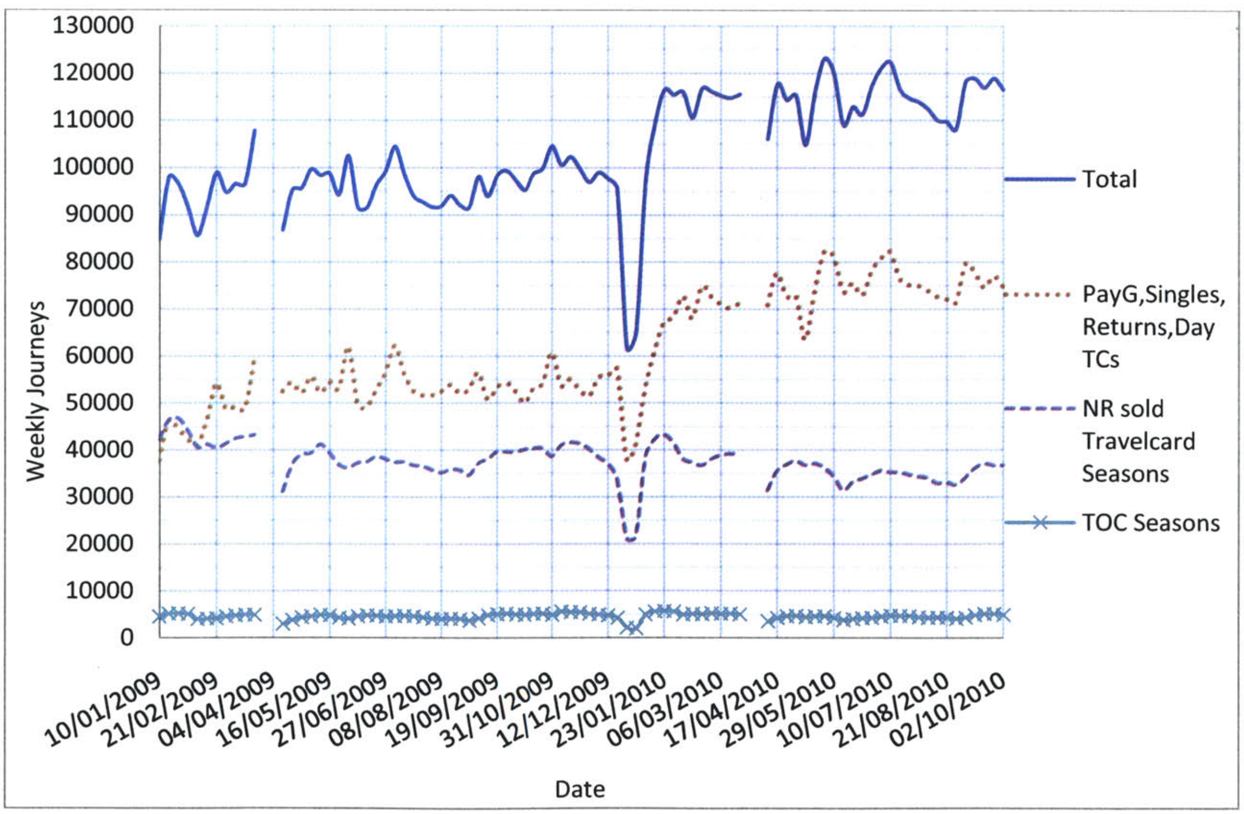


Figure E-20: Journeys by ticket type – Richmond 2



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