The Effects of Social Norms and Price Changes on Public Transport Demand: Empirical Evidence from London.

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Table of Contents

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Studying for a PhD in any field is no mean feat; studying for one in economics as a family man holding down a full time job is particularly challenging, I reserve all glory to God Almighty without whom I am nought.

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ABSTRACT

Demand for public transport in cities has been and is projected to increase, putting existing transport networks under increasing strain. It is therefore important to investigate different means of managing public transport demand and one of such means is through the price mechanism; policy makers need to know how demand might respond to changes in fares. This thesis begins by first exploring the presence of and the causes for asymmetric price elasticities of demand using transport demand data from London Underground and employing regression methods. This research finds that public transport demand is more sensitive to fare increases than to decreases; this is majorly due to loss aversion, at least on the intensive margin of demand. But how does public transport demand respond to a nominal decrease in fares? This thesis next analyse the effect of a change in the fare structure for bus journeys in London on different demand measures using a regression discontinuity design, following Transport for London's implementation of a new bus price policy in September 2016. The analyses show that the policy significantly increased the number of bus trips by 5% and follow-up journeys by 8%. Passenger numbers increased by 4%. The results show that the increase in demand was not only driven by new customers, but also by more intensive demand by existing customers. Price manipulations affect the cost functions of both the transport provider and passengers. This thesis finally proposes an alternative and less costly measure of managing public transport demand. Nudging passengers to behave in certain ways through the creation of a salient social norm has the potential to be a cost-effective mechanism to manage transport demand. Transport for London implemented in 2017 an experiment on one of its busiest metro train platforms. Using Difference-in-Differences method and different sets of assumptions about what the counterfactual change in waiting and delay times would have been in the absence of the intervention, this thesis analyses the effect of such intervention on dwell time and, by extension, the capacity to manage demand.

CHAPTER 1

Introduction

1.1 Prelude

Transport is not normally the end objective of a rational consumer, but aids the consumption of other activities such as family visits, work trips, shopping trips etc. The rational economic man, as postulated in classical economics, is always opting to maximise utility (McFadden et al., 1999; Simon, 1978) such that his demand for transport is derived from the utility he expects to enjoy from engaging in other economic activities. Transport providers can therefore influence utility maximisation through their pricing policies which may have some effects on the generalised costs of travel. Rational passengers generally base their mode and route choice on many factors of which fare is considered to be the most important (Takahashi, 2017). Transport is a key factor in any modern economy and its cost-effective management and supply are crucial if the ever-growing demand is to be met and development sustained (Duarte *et al.*, 2010). It is an integral part of our everyday lives; we travel to work, school, for business, for pleasure etc., the exchange of goods and services; both in peace and war times, have made transportation very important. Transport economics as a subset of economics studies the diverse and multiple variables that enter into the demand and supply functions of the movement of people from one origin to another destination.

Whether supply precedes demand or *vice versa* is subject to debate, but what is beyond debate is that the demand for transportation has increased over the centuries making it important for economies to find smarter, cost effective and sustainable ways of managing it. Since the 1990s the rail market has exhibited strong growth (ATOC, 2013; RDG, 2016). A collaborative report by Infrastructure UK and the National Infrastructure Commission finds that passenger demand – if unconstrained by supply limitations – would increase between

84% and 110% between 2015 and 2040 (Preston, 2018). Network Rail (2013) predicts an increase in demand of 58% for non-London commuting and 115% for London commuting between 2011 and 2043. Preston (2018) provides evidence that a generational shift is occurring among 'millennials' who favour public transport over car ownership and predicts a capacity crunch. Increases in demand will inevitably impact on the reliability of any transport network (Melo et al., 2011; Barron et al., 2013) and increase transport costs. This is reflected in the performance of many transport providers, e.g., declining punctuality in London and the South East counties (RDG, 2016). How can transport networks cope with these increases in demand in the face of capacity constraints?

The traditional methods of managing public transport demand are by hard or soft means. Hard means include capital infrastructural investments to increase capacity, while soft means have to do with non-capital ways of managing demand, like price manipulation, information dissemination and campaigns (see Offiaeli and Yaman, 2021). Price manipulation is essentially the use of different price mechanisms to control the demand for public transport. It can be deduced from many extant literature that when transport fares increase the demand for public transport decreases (Balcombe et al., 2004a; Bresson et al., 2003a; Gordon and Willson, 1984; Holmgren, 2007; McLeod et al., 1991). What is rare in literature is the analysis of the response of public transport demand to an actual decrease in price, because such occasions are scarce in practice. Most literature use inflation indexed prices to model the response of public transport demand to a decrease in price, but that ignores the importance of salience in consumer behaviour given that price changes impact on suppliers and passengers alike, depending on the direction of the change.

To begin, an empirical investigation of the existence of asymmetry in the response of demand to price increases and decreases is presented, using transport demand data. This finding is usually attributed to psychological phenomena such as loss aversion or to the different pace with which price changes become known to potential buyers. The first dissertation chapter analyses the presence of and the causes for asymmetric price elasticities of demand for the London Underground. Studying public transport demand offers unique advantages: the service cannot be stored and must be consumed at the point of purchase, and the consumption of public transport cannot be preponed or postponed. During the period studied some nominal fares on the network have increased while others have decreased, offering a unique opportunity to observe price elasticities for both cases. Comparing changes in price elasticities after a price decrease to changes after a price increase, it is evident that demand is more sensitive to price increases than to decreases (by 0.7 to 0.9 percentage points), in addition, there is evidence that loss aversion contributed to this asymmetry at least on the intensive margin of transport demand.

Next, an analysis of the impact of a nominal decrease in ticket fares on transport demand is presented. Conventional economics postulates that when prices drop individuals demand more of the commodity, but would this hold true in the case of transport demand? In a bid to control demand public transport providers may want to know if a price policy would have an impact on both or either the extensive and/or the intensive margin(s) of demand. Fare reductions in public transport is not the norm, but this research utilises a rare situation in public transportation to analyse the effect of a change in the fare structure for bus journeys in London on different demand measures using a regression discontinuity design. The research utilises data obtained from Transport for London following the implementation of a new bus price policy in September 2016, in which a follow-up journey made within the hour of first paying for a journey became free. Drawing on millions of individual paid and unpaid journeys, the effect of this price policy on the number of paid bus journeys, follow-up journeys and bus passenger numbers is estimated. The results suggest that the policy significantly increased the number of bus trips by 5% and follow-up journeys by 8%.

Passenger numbers increased by 4%. There is also clear evidence that the increase in demand was not only driven by new customers, but also by more intensive demand by existing customers.

Fares could be used to manage public transport demand, but fare manipulations have some effects on the generalised cost functions of both the public transport provider and users. Using fares to control demand impacts positively or negatively on both the transport provider and passengers depending on the direction of change, this thesis therefore proposes an alternative measure of managing transport demand. Social norm is presented as an alternative and a cost-effective measure of managing transport demand when enacted and implemented appropriately. It is widely accepted that norms are important in influencing human behaviour (Sherif, 1936; Cialdini *et al*., 1991; Merton, 1957; Coleman, 1990). Society and norms are ancient concepts, the rudiments of what constitutes a society have inter-generationally remained the same, but societal acceptability of norms and indeed values are temporally dynamic. For a norm to be considered as 'social' it must be acceptable to and shared by other members of the society (Elster, 1989). Using a statistical technique widely employed in econometrics, this thesis quantifies the effects of nudging passengers to behave in a certain way through the creation of a salient social norm. Transport for London (TfL) implemented in the second half of 2017 an experiment on one of its busiest metro train platforms. The platform surface was painted to highlight the exact location of the train doors once it comes to a full stop and to direct passengers to wait in parts of the platform that would not obstruct passengers from alighting from the train and leaving the platform. Using Difference-in-Differences method the thesis estimates the effects of this intervention on platform waiting and delay times, using different sets of assumptions about what the counterfactual change in waiting and delay times would have been in the absence of the intervention. The analyses suggest that the intervention has reduced train waiting times by up to 6.6% indicating the efficacy of using well implemented social norms to control transport demand. This reduction came about mainly through reducing delay times of trains once they are delayed. The reductions tend to occur during peak traffic hours. The implied cost-savings amount to a return of £6 per £1 investment.

1.2 Research Aims

The crux of this thesis is to analyse the response of transport demand to changes in transport fares, as well as propose an alternative, cost-effective and less intrusive measure of managing transport demand; no less than by empirical investigation. This has some important academic and policy implications. It presents researchers with a template to build on the effects on public transport demand when prices change, especially in the downward direction. Future research work on public transport price decreases could now benefit from this empirical study where actual prices decreased and the effects on demand articulated thereby reducing the reliance on real price decreases. It also has important policy implications for transport providers as they may need to estimate the effects of a proposed fare or revenue policy on the level of demand. Another important implication of this thesis is that public transport providers could adopt the findings and recommendations by sponsoring cheaper alternative ways of managing demand in the face of capacity constraint and increasing demand. In summary, the aims of this thesis are;

- To provide empirical evidence of the existence of asymmetry in the relationship between price and demand.
- To analyse the response of public transport to a nominal decrease in price. How does public transport respond to a salient decrease in price?

- And then to analyse the effectiveness of social norms as a cost effective and efficient alternative measure of managing public transport demand. Is the creation of a social norm effective in managing public transport demand?

This thesis sets out by initially analysing the presence of asymmetry in the response of demand to prices changes using transport demand data. Policy makers should be aware that demand might not respond equally to fare rises and reductions. The next step is to examine the efficacy of the price mechanism in controlling public transport demand by particularly looking at the response of public transport demand to a nominal decrease in fares, as fare rises is considered normal in public transportation. This is important for all the reasons highlighted above; no less than that the success of a price policy depends largely on how demand responds. This thesis finally presents and proposes a less intrusive alternative to price mechanism as a means of controlling demand, using empirical evidence. But first, a review of the extant literature is presented in chapter two.

CHAPTER 2

Literature Review

2.1 Prelude

This thesis is closely related to two strands of literature. Behavioural economics and the literature on social norms have analysed the effectiveness of relatively cheap and non-intrusive measures to affect behavioural changes resulting in socially desirable outcomes. In public transport a traveller is typically initially faced with the decision of whether or not to make a trip (trip generation or production), then they have to decide where to travel to (trip distribution), which is followed by the mode and route choice decision, all subject to a budget constraint of time and money costs, completing a fully priced typical Origin – Destination (O-D) matrix. Like other normal goods the demand for public transport is inversely related to fares normally included in the calculation of the generalised cost (Chen et al., 2011; Nunns and Denne, 2016; Rodrigue et al., 2016). Unlike normal goods public transport demand has the opposite relationship with income; the higher the personal income of a passenger and the lower the demand for public transport because people would rather drive than use public transport as personal income rises. Therefore any attempt at the inducement or curtailment of public transport demand must be geared towards the demand driving variables. These include service levels, socio economic factors, fares, quality of service, trip purpose, travel of travel, journey time, amongst others (Chen et al., 2011; Currie and Delbosc, 2011; Paulley et al., 2006a), with varying effects on an individual's demand function (see Nijkamp and Pepping, 1998; Bonnel and Chausse, 2000; Bresson et al., 2003; Canavan et al., 2018). Demand is frequently found to react differently to price increases than to price decreases; this is known as price asymmetry and is usually attributed to psychological factors.

2.2 Evidence of price asymmetry

Textbook models of consumer demand assume that consumers make decisions considering price levels. However, the observation of price stickiness in the downward direction suggests asymmetric consumer responses to positive and negative price changes. Marshall (1920) remarked that demand functions may be irreversible as demand does not necessarily revert to 'original' levels when prices reduce to previous levels. Price asymmetry has been tested for in the fields of economics, psychology and marketing (Bidwell et al., 1995; Farrell, 1952; Gately, 1992; Heidhues and Kőszegi, 2008; Kalyanaram and Winer, 1995; Mazumdar et al., 2005; Winer, 1986), as well as in agriculture and banking (see also: Chen et al., 2004; Hannan and Berger, 1991; Neumark and Sharpe, 1992; Panagiotou and Stavrakoudis, 2015; Pick et al., 1990; Ward, 1982).

One important reason for asymmetric price elasticities is the existence of a reference price. Consumers have memory and price expectations in that they can remember prices in the past (Kalyanaram and Winer, 1995; Muth, 1961) which then form their portfolio of reference prices; any increases or decreases in commodity prices would be compared to the reference prices which then results in a new demand function. Another reason is the existence of lags which enter into the price transmission process (Kitamura, 1990). Using household data from Great Britain, Cornelsen et al. (2018) show evidence of asymmetric consumer behaviour and loss aversion. Bonnet and Villas-Boas (2016) find that customers in the French coffee market react differently to positive and negative price changes; demand for coffee is less elastic to price increases than to price decreases. For Canada Noel (2009) concludes that gasoline prices tend to react more quickly to crude oil increase than to decreases. Borenstein et al. (1997) test and confirm that gasoline prices respond asymmetrically to increases and decreases in crude oil prices. Energy demand responds more quickly to price increases than to price decreases (Gately and Huntington, 2002).

In public transport, the only study that we are aware of that looks at the asymmetric response of transport demand to changes in price is by Chen et al. (2011). Utilising monthly commuter rail trip and fares data from New Jersey Transit from January 1996 to February 2009 for journeys to and from New York City, Chen et al. (2011) conclude that increases in gasoline prices lead to an increase in public transport demand, while decreases in gasoline prices do not lead to a significant decrease in transit demand. On the other hand, an increase in transit fares results in a reduction in demand while reduction in fare has no significant effect on demand. However, they consider real prices of transport, and price decreases occur only through inflation rather than a nominal reduction. Do commuters really respond to real price reductions which are very gradual and not salient in reality? The psychological reaction to a very gradual change in prices over an extended period would be very different to a sudden and discontinuous one. As such, reactions to a price increase and decrease are unlikely to be comparable. This thesis differs from any existing work on asymmetry because the data presents nominal reduction in fare prices which allows for a unique and rare empirical quantification of the response of demand to a reduction in public transport fares.

2.3 Effects of fare changes on public transport demand

The demand for public transport is a derived demand, which is generally driven by variables such as; service levels, socio economic factors, fares, quality of service, trip purpose, time of travel, journey time, income, amongst others (Chen et al., 2011; Currie and Delbosc, 2011; Paulley et al., 2006a), with varying effects on an individual's demand function (see Nijkamp and Pepping, 1998; Bonnel and Chausse, 2000; Bresson et al., 2003; Canavan et al., 2018). These variables however, should not be considered in isolation from each other as their effects on public demand functions can be complex and intertwined (Balcombe et al., 2004b; Paulley et al., 2006a). For instance, like other normal goods the demand for transport is inversely related to fares. Unlike other normal goods transport demand is assumed to have the opposite relationship with income; personal higher income is generally associated with increased mobility, leading to increase in the number of trips made by all modes of transportation (Dargay and Hanly, 2002; Goodwin et al., 2004). However, it is likely that higher incomes increase the possibility of owning a car and access to a car is assumed to result in decline in public transport trips. Therefore care must be taken in drawing such conclusions as there are many background factors that should enter into the income-demand function and the empirical evidence is not clear cut (Balcombe et al., 2004b; Holmgren, 2013). Furthermore evidence presented in Dargay and Hanly (2002) is in agreement regarding the long run negative sign of income elasticity, suggesting bus transport to be an inferior good.

This thesis concentrates on the effects of fare changes on public transport demand because the manipulation of fares is fundamental to the operation of public transport. The effects of a fare increase or decrease are usually measured in elasticities. As noted earlier, the response to a fare increase may not be equal and opposite to the response to a fare decrease. Fare elasticities are dynamic and may be affected by the magnitude of the fare change. They vary over time (peak or off peak), across journey purpose and periods (short, medium, or long runs), as well as across modes and locations (Dargay and Hanly, 2002; Paulley et al., 2006a). Monthly information on the different factors that influence public transport ridership, like fuel prices, unemployment rates, population and traditional bus fares, were used by Guzman et al., (2020) to estimate the effects of a nominal fare increase in Colombia's Bogotá. They find that the elasticity's absolute value decreases from -0.565 (1 week) to -0.408 after a month and that low-income users, as expected, are more sensitive to fare changes.

In estimating the response of transit demand to fare changes Nijkamp and Pepping (1998) compare 12 studies from 4 European countries (Finland, the Netherlands, Norway and the United Kingdom). They conclude that the range of elasticity values is quite wide, from as low as −0.15 in the UK study to as high as −0.8 in one of the studies for the Netherlands. Anciaes et al., (2019) show that manipulating price structures by reducing the complexity would lead to a substantial reduction in demand (11% to 45%, depending on route segment). By contrast, increasing complexity by adding new flexible or advance tickets (valid on the services immediately before or after the chosen service) would increase demand by anything from 4% to 15%. In the same vein Sharaby and Shiftan, (2012) use data from Israel's city of Haifa's new fare policy to evaluate travel behaviour. Haifa's new and integrated fare policy changed the historically complex per-boarding system to a simple five-zone fare system with free transfers, reducing fares for many passengers thereby making it very similar to London's Bus Hopper policy. They show a significant increase in single ticket sales of up to 25% over the first year following the launch of the reform, while the survey they carried out points to an increase of 7.7% in passenger trips and 18.6% in boarding numbers. It should be stated Haifa's public transportation system is 81% by bus; 17% by *sherut*, privately owned, fixed-route, communal transport services; and 2% by Israel rail, with a population of about 1million (Sharaby and Shiftan, 2012). Unlike London with multiple modes of transportation and a population that trumps Haifa's by a mile.

Variation in elasticity also depends on location. People who live in urbanised and high population density areas tend to rely more on public transport while those in low populated areas depend more on their cars and therefore have higher fare elasticities. The effects of fare changes on competing modes depend on the transport network integration; the greater the interchange ability the lower the fare elasticity. Aside from ticket fares other pricing methods such as congestion charges, parking charges and emission charges could also be implemented to encourage public transport ridership. Chen et al., (2011) use trip and fares data for travel between and New Jersey and New York to conclude that a rise in transit fares leads to a decrease in demand while a drop in fares has no significant effect on demand. We note that they consider only real prices from which they calculated price decreases using inflation index rather nominal or actual price changes.

Brechan (2017) performs an analysis of the results from 15 projects involving price reduction and 9 projects involving increased service frequency on some transit corridors in Norway. The results show that both price reduction and increased service frequency generated public transport demand, in particular, the average effect for the price reduction projects is reported to be 30%. Again, all the route and fare trials included in this meta-analysis took place in smaller cities (population<150,000), where the public transit system consists of almost exclusively buses, which probably accounts for the magnitude of the elasticity obtained. But our research differ from Brechan (2017) in that our data is set in London where passengers have a choice of alternative modes in a highly integrated transport system. The ease with which passengers could switch modes means that there are available substitutes which would have some effects on individual choice and behaviour, making our research significantly different. Prices are generally sticky in the downward direction and particularly so in public transport. Our data set is unique and presents an appropriate setting to explore the responses of demand to an actual decrease in price rather than an inflation indexed decrease used in most, if not all, existing literature.

2.4 Public transport demand elasticity: an overview

Elasticities are widely used in public transport delivery including the prediction of ridership and revenue effects of changes in any of the variables in the demand or supply functions (e.g., transit fares, service level, road tolls, parking fees, infrastructural changes.) The elasticity of demand for public transport to changes in fares varies among networks, but there is consensus in the literature on the direction of the effects (Balcombe et al., 2004a; Bresson et al., 2003a; Gordon and Willson, 1984; Holmgren, 2007; McLeod et al., 1991). In general the short run elasticity of transport demand to changes in fares range from -0.25 to -0.8 while the long run elasticities are normally much larger and differ between networks (Abrate et al., 2009; Dargay and Hanly, 2002; Paulley et al., 2006b). One rule of thumb states that for every 3% fare increase there is a corresponding reduction in transit ridership by 1% (Litman, 2017), but many other factors interplay in the fares-demand function. Matas (2004) examined the long-term impact of the introduction of a travel card scheme in a transport network using aggregate demand functions. The results conclude that passengers are highly responsive not just to fare changes but to other quality variables too, which is consistent with Balcombe et al. (2004). Paulley et al. (2006) report that bus-fare elasticities are around -0.4 in the short run and -1.0 in the long run. Gillen (1994) report that car owners have a greater elasticity (-0.41) than people who depend on public transport (-0.10), and work trips are less elastic than shopping or leisure trips. Lythgoe and Wardman (2002) find fare elasticities to depend on the direction of travel; elasticities were found to be lower for passengers travelling into the city than for those travelling outwards. Dunkerley et al. (2018) provide evidence on bus fare and journey time elasticities as well as recommendations on the values to be used in subsequent demand forecasting, appraisal and policymaking. There are reported differences between rail and bus elasticities depending on the method used. Rail transit fare elasticities tend to be relatively low in more advanced cities, probably a function of city transport priorities and policies, level of transport, environmental integration, as well as average income. Canavan et al. (2018) find negative fare elasticities in the range of -0.25 and -0.4 in the long run for miles travelled and number of trips, while the long run income elasticity is found to be positive for both miles travelled and number of trips. On the other hand, positive long run elasticities between 0.47 and 0.56 are reported for both passenger kilometres and passenger journey models. It should be stated that the study only used a proxy for metro fares estimated through dividing annual revenue from fares by the annual number of passengers, not nominal fare increases or decreases.

2.5 Hard and soft means of managing platform demand

If the final outcome of a change in price on public transport demand is dependent on both economic and psychological factors, it then presents the case for investigating other cheaper and non-intrusive measures of effecting a desired change in demand through influencing a change in human behaviour. These measures include interventions such as communication campaigns, pricing and other techniques that support and encourage behavioural change in a certain direction (Brög *et al*., 2009; Cairns *et al*., 2008; Taylor, 2007; Avineri and Goodwin, 2010; Bamberg *et al*., 2011). Managing congestion and capacity through the control of train platform dwell time is now receiving increased attention among researchers and operators (Avineri, 2011). Platform dwell time is an important variable that changes service level and reliability, so its extension or inconsistency can be detrimental to a network's capacity and ability to provide reliable service (Thoreau et al., 2016; Barron, 2016). It is the time a train remains on the platform while boarding and alighting takes place safely, this could be influenced or enhanced through hard and, or soft measures.

Hard measures represent heavy investments which include capital expenditure on structural adjustments like platform expansion, installation of platform edge doors (PEDs), station restructuring, line re-signalling and procurement of new rolling stock. Given train and platform infrastructure, the amount of boarding and alighting passengers, and in-train occupancy have been shown to explain 70% or more of dwell time variation (Lin and Wilson, 1992; Puong, 2000; Rashidi, Ranjitkar, and Hadas, 2014). Examining passenger movement in a laboratory setting, Fujiyama *et al*. (2014) find that adjusting train width and platform step height improved boarding and alighting. This hard measure is a useful consideration in the construction of new metro stations or procurement of new rolling stock but would be a very expensive investment for an existing network to retrofit platforms or adjust train doors. Karekla and Tyler (2012) analysed the Victoria line in London to determine the possibility of reducing dwell time by making specific changes to train system hardware which entails both trains and platform. Using data from London Underground and on-site observation they conclude that adjusting the width of train doors and platform step height are most effective in reducing dwell time, like the conclusion arrived at by Thoreau *et al*. (2016). Again, this is an expensive hard measure especially for an existing network. It would cost London Underground approximately £1.5m per platform to adjust the height (Karekla and Tyler, 2012).

Turning to soft measures, these can be very cost effective and as efficient in controlling dwell time. These measures include non-intrusive interventions such as communication campaigns, pricing and other techniques that support and encourage behavioural change in a certain direction. (Brög *et al*., 2009; Cairns *et al*., 2008; Taylor, 2007; Avineri and Goodwin, 2010; Bamberg *et al*., 2011). Pricing to control demand and therefore platform dwell time is effective (Douglas *et al*., 2011; Liu and Charles, 2013; Currie and Delbosc, 2011; Qu *et al*., 2018). But it comes at a cost to the transport consumer, and it may encourage modal switch to less energy efficient modes. Increasing or decreasing the level of service provision (supply of transport) is a major variable in managing platform dwell time. Subject to line or network capacity, running more or less service helps in managing demand and dwell time in high frequency networks.

Platform communication systems can also encourage passengers to pass along platforms to get on less crowded carriages of an arriving train (Olaverri-Monreal *et al*. 2018; Moncrieff, 2015), but can become counter intuitive as they may encourage ‘bunching up’ of passengers around the doors of the supposedly emptier carriage. In a field experiment carried out at Schiphol Airport station in Amsterdam, van den Heuvel (2016) finds that adjusting train stopping positions decreased dwell time by 30 seconds during the peak, however Oliveira *et al*. (2019) opine that the method does not help with crowd control and is only effective in facilitating the boarding of less busy train carriages.

Another major variable in the dwell time management equation is passenger behaviour (Oliveira *et al*., 2019; Barron, 2016; De Ana Rodriguez et al., 2016; Harris, 2006; Wiggenraad, 2001). It is widely accepted that norms are important in influencing human behavior (Sherif, 1936; Cialdini *et al*., 1991; Merton, 1957; Coleman, 1990). Norms can be private or social. For a norm to be considered "social", it must be acceptable to and shared by the other members of the society. Its sustainability is a function of both the approval and disapproval of the members of the society (Elster, 1989). The distinguishing feature of a social norm is that it does not benefit any one individual but (parts of) society, and the punishment for non-conformity cannot be enforced legally but through social sanctions imposed by others. Private norms on the other hand result in self-imposed sanctions by individuals such as the feelings of embarrassment, shame, and guilt when they do not conform (Sugden, 1987; Elster, 1988 & 1989; Coleman, 1990; Young, 2008; Garnett, 2009). Both private or personal and social norms influence how passengers behave in public spaces. It has been argued that social norms yield pareto-efficient scenarios (Coleman, 1990; Ullman-Margalit, 1977) and are quite efficient and effective in the equitable regulation of social welfare (Akerlof, 1976; Bicchieri et al., 2018; Nolan, 2015). In a situation where a norm leads to a pareto-inefficient situation it is expected to disappear with time. This is the case with most, if not all gender, race, or sexual orientation bias norms (Bicchieri *et al.*, 2018).

Perhaps the closest interventions to the Transport for London experiment are platform communications and markings encouraging passengers to pass along the platform or not to hold train doors. Seriani and Fernandez (2015) evaluate some interventions, including a keep-out zone on platforms. While simulation results suggest a potential to reduce dwell times by 50%, their laboratory experiments found no effect of the keep-out zone, most likely due to observed non-compliance by passengers waiting on the platform. This thesis is thus one of the few which seeks to analyse the implementation of such soft interventions and its impact on dwell times. To the best of our knowledge it is the only one which does so in a real-world setting rather than in computer simulations or laboratory experiments.

CHAPTER 3

Is the Price Elasticity of Demand Asymmetric? Evidence from Public Transport Demand*

Firat Yaman[1], Kingsley Offiaeli[2]

3.1 Prelude

As noted earlier, the demand for many products is frequently found to react differently in magnitude to price increases than it does for price decreases, as well as the importance of this phenomenon to public transport policy makers. This finding is often rationalised in terms of loss aversion as customers may perceive a price increase as a loss and a price decrease as a gain. If customers are loss averse as explained in Kahneman and Tversky (1979), then they will react more strongly to a price increase than they do to an equivalent price decrease. An alternative explanation is the lag in information dissemination or diffusion. Price changes might be immediately known to frequent buyers but not to those who do not buy a good but would buy it if they had knowledge of the new price. Therefore, the response of demand can depend on the timely dissemination of the appropriate information (Cason, 1994).

The literature on asymmetric price elasticities faces several obstacles in identifying, let alone interpreting, these elasticities. Studies based on demand for goods (e.g., sold in supermarkets) cannot distinguish between the purchase and the consumption of a good. Suppose customers buy more of a good when it is under price promotion and stock it. After the promotion ends demand does not revert to its initial level since customers have stocked up on it. This appears as an asymmetric response, but consumption of the good might not be affected at all. Since

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services cannot be stocked demand for services is not subject to such a misinterpretation due to storing and stockage. Furthermore, price changes occur rarely in isolation and are often disguised as or bundled with other promotions such as bundling of goods, or offering a free product ("buy 1, get 2", see Ahmetoglu et al. (2014)). Finally, it is not clear whether the past price of the good in question serves as the reference price. Indeed, the literature has also considered a competitor's price (Hardie et al., 1993), a price index (Dossche et al., 2010), or a 'usual' price (Ahrens et al., 2017) as reference price and found support for asymmetric responses for all of those.

Transport offers more compelling reasons to be analysed when looking for asymmetries in price elasticities. The purchase of many services can be delayed. Think of a haircut. A person might have an optimal point of time to have their hair cut but might be willing to prepone or postpone to take advantage of a promotion. They will, however, need to get a haircut eventually. These considerations again confound an accurate quantification of how sensitive demand really is to prices. Public transport offers a promising laboratory to study the relationship between demand and prices for those reasons: it is almost always consumed at the point of purchase, and it leaves very little to no room to be postponed due to price considerations. On the London Underground there are no price promotions, and since transport is rarely consumed for its own sake, the choice is rarely about whether to travel or not, but rather by which mode and perhaps what time of the day.[1] For the same reason we do not need to take into account phenomena such as brand loyalty and related reactions (e.g., a feeling of 'betrayal' when prices increase). Transport for London is a public monopoly and as such there is no competitor and there are no sales campaigns comparable to the marketing of a for-profit good. Any demand reactions to fare changes are therefore very likely to be pure price effects.

[1] Passengers can choose to travel during off-peak hours and pay a lower fare.

Transport is a key sector to any economy and as such of interest per se. The movements of goods and people are essential to the workings of an economy. The demand for transport thus grows with increasing population, employment, and trade. Transport will also play a key role in the global effort to combat climate change. Transport authorities in many economies now pledge and indeed implement policies to encourage the use of public transport wherever possible, as well as encourage private modes powered by renewable energy. Many transport users make their mode and route choice based on several factors, but perhaps most importantly based on their costs (Takahashi, 2017). It is therefore vital for policy makers and public transport authorities to understand how their price policies affect demand and the choice of travel mode.

A seldom opportunity is exploited in which the demand for public transport is observed both after nominal price increases – which are frequently observed – and an episode of nominal price decreases – a very rare occurrence. In 2016 Transport for London (TfL) decreased the fares of some journey types by rezoning the area which resulted in passengers paying actual cheaper nominal fares. This chapter is unique apart in that we estimate and analyse the asymmetry in the response of demand to changes in nominal fares using data from actual fare reductions from the world's oldest metro. Our identification relies on estimating how price elasticities have changed for journeys which were affected by this rezoning, compared to how they have changed for journeys which were not affected.

The results suggest that demand both in terms of journeys and passengers reacts asymmetrically between fare increases and fare decreases. The estimates of the difference between price-increase and price-decrease elasticities range from 0.18 to 1.00 percentage points. Further light could be shed on the underlying reasons for these asymmetries by looking at different measures of demand (journeys, passengers, and frequent passengers).

While not conclusive, the results suggest that at least some of this asymmetry is attributable to loss aversion.

3.2 Background and institutional features

London Underground is the oldest network in the world. The network consists of 17 different lines connecting 270 stations and extends to 250 miles of track making it the 7th largest (in served passengers) and 3rd longest (in kilometres of track) network in the world. In 2017 the network served about 4 million passenger journeys per day (Offiaeli and Yaman, 2021).

The network is managed and operated by Transport for London which revises their fares at the beginning of a year. It is divided into different zones, with zone 1 being the most central, and zone 9 the outermost zone. Most stations on the network fall into exactly one of the zones, but some stations fall on the boundary between two zones. The fare that a customer pays depends on the zones of the origin and the destination, the time of travel, and on several other features such as group travel and discounts. If the origin and/or destination station is a boundary zone, then the cheapest fare is applied to the customer. For example, a journey from a station on the boundary between zones 2 and 3 to a station in zone 1 will be treated as a journey between zones 1 and 2 rather than a journey between zones 1 and 3, as the former is cheaper. This is an important feature for our identification of asymmetries in price elasticities.

TfL typically revises their fares at the beginning of the year. All fares increased by £0.10 on January 2nd, 2015. In the following year, the full peak fare for travel from a zone 1 station to a zone 1 or zone 2 station (and vice versa) increased from £2.30 to £2.40. At the same time, seven stations in East London were rezoned. These stations had previously been in zone 3 but became boundary stations (zone 2/3) after the rezoning, effectively reducing the travel fare between them and a zone 1 station from £3.30 to £2.90. Figure 3.1 illustrates the re-zoning and lists the re-zoned stations. In November 2016, the decision was taken to freeze fares on the London Underground for the next four years.

Figure 3.1: Stations and zones before and after the rezoning [1]

The most common form of payment is pay as you go (PAYG). TfL issues their own PAYG travelcard (Oyster) which accounted for 85% of all bus and rail journeys within London in

[1] Before rezoning in 2016, stations under Rezoned were in zone 3 (upper panel). After rezoning, they became boundary stations on the boundary between zones 2 and 3 (lower panel). Adjacent stations are stations which directly connect to one of the rezoned stations.

2013 (TfL, 2014). PAYG has been extended to contactless payment by bank card and mobile devices in 2014, and contactless payment has accounted for 40% of all PAYG payments in 2017. For both Oyster and contactless payments, the fare is automatically calculated based on the stations where the passenger enters and exits, and daily caps are automatically applied.

3.3 The Data

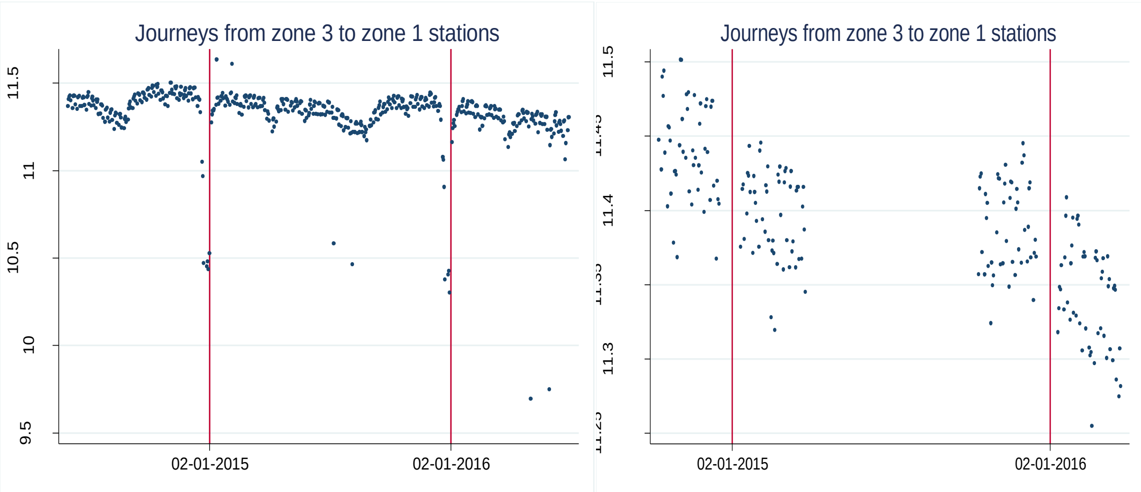
The data are from TfL's ODX database which records information on origin, destination, time, and payment information of each journey undertaken on the TfL network since mid-2014. TfL kindly consented to extract the number of peak period journeys and passengers (more on this below) distinguished by origin station, destination station, and day.[1] We only consider pay-as-you-go journeys. We aggregate origin and destination stations to fall under one of the following categories: Zone 1, zone 2, zone 3, zone 4, boundary zone 2/3, boundary zone 3/4, and stations which were rezoned in 2016. Finally, we also identify stations which are adjacent to the rezoned stations both in the inbound direction (A2) as well as in the outbound direction (A3), resulting in nine categories. We refer to any combination of distinct origin and destination categories as a journey *type*. Our data thus has 81 journey types. We consider only journeys made during peak hours which were subject to the full fare (without discounts).

To illustrate, the left part of figure 3.2 displays the natural log of journeys undertaken from zone 3 to zone 1 stations during peak times and subject to the full fare from June 2014 to July 2016. The figure displays some regularities. Most data points fall into the band between 11 and 12, or 60,000 and 160,000 journeys. Demand drops both before the Christmas period and during school holidays and picks up again shortly after New Year's Day and in late summer.

[1] We are indebted to Graeme Fairnie and Vasiliki Bampi, both TfL, for their help and patience.

There are also occasional outliers, mostly in the downward direction, which are typically driven by problems on the network, industrial action, or other events.

Figure 3.2: Log of daily demand during peak times and at full fare from zone 3 to zone 1. Left: all observations. Right: after removing troughs and outliers.



A distinction between a journey, which is any trip undertaken on the Underground, is made from passengers. A passenger might engage more than once on a journey type on the same day. In that case we would register only one passenger, but several journeys for this journey type. It should be noted that only separate payments sources are identified (the card from which payment was taken) rather than passengers per se, so that passenger numbers will be measured with some error (e.g., two people using the same debit card to travel, or the same person using two separate cards to travel, on the same day).

As fare changes become effective on the 2nd of January of each year, our identification of price elasticities will be driven by changes in demand which occur between years, in a local time window around the first day that a new fare schedule becomes effective. We first drop demand observations which fall between the 20th of December and the 9th of January. We also eliminate observations which fall into the school holiday season by keeping only observations which are up to 85 days away from the 2nd of January in either direction. We refer to such an 85-day period on either side of the New Year as a *period* (e.g., the 85 days before the 2.1.2015 are period 1, the 85 days after the 2.1.2015 are period 2, etc.). Finally, we eliminate any remaining outliers by dropping those demand observations which are more than two standard deviations away from their cell average, where cells are defined by period, and journey type. The data after applying all those filters can be seen on the right part of figure 2.

We complement the TfL data with weekly petrol price information (price paid at pump station) from the UK Department for Business, Energy, and Industrial Strategy.

3.4 Model specification and estimation

This research work looks at three different measures of demand: Journeys, passengers, and frequent passengers. *Journeys* of a journey type are the number of journeys made for that journey type during peak hours during a day (week). *Passengers* of a journey type are distinct passengers who make a journey of this journey type during peak hours during a day (week). *Frequent passengers* for a journey type are distinct passengers who travel at least 10 times both during the period before and after the fare changes. We also look at two different time aggregates: daily, and weekly. For example, weekly passenger data between zone 1 and zone 3 would be the number of distinct passengers who travelled between these two zones during a week. Using the above samples will allow us to differentiate between the intensive and extensive margins of demand changes, and therefore inform on the underlying reasons for asymmetric price elasticities. As we show below, journey demand reacts more strongly to price increases than price decreases. A behavioural explanation would be the presence of loss aversion provided that loss aversion at an individual level translates to loss aversion in aggregate demand. Customers perceive a strong loss of value when fares increase and reduce their demand. The value gain experienced by a fare decrease is not as strong as the corresponding loss and therefore demand does not increase as much. This is the *loss aversion hypothesis*.

An alternative explanation is that while fare increases are common knowledge among all who use public transport, fare decreases might not be known by some who do not use public transport but would use it if they had knowledge of the actual fares. This effect might even be more important in our case, as fare decreases come about through a re-zoning of certain stations, and the fare implications might not be immediately clear to some potential passengers. This is the *asymmetric information hypothesis*.

A third possibility might be that the travel mode choice set might change after a fare increase, e.g., someone might buy a car, and even if fares revert to their initial level, the person might not find it worthwhile to use public transport. However, this argument cuts both ways, and seems unlikely to be an important determinant of short-run demand for public transport. The frequent passenger sample eliminates the asymmetric information channel. Since the sample only contains passengers who travelled at least 10 times both under the old and the new fare regime, we assume that these passengers were fully aware of the fares. Any change in demand among this sample is thus on the intensive margin, and we attribute asymmetric responses to price changes to loss aversion. As a test of loss aversion, this is our preferred sample. Distinguishing between journeys and passengers also informs about the margin of adjustment and underlying reasons for asymmetry, though perhaps not as cleanly as the frequent passenger sample. Suppose the demand in terms of journeys (*D*), passengers (*N*), and average number of journeys per passenger (*d*), is given by:

$$\ln D_{jt} = \alpha_D + \beta_D \ln P_{jt}$$

$$\ln N_{jt} = \alpha_N + \beta_N \ln P_{jt}$$

$$\ln d_{jt} = \alpha_d + \beta_d \ln P_{jt}$$

Where P is the fare, and the subscripts denote journey type j and time t. Since $D_{jt} = N_{jt} d_{jt}$, the demand elasticity in terms of journeys could be decomposed as: $\beta_D = \beta_N + \beta_d$

If the number of passengers is fully inelastic ($\beta_N = 0$), then all adjustment must happen on the intensive margin, and the information asymmetry channel can be ruled out as all passengers would be exposed to the fares before and after fare revision. If, however, journey elasticity can be fully explained by the passenger elasticity, then all the adjustment happens on the extensive margin, and we cannot know to which extent the loss aversion and information asymmetry factors contribute.

The analysis based on daily demand is complemented by an analysis based on weekly demand, as daily data can lead to misleading classifications of journeys and passengers. Consider the example in figure 3.3. Both persons A and B travel every day before the fare increase. The daily data thus counts two journeys, and two passengers, every day. After the fare increase, A travels on odd, and B on even days of the week, and the daily journey data counts one journey, and one passenger every day. It seems that the entire adjustment happened at the extensive margin. But this is not true when we consider the whole week, where we still see two passengers, and half as many journeys as before. The latter scenario reflects more closely what we understand to be the intensive and extensive margins of demand. Weekly data reduces our sample by 80% compared to daily data.

Figure 3.3: A two person daily/weekly travel pattern sample

Time	**Person**	Monday	Tuesday	Wednesday	Thursday	Friday
Before fare change	A	×	×	×	×	×
	B	×	×	×	×	×
After fare change	A	×		×		×
	B		×		×	

Note: Both persons A and B travel every day before the fare change but travel on alternating days after the fare change. For daily data we observe a 50% drop of journeys and of distinct passengers. For weekly data we observe a 50% drop of journeys, but no drop in distinct passengers.

Thus, the empirical model accounts for demand specific to journey types, a quadratic time trend to capture global demand trends, a discontinuous change in demand on the 2^{nd} of

January, and petrol prices. For this analysis the most general specification also allows for price elasticities specific to journeys between zone 1 and rezoned stations, and for demand to be auto-regressive of order 1:

$$ln(Y)_{it} = \alpha_i + \beta_1 t + \beta_2 t^2 + \gamma_1 D_t(t > January\ 2^{nd}) + \gamma_2 ln(petrol)_{it}$$

$$+ \delta_1 ln(fare)_{it} + \delta_2 D_i(Rezone) \times ln(fare)_{it} + \kappa ln(Y)_{i,t-1} + u_{it} \qquad (3.1)$$

The subscript i refers to journey type, and t to time. Observations are daily or weekly. Y is demand, $D_t(t > January\ 2^{nd})$ is 1 if t is after January 2nd, and 0 else. $D_i(Rezone)$ is 1 if the journey type is between zone 1 and a rezoned station. The dummy variable D_t captures any effects which relate to the beginning of a new year (e.g., return to work, general fare increases, etc.). The coefficient δ_1 is the elasticity for journey types other than between zone 1 and rezoned stations, while D_i is a dummy that assumes the value of 1 if the station is a rezoned station and zero otherwise.

Finally, *petrol* is the price of petrol at the beginning of the week, and *fare* is the fare in pounds. The main parameters of interest are δ_1 and δ_2. Long term elasticities are calculated as $\delta/(1-\kappa)$. Our estimates for κ range from 0.14 to 0.28, providing strong evidence against a unit root. Long-term elasticities are thus higher than short-term elasticities by 16% to 39%. The model does not contain cross-price elasticities as these cannot all be identified in a model with year fixed effects, considerably complicating the interpretation of coefficients.[1] However, any price effects that are common to all journey types will be absorbed by the dummy for the new year $D_t(t > January\ 2^{nd})$. The fare increases in 2015 increased fares for all journey types, so that substituting between journey types due to new fares would be very unlikely. For the fare changes in 2016, we complement our main analysis by looking at

[1] Let there be j = 1,…,J journey types, and t = 1,2 years. Let p_{jt} be the price of journey type j in year t, and $D_{t=2}$ a dummy variable equal to 1 if t = 2. Then the price of journey type 1 in any year can be written as $p_{1t} = \left(\sum_{j=1}^{J} p_{j1}\right) - \left(\sum_{j=2}^{J} p_{jt}\right) + D_{t=2}\left(\sum_{j=1}^{J} \Delta p_j\right)$, that is, p_{1t} is a linear combination of a constant, the prices of other journeys, and a dummy for year 2 multiplied by a factor.

whether demand for journey types which had their fares changed crowded out (in) demand for other journey types.

Since an observation is a record of (the log of) how many journeys were undertaken for a certain journey type, observations are weighted by the average demand for the journey type over the sample period, so that more frequent journey types receive a higher weight in the estimation. Standard errors are clustered by journey type – period combinations.[1] For comparison purposes we also estimate our model under the restrictions $\delta_2 = 0$ and $\kappa = 0$.

3.5 Results and analyses

Table 3.1 reports estimated journey price elasticities for our entire sample of journey types (elasticity is denoted by ε). Model 1 does not allow for asymmetry ($\delta_2 = 0$) and does not differentiate between short and long-run elasticity ($\kappa = 0$), the second model freely estimates δ_2, the third model freely estimates κ and the fourth model places no restriction on either of those coefficients. We estimate these elasticities separately for periods 1 and 2 (2014/15, left), and for periods 3 and 4 (2015/16, right). The short-term elasticities in models (1) and (3) in 2014/15 are not significantly different from 0, suggesting very inelastic price elasticities of journey demand. If we allow for journeys between zone 1 and stations which were rezoned in 2016 to have a different elasticity (models (2) and (4)), then our results suggest that these journey types exhibit a stronger response to fare changes than the remaining journey types. Petrol prices are found to have a positive effect on public transport demand. This result is robust throughout all our estimations. We focus our discussion on the short-run elasticities, as these are better identified by the changes in demand around the time of the fare changes and generally show the same asymmetry features as long-run elasticities.

[1] We also considered Newey-West standard errors, but this did not generally change the inference. Significance levels for results in table 3 were reduced.

Table 3.1: Price elasticities trips - full sample

Year	2014/15				2015/16			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Short term ε	-0.13		-0.08		-0.71***		-0.55***	
	(0.20)		(0.14)		(0.07)		(0.07)	
Short term ε - not rezoned		-0.15		-0.10		-0.87***		-0.68***
		(0.20)		(0.14)		(0.06)		(0.07)
Short term ε - rezoned		-0.74**		-0.54**		-0.57***		-0.43***
		(0.35)		(0.27)		(0.08)		(0.06)
Long term ε			-0.11				-0.72***	
			(0.19)				(0.07)	
Long term ε - not rezoned				-0.13				-0.90***
				(0.19)				(0.07)
Long term ε - rezoned				-0.75**				-0.57***
				(0.36)				(0.08)
Petrol price ε	0.68***	0.68***	0.52***	0.53***	1.04***	1.04***	0.75**	0.76**
	(0.20)	(0.20)	(0.18)	(0.18)	(0.36)	(0.36)	(0.31)	(0.34)
Separate elasticity rezoned stations	no	yes	no	yes	no	yes	no	yes
Includes lagged demand	no	no	yes	yes	no	no	yes	yes
Number of observations	8,163	8,163	8,082	8,082	7,981	7,981	7,900	7,900

Note: Results are price elasticities of demand. Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

In 2015/16 rezoning became effective and fares for journeys between rezoned and zone 1 stations dropped by 12%. Demand for journey types not affected by re-zoning became more elastic (from -0.15 in 2014/15 to -0.87 in 2015/16), while demand for journeys affected by re-zoning (which saw fare decreases in 2015/16) became less elastic (from -0.74 in 2014/15 to -0.57 in 2015/16). The difference in these elasticity changes between rezoned and non-rezoned journey types is 0.89 and significant at 1% (see also table 3.3).

Does this suggest that price-elasticities are asymmetric? There are two challenges to this interpretation. First, only two journey types actually saw their fares increase in 2015/16, while all journey types became more expensive in 2014/15. Thus, the change in elasticity for journeys not affected by re-zoning is driven by sample selection (in terms of journey types) more than a genuine change in elasticities. Second, the observations who use journey types which involve fare decreases are not comparable to the remaining observations, in particular, their price elasticities are different. We address the first point below by looking only at the sub-sample of journey types which saw their fares change in either direction in 2015/16. The second objection is corroborated by the different elasticities between these journey types within a year (e.g., -0.15 for non-rezoned, and -0.74 for rezoned journey types within the same period 2014/15). But to say that the *difference* between price elasticity changes is driven by population differences would require a stronger, and less plausible, argument that the *change* in price elasticities between these two populations, all else equal, must be different. This is perhaps the case, and we cannot disprove it. We therefore progress on the *assumption* that price elasticities would have changed in the same direction and by the same magnitude if prices for journeys affected by rezoning had changed by the same percentage as journeys not affected by rezoning, making our estimate of price elasticity asymmetries effectively a difference-in-differences estimator.

It is possible that demand for journey types whose fares did not change in 2016 are inelastic relative to demand for journey types involving rezoned stations, while demand for journeys whose fares increased in 2016 are more elastic – regardless the direction of the price change. This would explain why elasticity estimates increased for journey types not affected by rezoning. To see if this is the case, we repeat our estimations restricting our sample to only those journeys which see a change in fares in 2016. The results can be seen in table 3.2. The price elasticities for this smaller sample are much larger than for the full sample in 2014/15, but we still observe that demand for journeys involving rezoned stations is more elastic.

Table 3.2: Price elasticities trips - small sample

Year	2014/15				2015/16			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Short term ε	-1.84***		-1.49***		-0.66***		-0.52***	
	(0.46)		(0.38)		(0.05)		(0.05)	
Short term ε - not rezoned		-2.10***		-1.71***		-0.71***		-0.56***
		(0.54)		(0.44)		(0.11)		(0.11)
Short term ε - rezoned		-2.79***		-2.31***		-0.62***		-0.49***
		(0.80)		(0.65)		(0.09)		(0.07)
Long term ε			-1.76***				-0.67***	
			(0.44)				(0.06)	
Long term ε - not rezoned				-2.02***				-0.72***
				(0.51)				(0.13)
Long term ε - rezoned				-2.72***				-0.63***
				(0.75)				(0.09)
Petrol price ε	0.58	0.58	0.54	0.54	1.20	1.20	0.95	0.95
	(0.42)	(0.42)	(0.40)	(0.40)	(0.69)	(0.69)	(0.60)	(0.60)
Separate elasticity rezoned stations	no	yes	no	yes	no	yes	no	yes
Includes lagged demand	no	no	yes	yes	no	no	yes	yes
Number of observations	911	911	902	902	898	898	889	889

Note: Results are price elasticities of demand. Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

However, in 2016 demand for the same journeys is less elastic than demand for journeys which have seen fare increases (the difference between the two elasticities is significant at the 5% level in both years). The difference in the elasticity changes is 0.78 which is in the ballpark of the 0.89 estimated for the complete sample.

Table 3.3 reports results of estimated price elasticities in a model with asymmetric price elasticities, and $\kappa = 0$ (no separate long-run elasticity) based on daily data. For journeys (left panel), we have discussed the results above: the elasticity for journeys affected by re-zoning become less elastic (as the elasticities are negative) compared to journeys not affected by re-zoning by 0.89 percentage points. This holds both for the full and the small sample of journey types. For passengers, we observe that for the full sample the elasticity for journey types involving fare increases changes from -0.47 to -0.60 (demand becomes more elastic, though not significantly so).

Table 3.3: Price elasticities with daily data

	Journeys			Passengers			Frequent passengers		
	2014/15	2015/16	Difference	2014/15	2015/16	Difference	2014/15	2015/16	Difference
Full sample									
Short term ε - not rezoned	-0.15	-0.87***	0.72***	0.12	-0.81***	0.93***	-0.16	-0.13***	-0.03
	(0.20)	(0.06)	(0.21)	(0.23)	(0.06)	(0.24)	(0.18)	(0.05)	(0.19)
Short term ε - rezoned	-0.74**	-0.57***	-0.17	-0.47	-0.60***	0.13	-0.75*	-0.54***	-0.20
	(0.35)	(0.08)	(0.36)	(0.43)	(0.02)	(0.43)	(0.42)	(0.02)	(0.42)
Difference	0.59**	-0.30***	0.89***	0.59**	-0.21**	0.79***	-0.59*	-0.41***	-0.18
	(0.23)	(0.12)	(0.25)	(0.28)	(0.08)	(0.29)	(0.33)	(0.06)	(0.34)
Number of observations	8,163	7,981		8,121	8,195		8,263	8,203	
Small sample									
Short term ε - not rezoned	-2.10***	-0.71***	-1.39***	-2.14***	-0.68***	-1.46**	-2.90***	-0.14*	2.76***
	(0.53)	(0.11)	(0.54)	(0.69)	(0.11)	(0.69)	(0.76)	(0.08)	(0.75)
Short term ε - rezoned	-2.79***	-0.62***	-2.17***	-2.80**	-0.64***	-2.16**	-3.82***	-0.54***	3.28***
	(0.78)	(0.09)	(0.79)	(1.02)	(0.04)	(1.01)	(1.14)	(0.03)	(1.12)
Difference	0.69**	-0.09	0.78**	0.66*	-0.04	0.70*	-0.92**	-0.40***	0.52
	(0.29)	(0.17)	(0.33)	(0.37)	(0.15)	(0.40)	(0.45)	(0.10)	(0.46)
Number of observations	911	902		912	903		936	919	

Note: Results are price elasticities of demand and their differences over time and between stations which were and were not rezoned. Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%. The number of observations varies between Journeys, Passengers, and Frequent passengers because the trimming of outliers (see Data section) does not affect the exact same observations across the three demand measures.

At the same time, passenger demand for other journey types sees a significant increase in its elasticity, from 0.12 to -0.81, resulting in a significant difference in differences of 0.79 (0.70 in the smaller sample). The implied difference in differences estimates for journeys per passenger (the intensive margin) are 0.11 in the full, and 0.20 in the small sample. As most of the elasticity changes are driven on the extensive margin, we cannot say whether the observed asymmetries are better explained by loss aversion or information asymmetry. If we only look at frequent passengers, we also find a positive difference between elasticity changes (0.18 for the full, 0.52 for the small sample) but they are not significantly different from zero.

We report results for weekly data in table 3.4. Journey demand appears to have become more elastic for both journey types which were and were not affected by rezoning in the full sample (from 0.14 to -0.64 and from -0.35 to -0.64 respectively). However, the estimates from the small sample suggest that elasticities have decreased (from -1.5 to -0.58 and from -1.89 to -0.66). In either case, the resulting difference in elasticity changes is estimated as 0.49 for the full, and 0.31 for the small sample, but their standard errors are too large to infer that journey demand exhibits an asymmetry in price elasticities.

Table 3.4: Price elasticities with weekly data

	Journeys			Passengers			Regular passengers		
	2014/15	2015/16	Difference	2014/15	2015/16	Difference	2014/15	2015/16	Difference
Full sample									
Short term ε - not rezoned	-0.14	-0.64***	0.5***	0.57***	-0.64***	1.21***	0.23**	-0.18***	0.41***
	(0.22)	(0.07)	(0.23)	(0.13)	(0.05)	(0.14)	(0.11)	(0.02)	(0.11)
Short term ε - rezoned	-0.35	-0.64***	0.29	0.09	-0.17***	0.25	-0.49***	-0.19***	-0.30
	(0.37)	(0.06)	(0.37)	(0.27)	(0.02)	(0.27)	(0.27)	(0.01)	(0.27)
Difference	0.21**	0	0.21**	-0.49***	-0.47***	0.96***	0.72***	0.01	0.71***
	(0.24)	(0.10)	(0.26)	(0.19)	(0.07)	(0.20)	(0.23)	(0.03)	(0.23)
Number of observations	1,532	1,493		1,563	1,556		1,611	1,596	
Small sample									
Short term ε - not rezoned	-1.50***	-0.58***	-0.92**	-0.44	-0.54***	0.09	-2.21***	-0.17***	-2.04***
	(0.40)	(0.13)	(0.42)	(0.34)	(0.07)	(0.35)	(0.29)	(0.04)	(0.29)
Short term ε - rezoned	-1.89***	-0.66***	-1.23*	-0.95*	-0.20***	0.75	-3.23***	-0.19***	-3.04***
	(0.77)	(0.07)	(0.61)	(0.53)	(0.03)	(0.53)	(0.47)	(0.01)	(0.47)
Difference	0.39	0.08	0.31	0.51**	-0.33***	0.84***	1.02**	0.02	1.00***
	(0.29)	(0.19)	(0.33)	(0.23)	(0.10)	(0.25)	(0.25)	(0.05)	(0.26)
Number of observations	171	164		175	173		179	178	

Note: Results are price elasticities of demand and their differences over time and between stations which were and were not rezoned. Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%. The number of observations varies between Journeys, Passengers, and Frequent passengers because the trimming of outliers (see Data section) does not affect the exact same observations across the three demand measures.

For passengers, we do observe statistically significant differences, and the asymmetry is close to one percentage point (0.96 and 0.84). This would imply that the elasticity for journeys per passenger has increased *more* for journey types affected by rezoning than the elasticity for other journey types.[1] For frequent passengers we observe similar magnitudes as for

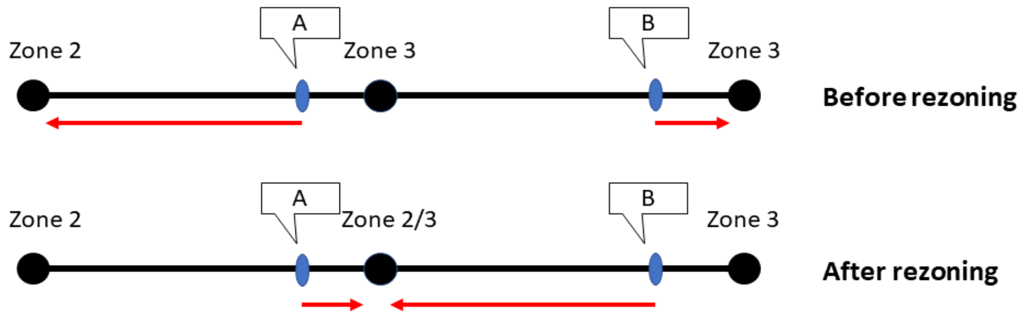
[1] Note that the elasticity for journeys per passenger is inferred according to the equations 1) to 3) rather than estimated.

passengers, with implied price elasticity asymmetries of 0.71 percentage points for the full and 1.00 percentage point for the small sample. This last result is perhaps the most convincing evidence to suggest that there is price elasticity asymmetry at least on the intensive margin. A fare increase results in fewer people using the London Underground in a week. An equivalent fare decrease, however, does not recover the same passenger numbers that would be lost to the equivalent fare increase. Since these passengers are exposed to both the new and the old fares many times, this asymmetry is not driven by the information asymmetry channel, but rather the loss aversion channel.

We now investigate whether the fare changes in 2016 have affected demand for journey types whose fares have not changed. Figure 3.4 illustrates this situation. Both passengers A and B travel to central London (zone 1). Passenger A lives close to a rezoned station but prefers to walk to the nearest zone 2 station before the rezoning to pay a cheaper fare. However, the fare advantage disappears once the rezoned station becomes a boundary station in 2016. Similarly, passenger B lives close to a zone 3 station and travels from that station before the rezoning. After the rezoning, they walk to a rezoned station since the fare from a rezoned station to a zone 1 station became lower after the rezoning.

We analyse whether the fare change for journeys between rezoned stations and zone 1 stations has also affected travel demand for journeys between zone 1 stations and stations which are adjacent to rezoned stations (henceforth adjacent journeys) on either side (in- or outbound). Similarly, since zone 1 to zone 1 or 2 stations became more expensive, we analyse whether this influenced travel between zone 1 and zone 3 stations.

Figure 3.4: An illustration of a two person travel pattern.



Note: Person A walks to the zone 2 station before (to pay a lower fare), and to the boundary station after rezoning. Person B walks to the zone 3 station before, and to the boundary station after rezoning (to pay a lower fare).

The results for this analysis are reported in table 5. In the full sample we find positive but mostly insignificant cross-elasticities. Only for weekly demand do we find evidence that fewer passengers travelled from stations adjacent to rezoned stations to zone 1 stations (and vice versa) after the rezoning – a cross-elasticity of 0.17% (last two columns). Interestingly, for the small sample we find strong evidence for crowding out of demand for the journey types affected by the fare increase in 2016, but not for journeys affected by rezoning. Some trips which previously would have been undertaken between zone 1 and zone 2 stations have been substituted for travel between zone 1 and zone 3 after the fare for travel between zone 1 and zone 2 increased.

Table 3.5: Cross price elasticities in 2015/16

	Daily			Weekly		
	Journeys	Passengers	Frequent passengers	Journeys	Passengers	Frequent passengers
Full sample						
Short term ε - not rezoned	0.09	0.06	0.10	0.17	-0.04	0.04
	(0.13)	(0.13)	(0.11)	(0.14)	(0.16)	(0.07)
Short term ε - rezoned	0.04	0.08	0.12**	0.02	0.17***	0.17***
	(0.06)	(0.06)	(0.05)	(0.07)	(0.06)	(0.06)
Small sample						
Short term ε - not rezoned	0.97***	0.61*	0.75**	1.68***	1.51***	-1.42
	(0.33)	(0.32)	(0.35)	(0.56)	(0.43)	(0.90)
Short term ε - rezoned	-0.27**	0.09	0.12	-0.33	-1.53	1.64***
	(0.12)	(0.09)	(0.09)	(0.19)	(1.15)	(0.41)

Note: Results are demand elasticities of journey types which are the closest substitutes to journey types which saw a change in their fares with respect to that fare change. Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

We have analysed whether public transport demand reacts more strongly to price increases than to price decreases. We have exploited a rare occasion of a nominal fare decrease on the London Underground to estimate the price elasticity for a price decrease and compared this to occasions when fares increased. Our results suggest that demand is indeed more responsive to price increases than to price decreases. Our estimates of the difference between price increase and price decrease elasticities range from 0.67 to 0.89 percentage points, where our estimates are differentiated by the exact sample of journey types, and the period over which we measure demand (daily and weekly). We also differentiate between demand for journeys and demand in terms of distinct passengers and find that passenger demand also displays significant elasticity asymmetries. This differentiation and looking at a sample of only frequent users of the London Underground helps us to identify the underlying reason for the asymmetry. We consider loss aversion, and information asymmetry as possible causes.

The evidence here is not conclusive, but our preferred specification suggests that loss aversion plays an important role in explaining why demand reacts more strongly to a price increase than to a price decrease. But how does public transport demand respond specifically to a nominal decrease in fares? Given the asymmetric response of demand to fare changes, a fare policy aimed at returning demand to previous level would largely depend on how demand responds to the proposed changes in fares. We examine such reactions in detail in the following chapter.

Chapter 4

The effect of an unconventional fare decrease on the demand for bus journeys*

Kingsley Offiaeli[1], Firat Yaman[2]

4.1 Prelude

To encourage the use of public transport and combat the effects of climate change transport policy makers invoke different transport demand management measures including hard and soft techniques (see Offiaeli and Yaman, 2021a). Transport providers can therefore influence transport decisions through their pricing policy which may have some effects on the generalised costs of travel. Transport for London, which oversees the transport network in London, implemented one such policy in 2016, namely the Bus Hopper Policy. A follow-up bus journey formerly paid for became free on the 12th of September so long as it was undertaken within the hour of paying for the first one;[3] akin to a 'buy one get one free within the hour' price promotion. Most of the extant literature on the effects of public transport fare changes on demand are based on fare increases. Perhaps the most pertinent literature is the work by Brechan (2017) who performs an analysis of the results from a trial involving 15 projects of price reduction and 9 projects of service increase on some transit corridors in Norway. However, the trials included in this meta-analysis took place in small cities (population<150,000), where the public transit system consists almost exclusively of buses.

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*We are greatly indebted to Vasiliki Bampi of Transport for London who extracted the data and who patiently answered all our queries.
[1] City, University of London, and Transport for London.
[2] City, University of London.
[3] In 2018 free journeys were extended to all follow-up journeys by bus or tram within the hour of the first one. We do not consider this extension here.

Urban public transport offers a good laboratory to gauge the price effects on demand. Firstly, it is consumed at the point of purchase so that a journey purchase truly reflects demand. Goods, on the other hand, can be purchased when prices are low for future consumption, leading observers wrongly to conclude that a price decrease increased demand. Secondly, while changes in fares are communicated to the public, non-profit transport providers typically do not try to 'lure' customers into buying their service by combining fare changes with other marketing tactics which further confound the estimation of price elasticities (see Offiaeli and Yaman, 2021b).

This chapter is unique in several ways. Firstly, the research is set in London with a large population and many modes of transport including trams, trains, subways, bicycles, cars, taxis, buses, cable car, etc. Unlike previously studied cases, London passengers have a choice of alternative modes in a highly integrated transport system. The ease with which passengers could switch modes means that there are available substitutes which would have some effects on individual choice and behaviour. Secondly the Bus Hopper policy represents a visible reduction in fares. Prices are often sticky in the downward direction and doubly so in public transportation. Scenarios where fares become nominally cheaper are very scarce in practice. This research is set apart because it examines a rare situation in London where journeys that were hitherto paid for became free.

Thirdly the policy provides a case study for an atypical change in fare policy. It is more akin to a 'buy one get one free' promotion than an actual price change. It is an economic truism that when prices drop more goods are demanded, but would this classical economic theory hold true when prices change in a rather unconventional manner?

This research adds to the body of literature on the effects of price policy changes on demand and travel behaviour by using data obtained on bus demand before and after the policy implementation. A rare situation in public transportation is exploited where the price of a mode of transport is reduced subject to certain conditions and we analyse how passengers respond to the price reduction. The identification relies on estimating how passengers react to the sudden change in price after the implementation date compared to before; only the immediate impact of the new fare structure is considered.

The average treatment effect is estimated using a sharp regression discontinuity design (RDD) as it enables the exploitation of a discontinuity in the treatment assignment to identify a causal effect (see Angrist and Pischke, 2009). An RDD is appropriate when a single continuous forcing variable (in this case time) is used to determine whether a trip is in the control or treatment group.

The analyses show that the London Bus Hopper price policy had significant effects on the number of initial trips (by 5%) as well as follow-up journeys (by 8%). It also led to an increase of passenger numbers by 4%. Bus journeys per passenger also increased, so that the total increase in bus usage was driven both by more intensive use by existing customers as well as new customers choosing to use the bus; a clear indication of the efficacy of the price mechanism in managing public transport demand.

4.2 The Bus Hopper Policy

Buses are by far the most used mode of transport in London, accounting for slightly over 2.2 billion passenger journeys in 2018 compared to just over 1.5 billion mustered by London Underground and Light Railway combined (TfL, 2019). On the 12th of September 2016, the Mayor of London, through TfL, introduced the Bus Hopper Policy. The policy was announced by press release a week prior to its stars, on the 5th of September. The policy was introduced for two broad reasons. Firstly, it enables millions of passengers to save on their generalised costs, in terms of fares and time, on the London transport networks. It benefits travellers on lower income who mostly use the bus network. The idea is that passengers could switch modes since travelling by bus would become cheaper. Secondly as a positive externality of the cheaper travel policy visitors and Londoners alike are encouraged to use public transport instead of cars to help reduce both congestion and pollution. By agreeing a 'Low Emissions Bus Zone' and only buying hybrid or zero-emission double-decker buses the Mayor of London, working with TfL, aims to reduce vehicle emissions within London significantly. At its introduction the Bus Hopper Policy allowed passengers to make one follow-up journey on London's bus network for a nominal fare of £1.50 within one hour from the first paid journey. Once a passenger touches in using a valid payment method the Hopper fare is automatically applied to the journeys of anyone who uses the same card or mobile device to pay as they go. In other words, passengers could 'hop' from one bus to another at no extra cost so long as it was done within the hour. This represents real savings for millions of people who live, work in, or visit London. September 2019 figures showed that more than 450,000 bus and tram trips were made every day using the Hopper fare, since its launch 160m journeys were made using the hopper fare (London Assembly, 2018).

4.3 The Data

The data are from TfL's ODX database which records every bus journey on London's network. Only paid weekday journeys are considered. The data used are individual journeys made between the 14th of June 2016 and the 11th of December 2016, which represent data for 3 months either side of the policy implementation date amounting to 6 months in total. To validate that changes in 2016 are driven by the new policy rather than other (seasonal) factors the same data for the year 2015 is used. For each passenger-day combination, there is data on the number of bus trips, distinguished by 'First trips' (subject to payment under the Hopper policy) and ‘Hops’ (not subject to payment, see also below). In addition the daily total number of distinct people travelling on the buses in the study period (Passengers) was obtained. Each passenger is identified by a unique number, the total number of distinct passenger numbers are then summed to get the total passengers. Since the policy was introduced on the 12th of September, time (measured in days) presents the forcing variable. Payment for bus journeys are made by tapping a payment card on the on-board fares collection equipment.

The analysis of the effect of the Hopper fare is complicated by a peculiarity in the data collection. Customers could tap in when entering a bus by using a so-called Oyster card. This card contained pre-paid credit and had to be topped up when the existing credit did not cover the fare. This was still the predominant payment method in 2017. Alternatively, customers could pay by tapping in their bank debit card. These payments were introduced in 2012 but started to be registered on TfL’s ODX database only in August 2016, which unfortunately is just before the Hopper policy became effective. Therefore, the analysis is restricted to bus journeys which were paid for by Oyster card only. As such, the analysis does not cover the entire demand for bus travel unless we assume Oyster card users to behave the same as customers paying by bank card.

The following variables are considered:

4.3.1 First Trips and Hops

First trips are trips which would be paid for under the Bus Hopper Policy. This terminology is applied irrespective of whether the Hopper policy was in place or not. Every first bus journey on a day counts as a *first trip*. A bus journey which is undertaken within an hour of a *first trip* is a *hop* (e.g., would be free under the Hopper policy). A bus journey that is undertaken after a *hop* is a *first trip* (since the Hopper policy allows for ONE free follow-up journey). A bus journey undertaken after a *first trip* which was more than an hour ago, is again a *first trip* (since the follow-up journey must be undertaken within one hour). If more people use the bus, then *first trips* should increase. If people use the bus more frequently, then both variables should increase. It is also possible that in response to the Hopper fare people time their trips such that they substitute a *hop* for a *first trip* (e.g., finishing their shopping quicker to take advantage of a *hop*).

4.3.2 Passengers

Passengers represent the daily aggregate number of distinct people using the bus network. As stated earlier, the data contains unique travel information of each individual passenger. A passenger may have one *first trip* and two *hops* or may have four *first trips* and nine *hops* within the day. In either case we would count this as one passenger. It is expected that an increase in the number of *passengers* since certain bus journeys became cheaper with Hopper fare. All things being equal, we expect a positive effect on *passengers* as more people would likely switch modes to enjoy the 'free ride'.

4.3.3 First trips per passenger, hops per passenger, hops per first trip

First trips per passenger and *hops per passenger* are informative about the intensive margin of demand for bus journeys. For example, if the increase in *first trips* is driven entirely by new customers, then we would expect no or little effect on *first trips per passenger*. On the other hand, if *first trips* is driven by existing customers who use bus services more often, then the increase in *first trips per passenger* should be similar to the increase in *first trips*. A similar reasoning applies to *hops per passenger*. Finally, *hops per first trip* is an alternative measure of the intensive margin of bus journey demand. If people switch to buses in anticipation of benefiting from the Hopper fare, or if people substitute *hops* for *first trips*, then this measure should increase.

Table 4.1 presents summary statistics on our outcome measures, divided by year and time period (before vs. after the 12th of September). It can be observed that in 2016 *first trips*, *hops*, and *passengers* increased by approximately 4%. However, compared to 2015, the most striking increase is in *hops* – this variable increased only by 0.3% in 2015, but by 3.9% in 2016 when the Hopper fare started. Similarly, while *hops per passenger* dropped in 2015 by 3.4%, it did so in 2016 by only 0.3%. It can also be seen that bus use in 2016 is lower than in 2015. This could be due to lower demand for public transport in general or could be explained by an increasing uptake of paying by bank card which is not included in our data.

Table 4.1: Summary Statistics (Daily average)

	2015			2016		
	Before	After	% change	Before	After	% change
First Trips (in 1,000)	3,465	3,579	3.29	3,177	3,300	3.87
Hops (in 1,000)	1,274	1,278	0.31	1,133	1,177	3.88
Passengers (in 1,000)	1,797	1,869	4.01	1,660	1,731	4.28
First Trips / Passenger	1.93	1.92	-0.67	1.91	1.91	-0.42
Hops / Passenger	0.71	0.68	-3.39	0.68	0.68	-0.29
Hops / First Trip	0.37	0.36	-2.72	0.36	0.36	0.28
Number of days	57	60		58	60	

Averages of daily outcomes by year and period. Before is the period from mid-June to September 11. After is the period from September 12 to mid-December. % change is the percentage change from Before to After.

4.4 Model Specification

This research estimates the effect of the Hopper policy on impact, that is upon its launch, using a Regression Discontinuity Design (RDD). RDD has become increasingly popular in economics since its introduction by Thistlethwaite and Campbell (1960). RDD requires relatively mild assumptions compared to other non-experimental approaches to econometrics (Angrist and Lavy, 1999; Angrist and Pischke, 2009; Lee and Lemieux, 2010). Treatments are assigned to units above or below a threshold; in this case the 12th of September is the cut-off (treatment) date. Since time perfectly sorts our observations into treatment and control days, the RDD is sharp. An RDD is appropriate when a single continuous forcing variable is used to determine whether a trip is in the control or treatment group. While the RDD produces an impact estimate which can confidently be interpreted as causal, it can identify this effect only in a narrow window around the forcing variable. In this scenario, the research estimates the impact of the Bus Hopper policy when it was introduced – and arguably no other change occurred which could cause a discontinuous change in bus travel demand. However, no attempt is made to uncover its medium- or long-term effect on bus travel demand.

In this analysis the forcing variable used is date while the threshold is determined by the date of the implementation of the Bus Hopper policy (12th September 2016). If a trip is made on or after the 12th of September 2016 then it is classed as treated (subject to the Hopper policy), while those trips made before the 12th of September are in the control group.

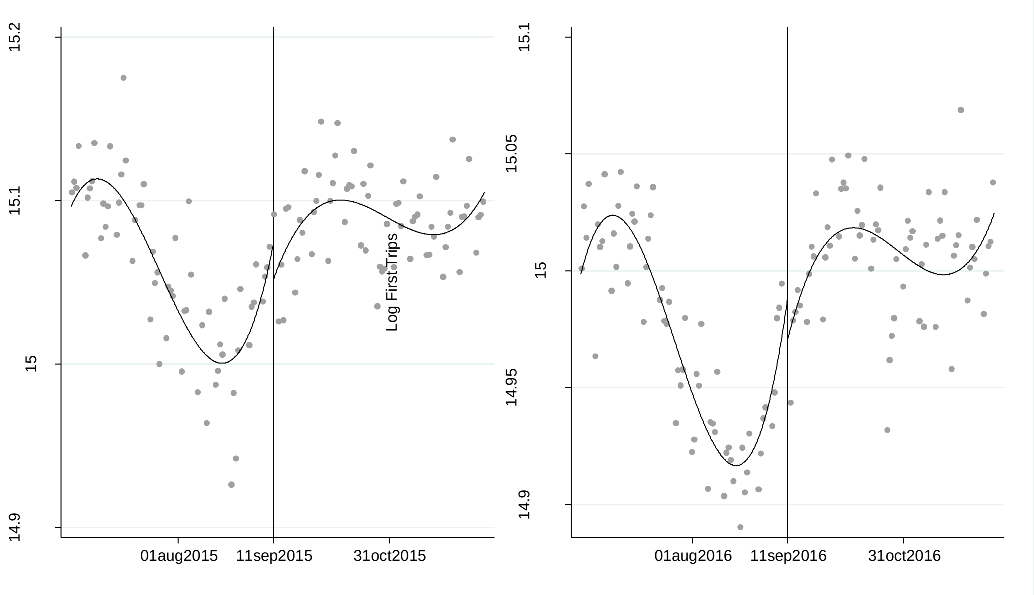
The general econometric model for the estimation is of the following functional form:

$$Y_t = \beta_0 + \beta_1 \, Post_t + \beta_2 X_t + f(t) + \mu_t \qquad (4.1)$$

Where $Post_t = \begin{cases} 1, & t \geq c \\ 0, & t < c \end{cases}$

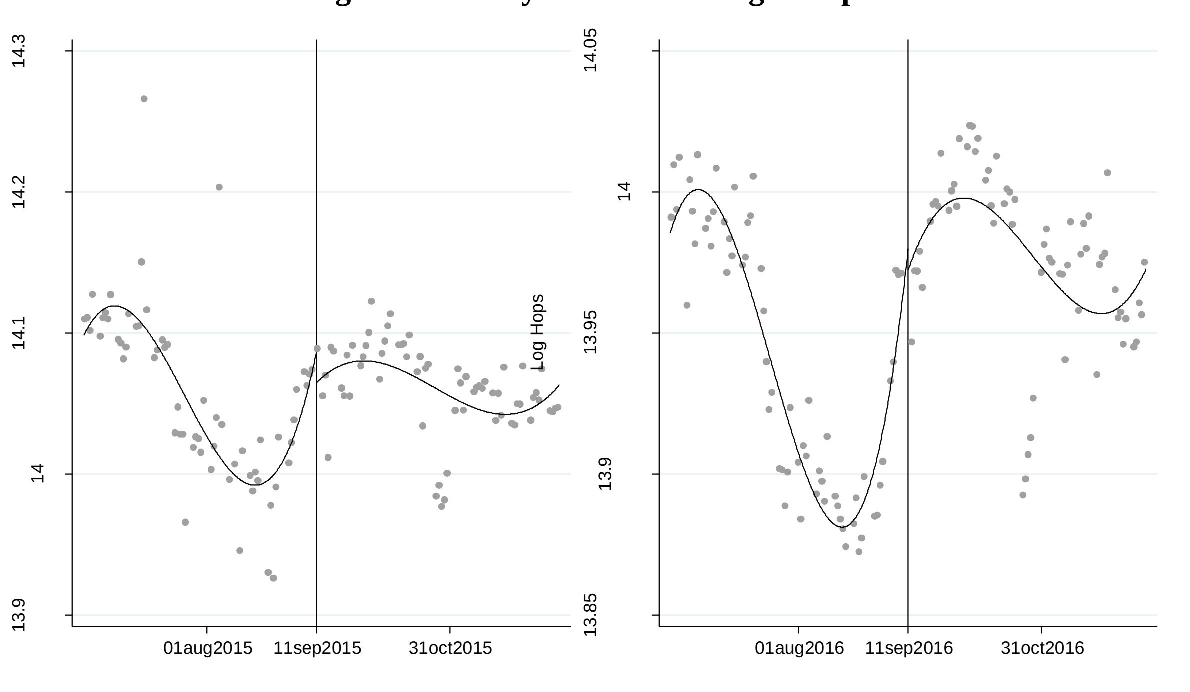
The receipt of treatment or participation in the policy, $Post$, at any time t, is determined by the threshold c (=the 12th of September, which we set to 0). β_1 is the immediate effect of the treatment on outcome Y. X is a vector of dummies for the day of the week, and $f(t)$ is a polynomial function of time t, on either side of the threshold c, which captures the trend in Y over the sample period. The random error term μ is assumed to be normally distributed and has mean 0. The equation represents a *sharp* RDD because treatment assignment is deterministic and discontinuous at the cut-off: all observations with $t < c$ do not receive treatment and all observations where $t \geq c$ are treated.

Figure 4.1: Daily values of the log of first trips



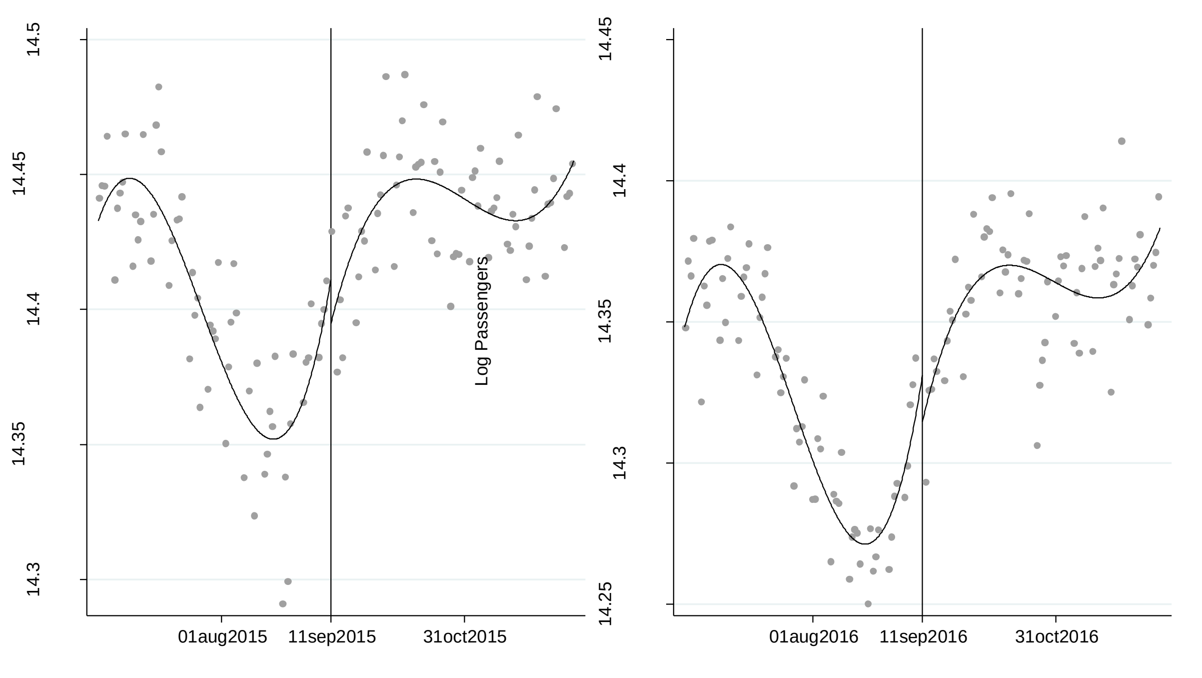
Scatter plot of daily first trips (in natural logs) in 2015 (left) and 2016 (right). The vertical line is 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

Figure 4.2: Daily values of the log of hops



Scatter plot of daily hops (in natural logs) in 2015 (left) and 2016 (right). The vertical line is 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

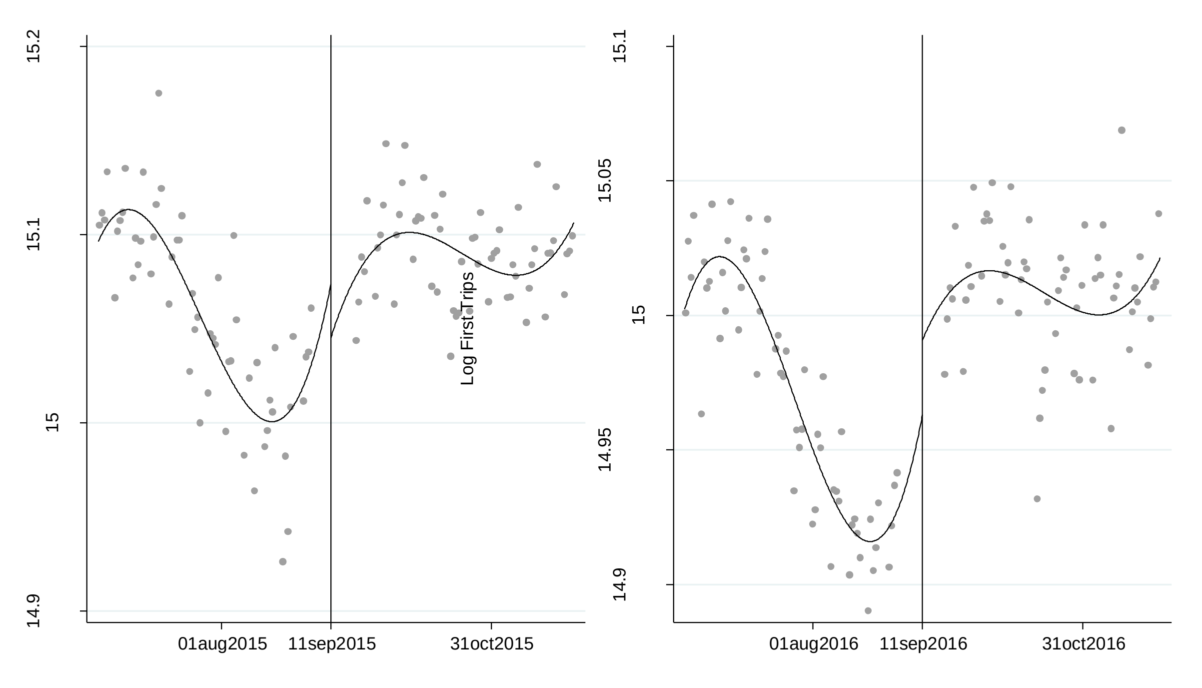
Figure 4.3: Daily values of the log of passengers



Scatter plot of daily passengers (in natural logs) in 2015 (left) and 2016 (right). The vertical line is 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

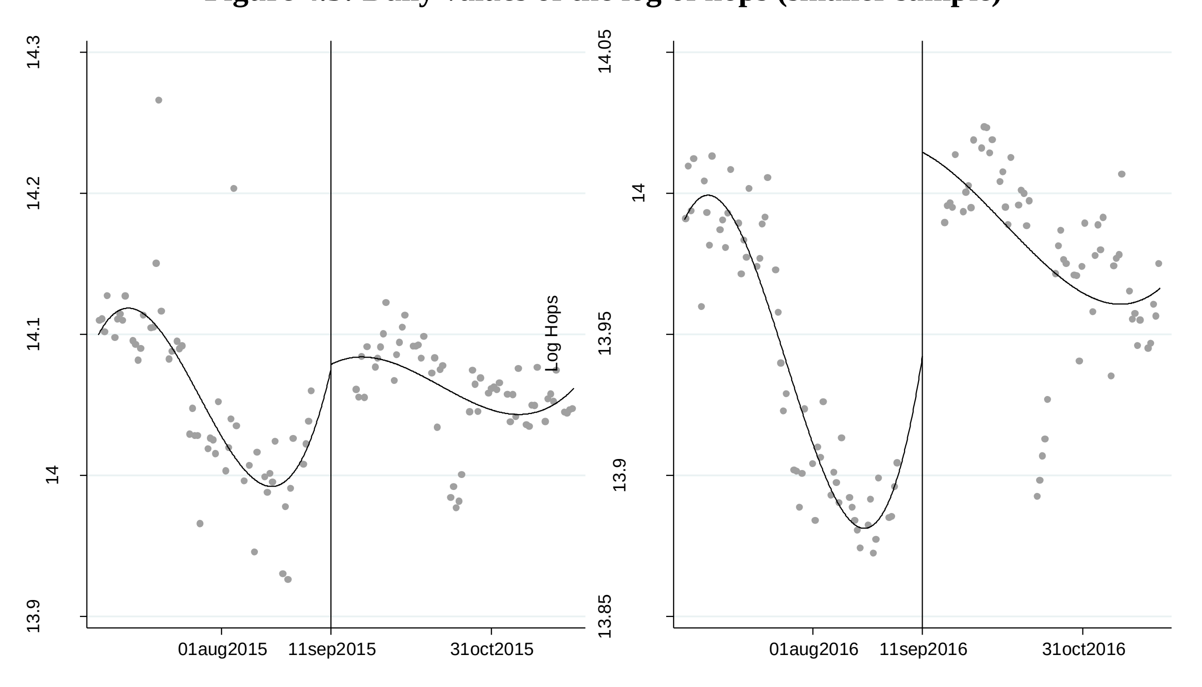
Figures 4.1 to 4.3 above show the log of daily averages of *first trips*, *hops*, and *passengers* in 2015 and 2016. The cut-off date of September 11 – the day before the Hopper policy became effective – is marked by a vertical line. On both sides of the cut-off date, a third-degree polynomial is also fitted. All graphs indicate that bus use drops off towards the end of July, marking the beginning of the summer school holidays, and picks up again in September. Judging from the polynomial fit, there does not seem to be a significant change in bus usage just around the cut-off date. However, the polynomial is misleading. It could be clearly observed from the scatter plot of *hops* in 2016 (Figure 4.1, right hand panel) that *hops* are more frequent after September 12 than before. Yet, in trying to fit the unusually high number of *hops* just before the cut-off date, and the unusually low number of *hops* just after, the polynomial function increases sharply before and again after the cut-off.

Figure 4.4: Daily values of the log of first trips (smaller sample)



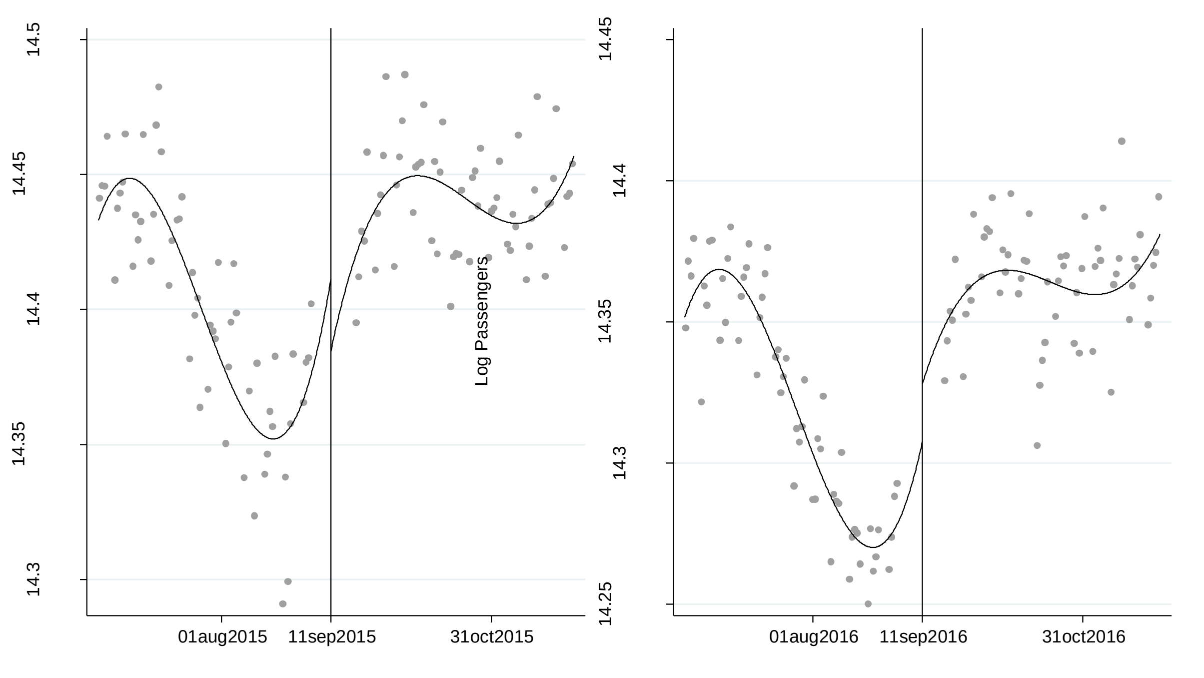
Scatter plot of daily first trips (in natural logs) in 2015 (left) and 2016 (right) after removing the five days before and after the cut-off date. The vertical line is 11^{th} of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11^{th} of September.

Figure 4.5: Daily values of the log of hops (smaller sample)



Scatter plot of daily hops (in natural logs) in 2015 (left) and 2016 (right) after removing the five days before and after the cut-off date. The vertical line is 11^{th} of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11^{th} of September.

Figure 4.6: Daily values of the log of passengers (smaller sample)



Scatter plot of daily passengers (in natural logs) in 2015 (left) and 2016 (right) after removing the five days before and after the cut-off date. The vertical line is the 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

Figures 4.4 to 4.6 above are a graphical representation of the data after leaving out the five days just before and just after the cut-off. The data series now look smoother and the upward jump in the polynomials around the cut-off date in 2016 now point towards the expected effect of the Hopper policy. In 2015 there is no sudden change around the same cut-off date. Thus, the changes observed in 2016 seem unlikely to be explained by seasonal and other factors, since we should observe these effects also in 2015.

4.5 The Results

Table 4.2 reports the estimated 'treatment' effects on the dependent variable. Since the dependent variables are in logs, the estimated β_1 translate into $(100*\beta_1)$% changes in the dependent variable. All our models include day-of-the-week fixed effects to control for any changes in daily demand within the week. Standard errors are calculated as heteroskedasticity robust standard errors.

Table 2: RDD estimates for 2015 and 2016

	(1) First Trips			(2) Hops			(3) Passengers		
	2015	2016	Difference	2015	2016	Difference	2015	2016	Difference
Coefficient	0.001	0.052**	0.052	0.018	0.081***	0.063	-0.003	0.041**	0.043
Standard error	(0.028)	(0.020)	(0.035)	(0.050)	(0.030)	(0.058)	(0.021)	(0.016)	(0.026)
	(4) First Trips per Passenger			**(5) Hops per Passenger**			**(6) Hops per First Trip**		
	2015	2016	Difference	2015	2016	Difference	2015	2016	Difference
Coefficient	0.003	0.012**	0.009	0.021	0.041**	0.020	0.018	0.029**	0.011
Standard error	(0.009)	(0.006)	(0.011)	(0.033)	(0.017)	(0.037)	(0.026)	(0.013)	(0.029)

Estimated effects of the September 12 cut-off ($ß_1$) on bus demand measures. All measures are in natural logs. Coefficients are semi-elasticities ($ß_1$*100 percent change). The Bus Hopper was introduced on September 12, 2016. First trips are trips that would be paid for under the Bus Hopper fare. Hops are trips which would not be paid for under the Bus Hopper fare. Passengers are the number of distinct passengers on a day. All regressions include day-of-week dummies and third degree polynomials of Date on either side of the cut-off date (see also Figures 2 to 7). Standard errors are in parentheses. * p < 0.1 ** p < 0.05, *** p < 0.01.

The results indicate that the number of *first trips* (panel 1) increased by 5.2% after the introduction of the Hopper policy in 2016 – an estimate significantly different from zero at the 5% level. In the previous year, there is no discernible difference in *first trips* around the 11th September. If the effect in 2015 constitutes a valid counterfactual scenario to what would have happened to demand if there had not been the Hopper policy, then the difference between the estimated effects for 2016 and 2015 can be given a causal interpretation. This difference is also 5.2%, but the difference is not as precisely estimated and thus insignificant. Not surprisingly, the strongest effect is found for *hops* (panel 2). *Hops* increased by 8.1% after the Hopper policy, and the difference to previous year's increase was 6.3%. *Passengers* (panel 3) increased by 4.1% (4.3% compared to 2015).

The results for our measures of the intensive margin of demand (panels 4 to 6) also suggest positive effects of the Hopper fare. A typical passenger undertook 1% more *first trips* (0.9% compared to 2015), and 4.1% more *hops* (2% compared to 2015). Finally, 2.9% more *hops* were undertaken for every *first trip*.

This chapter has evaluated the performance of the London Bus Hopper policy by examining the effects on 6 key variables: number of *first trips*, number of *hops*, number of *passengers* and the measures of the intensive demand margin *first trips per passenger*, *hops per passenger*, and *hops per first trip*. The results show that the London Bus Hopper price policy had significant effects on bus usage on all of those dimensions, with the strongest effect on the number of hops and concludes that the policy was effective and worked as intended upon its launch.

Chapter 5

Social Norms as a Cost-Effective Measure of Managing Transport Demand:

Evidence from an Experiment on the London Underground[*]

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5.1 Prelude

In this chapter we now propose an alternative to the price mechanism as a measure of managing demand. Many metros now invest in acquiring more capacity for their networks through different means like technical and structural solutions to manage travel demand (Barron, 2016). In managing dwell times at platforms, which invariably manages platform demand and capacity, one could resort to hard and soft measures (Bamberg *et al*., 2011), however where there exist capacity constraints, it is imperative that the providers of the transport network seek smarter and cost-effective ways of managing passenger flow and demand. To this end many researchers now question the efficacy of using only traditional economic methods in controlling transport demand. Economists and transport policy makers have hitherto focused on prices to control passenger demand (e.g., charging more during peak hours), but the efficacy of price in the demand function of any public transport network depends critically on its price elasticity, transport policy and passengers' behavioural norms. In addition, there is evidence that non-price interventions can be very effective and relatively inexpensive in some scenarios (Allcott, 2011; Bertrand *et al*., 2010).

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This chapter addresses the question of whether using social norms to nudge passengers into conformity has affected a reduction in dwell times on a key platform on one of the busiest metro networks in the world. We employ data from London Underground's Green Lane experiment at King's Cross station. The experiment was aimed at influencing passenger behaviour by laying green vinyl on the platform supported by audio and visual cues that encourage customers to pass along the platform until they find a non-green space to stand and wait for a train. The green vinyl was laid only on the Southbound Victoria line platform at King's Cross (providing the treated platform), owing to its vantage position as a pinch point location and a central hub on the network created by persistent increase in demand and connections to other inter-urban lines. The vinyl on the platform also shows where the doors would open when the arriving train completely stops at the platform thereby helping passengers know exactly where the doors would be. Data were retrieved for periods before, during, and after the experiment (after the vinyl was removed) for every London Underground train through King's Cross and adjacent stations using specialist software.

We observe a significant reduction in dwell time by 6.6% (2.3 seconds), which is a profound result for London Underground by its own standard. London Underground values one second savings in dwell time at King's Cross station at £68,000 worth of customer benefits (Goodwin, 2017). Therefore, our research indicates that the Green Lane intervention generated customer benefits of £156,400 per year for London Underground at a cost of £25,000 (total costs of materials and labour for installing and decommissioning the Green Lanes at one platform). If dwell times could be reduced by a total of 2.7 seconds, the frequency of trains going through the affected platform could be increased from 36 to 37 trains per hour, resulting in additional customer benefit of £3.6 million.[1] The dwell time reductions mainly occur during peak demand times, and can be mostly attributed to

[1] This figure comes from conversations we have had with TfL personnel. Operating more trains would decrease the waiting time between trains and the congestion in trains.

reductions in delayed departures. We further investigate whether the dwell time reductions are sustained after the removal of the signals which caused the behavioural change in the first place, thereby adding to the important discussion on how sustainable interventions suggested by the behavioural science literature are. Our results suggest that any beneficial effect of the Green Lanes on dwell times disappeared after the Green Lanes were removed.

Methodologically, this research is distinct from the existing literature in two important respects: First, it is based on a real-world intervention at one of London's busiest stations, and exploits its quasi-experimental nature by comparing the dwell time changes on the treated platform to a number of different potential control platforms, accounting for the possibility of seasonal variations in dwell time, changes affecting the entire station, and changes affecting the entire service line. Our empirical strategy is to estimate the effect of the Green Lanes on dwell times under a set of different assumptions about how dwell times would have evolved in the absence of the experiment. We obtain statistically and economically significant effects in most of our models. The results show that while the correctness of any of those assumptions cannot be known, it seems very improbable that all our estimated treatment effects should be attributable to a factor other than the Green Lanes.

The second methodological contribution is to explicitly model the operating procedure for trains to stop and depart. Not every potential dwell time saving translates into actual savings. If the train is on schedule and needs to wait for its scheduled departure, its dwell time will not decrease, even if alighting and boarding terminates quicker. We model dwell and delay times as latent variables and allow for the Green Lanes to have different effects on dwell and delay times.

5.2 Background

5.2.1 The London Underground (LU) Network.

London Underground is the oldest network in the world, which ran its first train service in 1863. Consequently, LU faces capacity and structural challenges as many of the modernisation works to the network are either impossible or very expensive to retrofit. The network consists of 17 different lines connecting 270 stations and extends to 250 miles of track making it the 7th largest (in served passengers) and 3rd longest (in kilometres of track) network in the world. In 2017 the network served about 4 million passenger journeys per day. The central zones are the busiest and connect passengers to many of London's landmarks and financial hubs.

Users of this network face overcrowding on the platforms in the peak times (0700 – 1000 hours and 1600 – 1900 hours). Critical congestion occurs particularly in the 'peak of the peak' (0800 – 0900 hours and 1645 – 1730 hours) when the network is busiest and operating close to its maximum capacity. At these times passengers face delays as they may be unable to board the first available train and even the subsequent ones depending on their position on the platform and level of congestion on both the platform and the arriving train. Consequently, LU is constantly exploring innovative and cost-effective methods of improving customer experience and reducing the generalised cost of travel. One of such ways is the Green Lane project designed to influence passenger travel in a certain way to aid the reduction of dwell times, travel time and costs.

5.2.2 The Experiment

The Green Lanes project was aimed at influencing passenger behaviour in a transport setting. It was an experiment performed at the platform level in a bid to reduce the generalised cost of travel for customers by decreasing dwell and journey times which would, consequently, increase the capacity for more service frequency at the treated station. This could be achieved through ‘nudging’ passenger behaviour using visual and audio cues, but without incurring high costs or imposing physical or financial impediments. The installation of the Green Lanes started on July the 18th, 2017 and was completed by the 1st of September 2017. The lanes remained in place until early 2018.

To perform the experiment the southbound platform of the *Victoria line* at London *King’s Cross* station (henceforth referred to as the *treated platform*) was chosen because of its central location and the persistent increases in dwell times in recent years. King’s Cross station is a major hub and terminal with connections to many parts of London and the United Kingdom. The Victoria line serves several central and important stations linking many of London’s landmarks, central and suburban districts. Dwell times on the Victoria line have increased due to congestion brought about by persistent rise in travel demand over the years. King’s Cross station constitutes a pinch point location and a bottle neck on the Victoria line. The southbound platform was chosen for treatment because the dwell times on this platform increased significantly from 35 seconds to 47 seconds between 2015/16 working timetables (Goodwin, 2017).

Figure 5.1: Green lanes at London King’s Cross station.

Adapted from Goodwin, 2017.

The experiment was simple. As can be seen in Figure 5.1, green vinyl was laid on the platform in such a way that encourages customers to pass along the platform until they find a non-green space to stand and wait for a train. The green vinyl also showed where the doors would open when the arriving service train comes to a complete stop at the platform edge. The choice for the green colour is in accordance with international convention for green indicating ‘clearance to proceed’ and made violation of the social norm that TfL was trying to establish (do not stand in the lane) highly salient.

This salience-of-violation feature also distinguishes the experiment from previous attempts by TfL to control passenger behaviour via conventional methods such as speaker announcements and encouragement by staff not to stand in front of the doors, which were effective only for the duration of one dwell time occurrence, but would have to repeated for the next arriving train. If passenger behaviour could be altered by appeals to personal norms only, then we would expect the desired behaviour to become established over time. The Green Lane experiment adds a social dimension by making the norm violation immediately visible – and costly – for other passengers waiting on the platform who can then express their disapproval by established signs (e.g. body language). For example, it is an established norm on the London Underground to stand on the right of a moving escalator to allow people to pass on the left. The salience of the norm violation might have contributed to the relative success in establishing this norm.

The passengers are expected and encouraged to keep moving on any green section of the platform and not to stop until they get to any non-green section. When a train arrives at the platform, the alighting passengers use the space on the Green Lanes spurs to exit the platform so that passengers waiting in the non-green sections can board quicker. In theory, this should eliminate or at least reduce the pushing, bumping and shoving that happens at peak times when the platforms are crowded.

The Green Lanes have been successful in reducing the number of waiting passengers who stand in front of the train doors before they open (TfL, 2018b). They might also have helped to reduce platform train interface (PTI) issues such as passengers or staff getting caught in the closing doors or having items caught between the doors at the platform edge. At all times during the experiment there were visual cues like posters and direction markers encouraging passengers not to stand or wait on any green section but to keep moving while on it. At peak times there would be a member of station staff on the platform giving audio messages, managing overcrowding on the platforms and assisting the train driver in ensuring safety on the platform during train arrival and departure. A close alternative to the Green Lanes are platform edge doors. As the London network is old and extensive, updating them by retrofitting platform edge doors on old and curved platforms would be an engineering challenge and significantly more expensive than the Green Lanes vinyl.

5.2.3 Operating Procedure.

The Victoria line runs an automatic train operation process, but all the trains have drivers in the front cab. The driver can intervene when automation breaks down as well as assist with doors opening and closing to minimise PTI issues resulting in injuries. There are 16 stations on the route and King's Cross station is somewhat in the middle in Zone 1 (centre) providing interchanges with other LU lines and National Rail services. When the train arrives at the platform, the driver opens the doors for alighting and boarding to commence. The driver monitors this process through the in-cab and platform CCTVs depending on location. Provided the station starting signal is clear, the driver then pushes the 'doors-close' button which effectively brings boarding and alighting to completion. This usually begins with an audible sound that only lasts for a couple of seconds before the doors begin to shut. The trains are fitted with sensitive edge technology; this is a safety device which ensures the doors are completely shut without which the train would be unable to proceed. A 'clear' signal indicates that the route ahead is clear of any train, secure, and safe for the train to proceed. As soon as the doors close the train departs. Once it clears the platform and section of track, it is then safe for the next train to arrive. The process is repeated at the arrival of the next train.

The station starting signal is automatically controlled by a computer preloaded with a predetermined running timetable which has the scheduled arrival and departure times of every train going through every platform on a line. If a train arrives before the scheduled arrival time, the starting signal remains at danger (red) and would only clear at the scheduled departure time. This always remains the case safe for when a failure occurs, at which point the signalling process would be controlled by a duty Signalling Operator and the service itself regulated by a duty Service Controller. The passengers are encouraged to stand at the non-green areas so as not to obstruct the flow of traffic especially at peak times. At both the AM and PM peak times there is usually a station staff member on the platform assisting with platform duties. They were tasked with encouraging passengers to acknowledge the Green Lane and to conform to the rule of not standing or waiting anywhere on the Lane. The Green Lane keeps the walkways clear for alighting passengers to easily disembark from the train so that boarding can commence quicker.

5.3 Data and methodology

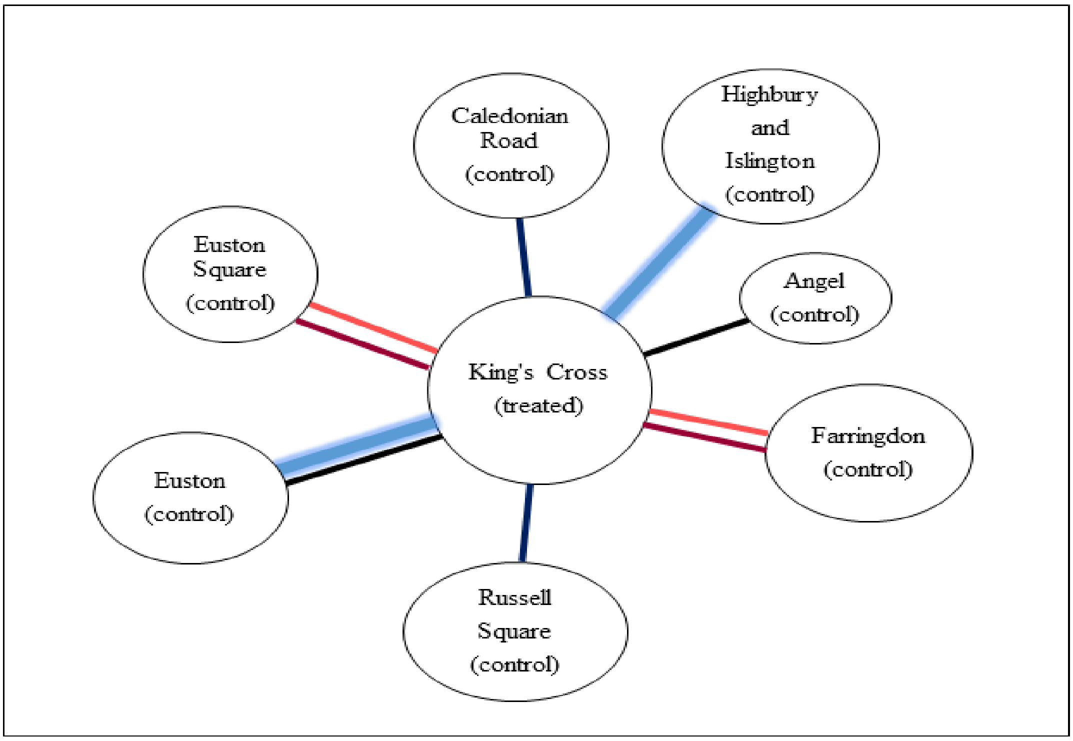
The Green Lane installation commenced on the 18th of July 2017 with the lanes laid on the inbound Victoria line platform.[1] As it was not completed until the 1st of September of the same year, for the main analysis we exclude the time period during which the installation was in progress (18.7. to 1.9.). The Green Lane experiment was not announced or made public to passengers before its start. The dwell time data were supplied by TfL using specific software that records detailed real time train movements to the second. The data includes dwell time

[1] Our main analysis therefore only uses trains travelling *towards* the City centre. We repeat the analysis for trains travelling outwards as a placebo-experiment. See section 8.

counts for London Underground services from 5am to 1.30am from Monday to Friday (weekdays), but we restrict our sample to trains departing between 6am and 11pm, since platform crowding does not occur outside this time interval. The weekend data have been excluded owing to lower weekend service frequency, prevalence of engineering works leading to platform or station closures and decreased weekend demand. Any abnormally long (>70 seconds) or short (≤10 seconds) dwell time is disregarded, retaining 98% of dwell time observations. We discard the right tail of dwell times as these long times are likely to have been caused by incidences such as train or signal failures. We exclude the left tail of dwell times as these short times could only be achieved with very low passenger numbers (both on the platform and in the carriage). The Green Lanes would not have any effect on dwell times in both of those scenarios. We have also repeated our analysis for dwell time observations between 5 and 75 seconds. This did not change any of our main results.

All trains arriving at the study platforms have an arrival time and a departure time. The time difference between these variables gives the dwell time (Dwell) in seconds. We extracted dwell times for all trains which pass through King's Cross station or an adjacent station, for the time periods from 21st of May to 30th of November for 2016, 2017 and 2018. For any train in our data we have the following information: its arrival and departure times, which station it dwelled at, which service line it served, and which direction it was travelling in.

Figure 5.2: *Stations and services lines of the study*



Note:*King's Cross, the treated station, is served by the Victoria line (treated line, thick light blue), the Northern line (black), the Piccadilly line (dark blue), the Metropolitan line (dark red), and the Hammersmith and City line (light blue).*

Figure 5.2 shows the scope of our data and highlights the treatment and the control stations and service lines. The treated platform is the Victoria line platform at King's Cross station. Service lines other than the Victoria line (thick line) are control lines, and stations other than King's Cross station (circle in the middle) are control stations. For each year, we have approximately 1 million dwell time observations.

5.4 Empirical Strategy

Comparing average dwell times at the treated platform after the Green Lanes installation to before their installation is unlikely to produce the true effect of the Green Lanes on dwell times. The Green Lane intervention deviates from an ideal experiment in three important ways:

- All dwell times under treatment only fall into the period of September 1st to November 30th,
- All dwell times under treatment are observed only on the Victoria line,
- All dwell times under treatment are observed only at King's Cross station.

Thus, treatment status is deterministic rather than random. Knowledge of date, station, and service line of an observation would perfectly reveal its treatment status. If we only compared observations on the treated platform after and before the intervention, then we would be picking up the effect of the intervention *and* any other factors which might cause dwell times to be different between September 1st and November 30th compared to the pre-treatment period (e.g. weather conditions, passenger demand, etc). For this reason, we rely on quasi-experimental methods which are frequently deployed in empirical economics.

The Difference-in-differences (henceforth 2D) estimator seeks to mimic experimental designs by identifying observations which would serve as an appropriate control group to the treated observations. If, for example, the above-mentioned factors affect all platforms equally, then the effect of the Green Lanes can be identified as the change in dwell times for the treated observations, *over and above* the change in dwell times of (a subset of) all other platforms. In practice, it is unlikely that all other platforms would have been affected by factors affecting dwell time in equal measure. We thus must be more careful in the selection of appropriate control observations. We consider the following scenarios:

1. The factors affecting dwell times on the treated platform (other than the Green Lanes) are the same in 2016 and in 2017. This would qualify observations on the treated platform *in the previous year* as appropriate control observations.
2. The factors affecting dwell times (other than the Green Lanes) affect all observations in King's Cross Station equally. This would qualify observations on

non-treated service lines at King's Cross Station as appropriate control observations.

3. The factors affecting dwell times (other than the Green Lanes) affect all stations on the Victoria line equally. This would qualify observations on the Victoria line in stations other than King's Cross Station as appropriate control observations.

All three scenarios are much less restrictive and more plausible than saying that *all* other platforms would constitute a good control group. Each scenario requires that we assume that external factors affect dwell times for treated and control observations equally.[1] Since we cannot know or test which of the three scenarios is closest to reality, we estimate the Green Lane effect for all three scenarios.

The above-described scenarios highlight the limitations of the 2D estimator. What if, for example, the dwell times of treated observations are affected by the Green Lanes, *and* by time-of-the-year effects which affect dwell times equally in 2017 and in 2016, *and* by effects which affect all platforms in King's Cross Station equally? We would need to combine scenarios 1 and 2 to reflect this. The triple difference (henceforth 3D) estimator does precisely that. For this example, for observations at King's Cross Station, we would first obtain the change in dwell times (first difference) in 2017 and subtract from this (second difference) the change in dwell times in 2016, only for observations which are not on the Victoria line. This quantity would tell us by how much the time-of-year effect at King's Cross Station has changed from 2016 to 2017 on service lines other than the Victoria line. *If* we assume that this change in the time-of-year effect would affect the Victoria line equally, *then* the difference (third difference) in this change between the Victoria line and other service lines would recover the pure effect of the Green Lanes. Combining any two of the

[1] We can recover two quantities: The effect of other factors for control observations, and the combined effect of other factors for treatment observations *and* the Green Lanes. We can recover the Green Lanes effect only if we assume that other factors affected control and treatment observations equally.

above three scenarios results in three different 3D models. Again, we estimate all three of those models.

Finally, all three confounding scenarios described above might be present. In a further generalisation of the 3D estimator we propose a quadruple difference (4D) estimator. If we followed the same steps as described in the previous paragraph, but this time for stations other than King's Cross Station, then we would have a 3D estimate of combined service line and time-of-year effects on dwell times for other stations. Under the assumption that this combined effect is the same for King's Cross and other stations, the difference (fourth difference) between the 3D estimate for King's Cross Station and other stations would recover the effect of the Green Lanes. We summarise the different models that we estimate in table 5.1 along with the assumptions which are required to recover the effect of the Green Lanes. Appendix 1 contains the statistical models and their explanations. All models include, where applicable, the control variables described in the next section

Table 5.1: Different estimators and assumptions

Estimator	*Control group*	*Identifying Assumption*
Simple difference (Before-after)	Treated platform before the Green Lanes	There would be no difference in dwell times on the platform between fall and summer
2D estimator	Treated platform in previous year	The difference in dwell times on the platform between fall and summer would be the same in 2016 and 2017
2D estimator	Other stations on the same service line	The difference in dwell times between fall and summer would be the same for all stations on the service line
2D estimator	Other service lines in the same station	The difference in dwell times between fall and summer would be the same for all service lines in the station
3D estimator	Treated platform in previous year and other stations on the same service line	The change from 2016 to 2017 in the difference in dwell times between fall and summer would be the same for all stations on the service line
3D estimator	Treated platform in previous year and other service lines in the same station	The change from 2016 to 2017 in the difference in dwell times between fall and summer would be the same for all service lines in the station
3D estimator	Other stations on the same service line and other service lines in the same station	The difference across stations in the difference in dwell times between fall and summer would be the same for all service lines
4D estimator	Treated platform in previous year and other stations on the same service line and other service lines in the same station	The difference across stations in the change from 2016 to 2017 in the difference in dwell times between fall and summer would be the same for all service lines

Notes: Summer refers to the pre-treatment period May 21st to July 17th, fall refers to the treatment period September 1st to November 30th.

5.4 Variables

The dependent variable in our analysis is the natural logarithm[1] of dwelling time denoted Y_{tsl} where t is time, s denotes the station, and l the service line. The main independent variables for the 2D, 3D, and 4D estimators are:

[1] Residuals from a dwell time regression exhibit a log-normal distribution. We therefore use the natural logarithm of dwell times as the dependent variable, which also results in a better model fit in terms of R^2.

$Post_t$ = 1 if t is later than 6am, September 1st, in either year (2016, or 2017), and 0 otherwise,

$D2017_t$ = 1 if t is in 2017, and 0 if t is in 2016,

$Kings_s$ = 1 if s is King's Cross station, and 0 otherwise,

$Victoria_l$ = 1 if l is the Victoria line, and 0 otherwise.

An observation is identified as subject to the Green Lane treatment, if (and only if) all those indicator variables are equal to 1. Appendix A1 describes in detail how these variables are used in the consistent estimation of the Green Lanes effect on dwell times.

Where applicable, we also include the following control variables: *Demand* is the sum of daily station entries and exits. We include it as a control variable since higher demand is likely to increase dwell times. Since the demand variable is a total daily count of the number of passengers through the gates of a station, it is difficult to apportion the passengers to individual platforms at the stations of entry or exit. We thus assume demand to be constant throughout the day and across station platforms. *Lines* is the number of service lines through a station: given a level of demand, more service lines would distribute station demand over more platforms and result in less crowding on the platform. In addition, *DemandPerLine* (*Demand* divided by *Lines*) has been added to account for average demand per platform in a station. *ServiceLevel* (in seconds) measures the time interval between two scheduled train arrivals and is expected to be negatively correlated to dwell time; higher service frequency reduces station dwell times. *ServiceLevelDemand* is a variable interacting demand and the level of train service on a line, allowing the effect of service frequency on dwell times to depend on demand. Since demand will not be uniformly distributed over the time of day, or over the days of the week, we also include dummies for each 15-minute interval of a day (from 6am to 23pm), and for each weekday. Finally, we include a linear time trend[1] which is restricted to be the same for all trains and both years (that is, we include a variable equal to x if the observation is for the x^{th} day of any year). We relax this restriction in section 7 when allowing for heterogeneous trends. For simplicity, we collect the control variables described in this paragraph in a vector X. Table 5.2 provides the complete list and description of variables.

5.5 Delay Time Analysis

Given scheduled departure times of trains, any intervention to speed up alighting and boarding times of passengers would affect dwell times only if the train exceeds or is close to exceeding its scheduled departure time. Otherwise, even if alighting and boarding completes faster, the train would have to wait on the platform until its scheduled departure time, thus only prolonging the time where it is idle.

We therefore extend the analysis to an investigation of whether the Green Lanes had a stronger effect on reducing delay times rather than dwell times in general. To do this, we have to take into account that 1) we observe delay times only once a train exceeds its scheduled departure time, and 2) we do not observe the train's regular dwell time once it is delayed (rather, the dwell time is censored). Consider the following empirical model. A train is scheduled to stay on the platform for $\bar{t}$ seconds.

[1] We have also estimated our models with quadratic time trends, but this had only a negligible impact on our estimates.

Table 5.2: Variables

Variable	Description
Dependent variable	
Y_{tsl}	Natural log of dwell time at time *t*, station *s*, and service line *l*
Main independent variables	
$Post_t$	Binary variable equal to 1 if *t* is between September 1 and November 30 (in either year)
$D2017_t$	Binary variable equal to 1 if *t* is in 2017
$Kings_s$	Binary variable equal to 1 if *s* is King's Cross station
$Victoria_l$	Binary variable equal to 1 if *l* is the Victoria line
Control variables	
$Demand_{ts}$	Number of entries and exits into station *s* (daily)
$Lines_s$	Number of service lines through station *s*
$DemandPerLine_{ts}$	$Demand_{ts}$ / $Lines_s$
$ServiceLevel_{tl}$	Scheduled time interval between two trains in seconds. Indexed also by *t* as service levels can vary over the day.
$ServiceLevelDemand_{tsl}$	$ServiceLevel_{tl} \times Demand_{ts}$
$D600_t$	Binary variable equal to 1 if *t* is between 6am and 6.15am
…	…
$D2245_t$	Binary variable equal to 1 if *t* is between 10.45pm and 11pm
$DMonday_t$	Binary variable equal to 1 if *t* falls on a Monday
…	…
$DFriday_t$	Binary variable equal to 1 if *t* falls on a Friday
$Trend_t$	Linear time trend: 0 for May 21 (in either year), then incrementing by 1 for each calendar day

A latent dwell time variable Y^*_{tsld} and a latent delay time variable Z^*_{tsld} are given by

$$Y^*_{tsld} = \beta X_{tsld} + \epsilon^y_{tsld}$$

$$Z^*_{tsld} = \gamma X_{tsld} + \epsilon^z_{tsld}$$

The actual dwell time Y_{tsld} is observed only if $Y^*_{tsld} \leq \bar{t}$, in which case $Y_{tsld} = Y^*_{tsld}$, and the delay time is unobserved. If, on the other hand $Y^*_{tsld} > \bar{t}$, then the actual delay time is given by $Z_{tsld} = Z^*_{tsld}$, and we know that the latent dwell time exceeds the schedule $\bar{t}$: $Y^*_{tsld} > \bar{t}$. We assume that the errors are jointly normally distributed.

Amemiya (1985) derives closed form solutions of the likelihood of this class of models (p. 386). We estimate this model with maximum likelihood. No restrictions are placed on the parameters within or across the latent variable equations. We thus allow the Green Lanes to have differential effects on regular dwell and delay times.

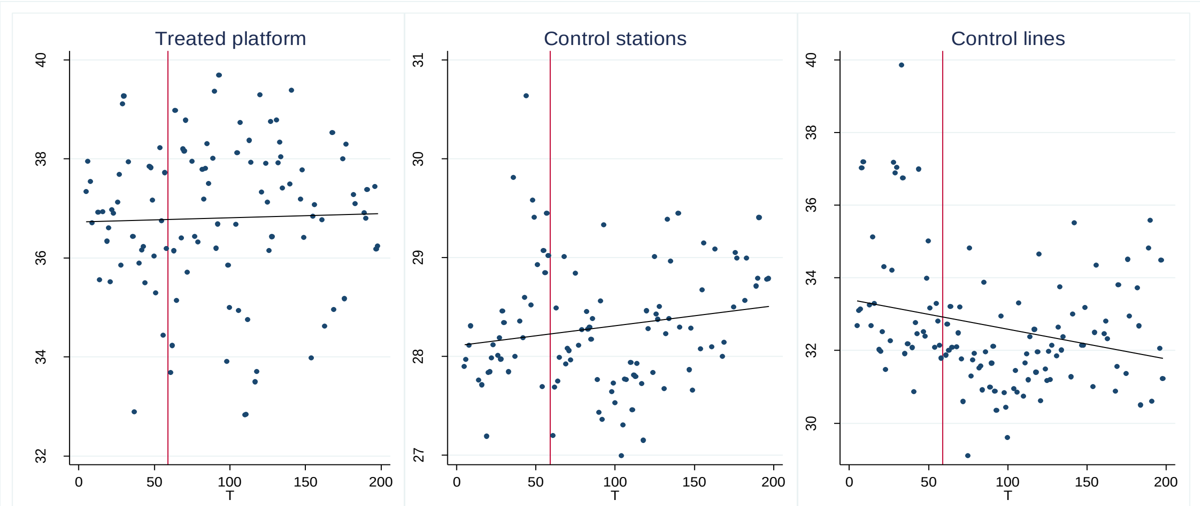
One constraint that we face is that we do not observe the scheduled arrival and departure times of all trains. However, from trains for which we do observe these data, we can impute a train's scheduled dwell time. Our delay time is thus based on the difference between scheduled and actual *dwell* times, rather than the scheduled and actual departure times. For example, if a train arrives 5 seconds behind schedule, and departs 5 seconds behind schedule, it would be classified as departing just on time according to our imputation. Because the service frequency is high (on the Victoria line a train runs every 2-3 minutes), this misclassification should not be of great concern, as passengers do not arrive at the platform with the intention of catching a particular scheduled train, but rather to get on the next available train regardless its scheduled departure (actual timetables for the Underground are not displayed on the platforms or on TfL's website).

5.6 Graphical analysis

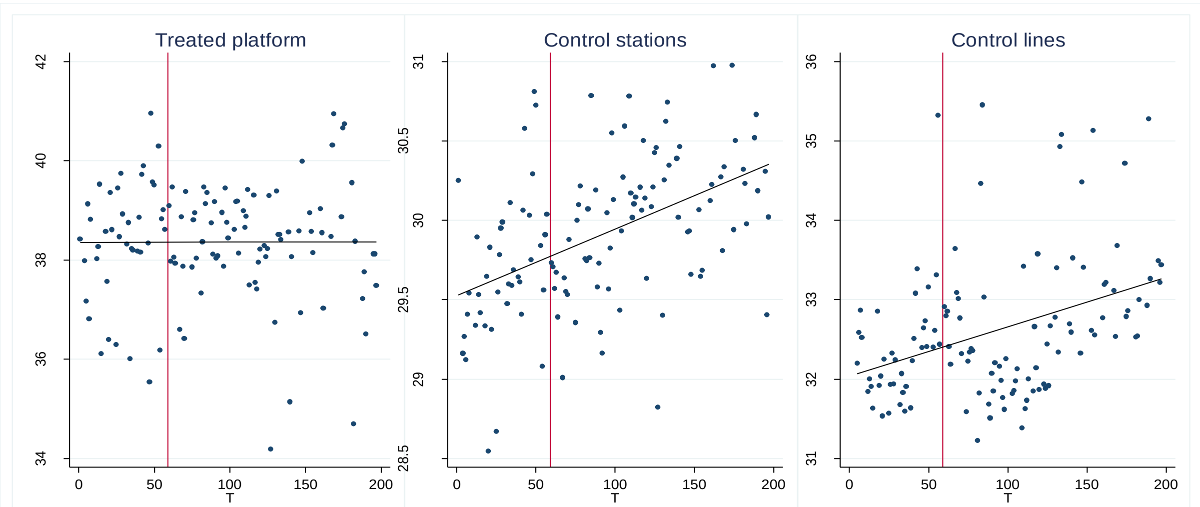
We begin by visually inspecting the average daily dwell times of trains. The upper panel of figure 5.3 shows dwell times in 2016, while the lower panel dwell times in 2017. The vertical line corresponds to the 18th of July, the day at which the Green Lane installation began in 2017.[1]

[1] Figure 5.3 includes all days. For the regression analysis, we exclude observations from the installation period (18th July to 1st September).

Figure 5.3: Daily average platform dwell times for 2016 and 2017.



Dwell time = 36.7 + 0.0008T R^2 = 0.1% Dwell time = 28.1 + 0.002T R^2 = 2.8% Dwell time = 33.4 - 0.008T R^2 = 6.4%



Dwell time = 38.4 + 0.000T R^2 = 0.0% Dwell time = 29.5 + 0.004T R^2 = 23.0% Dwell time = 32.0 + 0.006T R^2 = 14.3%

Figure 5.3: Average daily dwell times in 2016 (top) and 2017 (bottom) at treated platform (left), adjacent stations on the Victoria line (middle), and other service lines at King's Cross station. The vertical line corresponds to the 17th of July (when the installation of the Green Lanes in 2017 started).

We observe that dwell times on the treated platform (graph on the left) are longer in 2017 than in 2016 by about a second. However, the dwell time trend over the year is flat in both years. Thus, since dwell times did not trend down in 2017 compared to 2016, one would conclude that the Green Lanes have not reduced dwell times. We stress here that the graphs only show unconditional regression lines of dwell times against a linear trend while our main analysis includes a rich set of explanatory variables.

If the comparison is made against other stations (graph in the middle) or other lines (graph on the right) in 2017, we see that while dwell times on the treated platform were flat, dwell times at other platforms increased over the same period. Thus, if the counterfactual trend of dwell times on the treated platform would be captured by either of those control platforms, one would conclude a successful reduction (or prevention of increase) of dwell times. The graphs also give an intuition about what we could expect from a triple difference estimation. The difference in the slope of the regression lines between 2017 and 2016 is close to zero on the treated platform. For other stations, we see a steep increase in 2017, and a less steep increase in 2016.

Thus, a difference in differences estimate involving other stations in 2017 should produce a strong negative effect. However, if we assume that the difference in slopes on the treated platform between 2017 and 2016 would have followed the same trend as the difference in slopes in the control stations, then the estimated treatment effect will be smaller.

The graphs show that choice of control observations is crucial. While inspecting trends in the pre-treatment period can be suggestive, uncertainty about the counterfactual evolution of dwell times on treated observations cannot be resolved. We therefore present in the next section results from alternative models.

5.7 Main Results

The main results are presented in Table 5.3. The first column shows results from the linear dwell time model, while the second and third columns are results for the delay time model described above. The second column shows the impact of the Green Lanes on latent dwell times, while the third column shows the effect on delay times. We start by comparing the dwell times before and after the Green Lane intervention on the Southbound Victoria line at King's Cross station. The result suggests a modest and statistically insignificant increase in dwell time by

Table 5.3: Treatment effect estimates of Green Lanes

Model	Dwell Analysis Effect on dwell time	Delay Analysis Effect on dwell time	Effect on delay time
Simple difference (before-after)	1.3*	5.0	-5.6
	(0.6)	(4.0)	(3.0)
Difference-in-differences (1)	0.2	3.9*	-4.6**
	(0.3)	(1.8)	(1.2)
Difference-in-differences (2)	-1.2**	0.5	-2.1
	(0.3)	(1.6)	(1.4)
Difference-in-differences (3)	-1.0**	1.7	-5.1**
	(0.3)	(2.1)	(1.1)
Triple difference (1, 2)	-2.0**	0.2	-8.7**
	(0.4)	(2.3)	(1.9)
Triple difference (1, 3)	-5.1**	-0.1	-12.6**
	(0.4)	(2.6)	(1.7)
Triple difference (2, 3)	-2.1**	1.4	4.4**
	(0.4)	(2.3)	(1.5)
Quadruple difference (1, 2, 3)	-6.6**	-1.5	-3.9
	(0.5)	(3.2)	(2.3)

Notes: The coefficients are percentage changes in dwell/delay times. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$. (1) uses the treatment platform in 2016 as control observations, (2) uses adjacent stations on the Victoria line as control observations, (3) uses other service line platforms at King's Cross station as control observations. All regressions control for *Demand*, *Lines*, *DemandPerLine*, *ServiceLevel*, *ServiceLevelDemand*, day of the week dummies, dummies for each 15-minute interval of the day, as well as a linear time trend. See also methodology section.

1.3% on the treated platform from pre to post treatment (*Simple difference*). We then use dwell time on the same platform and in the same period in 2016 as control to measure the possible treatment effects in 2017; this is intuitive as it accounts for any seasonal patterns on dwell time by comparing platform dwell times for both years (*Difference-in-differences (1)).* Here, we observe no significant reduction in dwell time on the treated platform compared to 2016. However, if we compare the dwell times in 2017 between King's Cross and its adjacent stations (*Difference-in-differences (2)*), we find a 1.2% reduction in dwell times. For the model that uses other service lines as a control group (*Difference-in-differences (3)*) we find a dwell time reduction of 1.0%.The next three rows display the estimated treatment effect for the triple difference estimator. *Triple difference (1, 2)* uses adjacent stations on the Victoria line and the treated platform in 2016 as the two groups of control observations. *Triple difference (1, 3)* uses other service lines at King's Cross station and the treated platform in 2016 as control observations. *Triple difference (2, 3)* uses adjacent stations on the Victoria line and other service lines at King's Cross station as control observations. The estimated reductions in dwell times range from 2.0% to 5.1%. Finally, the quadruple difference estimator – the most general model – suggests that dwell times were reduced by 6.6% – a reduction of 2.3 seconds.

The second and third columns explain whether these changes in dwell times came about through a general reduction of dwell times or through cutting the delay times of trains which were behind schedule. Since the service level and timetable in 2017 was not changed we would expect the reduction to come mainly through reduced delay times. For most specifications we observe reductions of delay time, ranging from an insignificant 2.1% to 12.6%. Only the *Triple difference (2, 3)* model finds a positive impact of the Green Lanes on delay times.

5.8 Heterogeneous trends

The identification of the treatment effect relies on the assumption that the dwell times of the treated observations would have changed by the same amount as the dwell times of the non-treated observations in the absence of the treatment.[1] While we cannot know whether this is the case, we can check whether treatment and control observations were trending in parallel before the treatment. We conduct tests for all our models in table 12 in the pre-treatment

[1] Analogous parallel trend assumptions can be formulated for the triple and quadruple difference models. See methodology section.

period with the null hypothesis of parallel trends for control and treatment observations. Unfortunately, in all cases this hypothesis is rejected (results not reported). All our tests strongly indicate that the treatment observations were trending up relative to the control observations in the pre-treatment period. How would this bias our coefficient of the Green Lane effect? If we extrapolated these trends, then the difference in dwell times between treatment and control observations would increase over time, resulting in a positive, but spurious, estimate of the Green Lanes. If after the treatment the trends run in parallel, we would still have a positively biased estimate, as the difference in dwell times between treatment and control observations after the treatment would still exceed the same difference before the treatment. A negative, and therefore compromising, bias occurs only if the growing gap in dwell times before the treatment reverts. In that case, if the difference in dwell times after the treatment is smaller than before the treatment, we would obtain a negative estimate for the Green Lane effect. The visual inspection of the dwell times does not suggest that this is the case.

To analyse the robustness of our results with respect to different pre-existing trends we re-estimate our models allowing for separate trends between different observations. For example, for the first difference-in-differences model, we allow for different trends in 2016 and 2017, while for the triple difference model which uses both years and different stations, we allow for different trends for King’s Cross station in 2016, King’s Cross station in 2017, other stations in 2016, and other stations in 2017. The results of these alternative models are in table 5.4. One important difference compared to the main results is the reversal of the effect for model *Difference-in-differences (3)*. Since we can see that the dwell times of observations on other service lines are increasing over time, allowing for separate trends does not attribute the growing gap between other lines and the Victoria line to the treatment anymore and reverses the effect.

Table 5.4: Treatment effect estimates of Green Lanes - Heterogenous trends

Model	Dwell Analysis Effect on dwell time	Delay Analysis Effect on dwell time	Effect on delay time
Difference-in-differences (1)	-0.0	8.5	-24.9**
	(0.8)	(4.9)	(4.0)
Difference-in-differences (2)	-0.7	0.6	-1.4
	(0.7)	(4.6)	(3.8)
Difference-in-differences (3)	4.0**	11.0	-9.1**
	(0.8)	(5.7)	(2.9)
Triple difference (1, 2)	-7.6**	1.6	-38.5**
	(1.0)	(6.0)	(5.0)
Triple difference (1, 3)	-0.9	5.4	-40.3**
	(1.1)	(7.0)	(4.5)
Triple difference (2, 3)	-2.0*	3.1	-26.2**
	(0.9)	(6.3)	(4.0)
Quadruple difference (1, 2, 3)	-9.5**	0.6	-70.1**
	(1.4)	(8.5)	(6.1)

Notes: The coefficients are percentage changes in dwell/delay times. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$. (1) uses the treatment platform in 2016 as control observations, (2) uses adjacent stations on the Victoria line as control observations, (3) uses other service line platforms at King's Cross station as control observations. All regressions control for Demand, Lines, DemandPerLine, ServiceLevel, ServiceLevelDemand, day of the week dummies, dummies for each 15-minute interval of the day, as well as linear time trends for each combination of treatment and control platforms. See also methodology section.

The negative effects of the Green Lanes in the triple and quadruple difference models however are preserved for dwell times, and we estimate very substantial reductions for latent delay times.

5.9 Further results

We next turn to the analysis of dwell times differentiated by time of day. London Underground typically splits the day into AM peak (07.00 to 10.00), PM peak (1600 to 1800), Inter-peak (10.00 to 1600) and off peak (any time outside these times). Trains dwell longest in the AM and PM peaks due to demand as these are when commuters go to work, do school runs, etc. The purpose is to examine if the Green Lane policy had a differing effect in any part of the day. Figure 5.4 is a plot of the estimated effects and confidence intervals from the quadruple difference model by time of the day in 15-minute intervals. We observe reductions in dwell time throughout the day, but significant effects are concentrated around the morning and evening peak hours. As platform demand ramps up in both peak periods, it appears that passengers tend to conform to the platform norm by obeying the Green Lane policy; this in turn drives down dwell time by a fraction. During periods of less demand the Green Lane's effect is not so significant because the main driver of dwell time and a major cause of impedance to boarding and alighting is demand.

The graph suggests that the Green Lane had higher peak effects (both AM and PM) than on the inter-peak and off-peak periods. This concurs with the normative theory that passengers tend to conform more when they know their actions impact on others, which is more pronounced at peak times because of high demand for waiting area. At other times, when the supply of waiting area exceeds demand, passengers do not bother so much about how or where they wait as there is abundant space for alighting and boarding to take place, sometimes simultaneously.

Figure 5.4: Plot of the Green Lane effect.

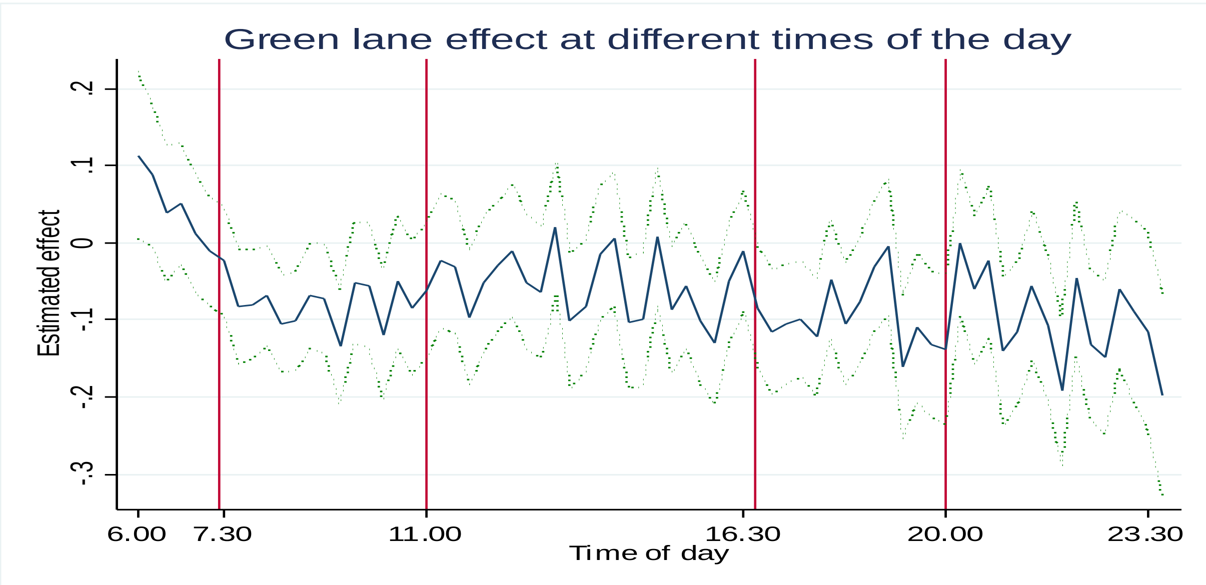


Figure 5.4: Estimated effects (solid blue) and confidence intervals (dashed greed) of Green Lanes on dwell times.

We next analyse whether the Green Lanes had any effect on the opposite direction of travel. It is tempting to think of the opposite travel direction as a placebo experiment because of the similarities of the two platforms. The outbound platform of the Victoria line at King's Cross station shares most characteristics with the inbound platform: it serves the same line, and therefore has the same service level; it is located at the same station (the two platforms are immediately connected, only separated by a passenger corridor; in particular, the platforms are not on opposite ends of the rails), and therefore has the same daily station demand and the same number of interchanges. The exact number of passengers served by a platform is not observed, but it is probable that the platforms serve roughly the same number of people within a day – e.g. commuters whose return journey is the reverse of their onward journey. The outbound platform differs from the inbound platform in two respects: First, the distribution of passengers over the day is probably different, e.g. most traffic on the inbound platform might be concentrated in the morning, while most of the traffic on the outbound platform might be concentrated in the evening. Unfortunately, we observe only daily station demand, but do not know the exact time of day, nor how it is distributed across the service lines. Second, the outbound platform was not treated with the Green Lanes.

However, there would be a great intersection between people using the platform in the inbound and the outbound direction, for example commuters. It is conceivable that changes to their behaviour on the treated platform extend to other platforms as well. Table 5.5 presents results for the outbound direction.

Table 5.5: Treatment effect estimates of Green Lanes - outbound direction

Model	Dwell Analysis	Delay Analysis	
	Effect on dwell time	Effect on dwell time	Effect on delay time
Simple difference	2.2**	9.3*	-5.6*
	(0.6)	(4.7)	(2.6)
Difference-in-differences (1)	0.4	1.7	2.7
	(0.3)	(2.1)	(1.5)
Difference-in-differences (2)	-0.9**	-0.8	-0.4
	(0.3)	(2.0)	(1.2)
Difference-in-differences (3)	1.4	3.2	-2.3*
	(0.3)	(2.3)	(1.1)
Triple difference (1, 2)	-1.0*	-2.4	2.0
	(0.4)	(2.4)	(1.9)
Triple difference (1, 3)	-1.0*	-0.0	5.1**
	(0.4)	(2.8)	(1.7)
Triple difference (2, 3)	-0.4	-1.5	1.4
	(0.4)	(2.7)	(1.3)
Quadruple difference (1, 2, 3)	-1.8**	-5.1	6.8**
	(0.5)	(3.5)	(2.2)

Notes: The coefficients are percentage changes in dwell/delay times. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$. (1) uses the treatment platform in 2016 as control observations, (2) uses adjacent stations on the Victoria line as control observations, (3) uses other service line platforms at King's Cross station as control observations. All regressions control for Demand, Lines, DemandPerLine, ServiceLevel, ServiceLevelDemand, day of the week dummies, dummies for each 15-minute interval of the day, as well as a linear time trend. See also methodology section.

The treatment effects on dwell times are much smaller in magnitude compared to the inbound observations, but we still find significant dwell time reductions on the order of 1.0% to 1.8% in the triple and quadruple difference models. In most specifications no significant effect on latent dwell and delay times are found. The result could mean two things: perhaps the outbound direction is an accurate scenario to describe what would have happened to the inbound direction in the absence of treatment, suggesting that our main results are somewhat negatively biased (they overestimate the reduction in dwell times). Alternatively, passengers might have extended their platform behaviour to the outbound platform as well, also reducing dwell times there, though not as strongly as on the treated platform.

5.10 Removal of the Green Lanes

Our final analysis is on whether the Green Lane effect has been permanent. The Green Lanes were removed in early 2018. Did passengers revert to non-compliant behaviour and thus cause a reversion in dwell times? To this end, we now define the year 2016 as pre- and the year 2018 as post treatment periods and omit the year 2017 altogether. This causes us to lose one dimension of control, so we have two difference-in-differences and one triple difference model. However, the concern that led us to include the year 2016 as one control dimension in the main section was the possibility of seasonal patterns in dwell time. Since we are now comparing across rather than within years, seasonality should not be a problem.

Table 5.6 shows what happened to dwell times after removal. Relative to 2016, dwell times are greater when compared against control stations, and when compared against control stations and control service lines. Only when compared against control service lines do we find a negative effect. However, the effect is statistically not distinguishable from zero. For delay times, two specifications support a reduction, while one supports an increase in dwell times. Overall, the evidence points to the disappearance of any beneficial effect of the Green Lanes after their removal.

Table 5.6: Treatment effect estimates of Green Lanes after removal

Model	Dwell Analysis Effect on dwell time	Delay Analysis Effect on dwell time	Effect on delay time
Simple difference	2.6**	10.4**	-28.9**
	(0.2)	(1.4)	(1.1)
Difference-in-differences (2)	8.4**	21.2**	18.8**
	(0.2)	(1.3)	(1.1)
Difference-in-differences (3)	-0.1	-5.3**	-29.6**
	(0.2)	(1.3)	(0.8)
Triple difference (2, 3)	1.6**	2.6*	-4.3**
	(0.2)	(1.3)	(1.1)

Notes: The coefficients are percentage changes in dwell/delay times. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$. (2) uses adjacent stations on the Victoria line as control observations, (3) uses other service line platforms at King's Cross station as control observations. All regressions control for Demand, Lines, DemandPerLine, ServiceLevel, ServiceLevelDemand, day of the week dummies, dummies for each 15-minute interval of the day, as well as a linear time trend. See also methodology section.

CHAPTER 6

Conclusion

Is there a cost-effective alternative method of managing public transport demand subject to capacity constraint, other than price mechanism and infrastructural investments? Transport is a unique good that cannot exist alone, and movements cannot be postponed or preponed. A product would remain on the shelf until sold but an unused ticket for a train service remains unused. The uniqueness of transport as a commodity plays a major role in setting the papers included in this thesis apart. In seeking to manage public transport demand providers may change their pricing policies, this research sheds more light on the effects, *ceteris paribus*, on passenger behaviour. Increasing fares for any transport corridor would make users consider their options, they may decide to walk, cycle, or even drive. This decision is a function of different variables including the elasticity of demand. It is important for transport providers and policy makers to consider the response of demand to price manipulations. The response of demand to an increase in price is considered to be in the downward direction as demand is inversely related to price.

This thesis concurs that the price mechanism is effective in controlling public transport demand. The concept of asymmetry has been tested in different fields; it has been found that demand reacts differently to price increases than to price decreases. But this is yet to be tested in the field of public transportation with actual data on a nominal decrease in ticket price; this research finds that there is asymmetry in the price elasticity of demand. The policy implication for transport providers is that they acknowledge that passengers may react differently to an equivalent fare increase and decrease.

Using fares to manage demand may be deemed to be costly. A price decrease represents a loss in revenue for the transport provider while a fare rise increases the generalised cost of travel for passengers. Therefore a relatively cost-effective measure of public transport demand is proposed in this research where passengers are nudged to conform to a social norm to achieve a desired network goal, without the need for heavy investments in infrastructure improvements, fleet procurements, or price manipulations. This thesis shows that norms can be very cost efficient when applied properly as was achieved at London King's Cross station. The Green Lanes changed passenger behaviour as people conformed to the existing platform norm, which in turn reduced waiting time for passengers and increased traffic flow. This is particularly relevant to established transport networks whose demand are relatively inelastic and are operating close to or at full capacity and for which infrastructural adjustments can be prohibitively expensive. For a fraction of the cost of procuring new rolling stock or adjusting station structure to meet growing demand, the Green Lane policy achieved a reduction or at least prevention in the increase in waiting time and generalised cost for passengers.

Further Research

The questions addressed in this thesis create opportunities for further research. Writing a thesis can sometimes be heavily time and data constrained. But concerning the Hopper policy it would be interesting and relevant to policy makers to know the type of passengers that used the policy more and for what purpose. A more granular analysis of the data is required to track the daily travel activities of individuals in order to delineate the particular beneficiaries of the Hopper policy and how much cost they save in terms of time and money. Other social norms could also be established in other fields to test conformity and achieve societal or organisational goals. Price and demand are two of the fundamental and most research topics in economics, but there is always room for further research questions. The demand for public transport is made up different passenger types with different elasticities. Further research is required to determine the point beyond which a passenger would switch mode when price changes.

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Appendix A1 – Methodology Details

The difference-in-differences estimator

Let Y_{tsl} represent the natural logarithm of dwell time of a train at time t, at station s, on service line l. We consider only inbound trains. Here, t is any moment in time from 6am on May the 21st to 11pm on November 30th in 2016 and 2017. We define the following variables:

> $Post_t$ = 1 if t is later than 6am, September 1st, in either year (2016, or 2017), and 0 otherwise.
>
> $D2017_t$ = 1 if t is in 2017, and 0 if t is in 2016.
>
> $Kings_s$ = 1 if s is King's Cross station, and 0 otherwise.
>
> $Victoria_l$ = 1 if l is the Victoria line, and 0 otherwise.

An observation is identified as subject to the Green Lane treatment, if (and only if) all those indicator variables are equal to 1. The error term ε_{tsl} is assumed to be independent of the independent variables. Robust standard errors are used to account for heteroscedasticity. We estimate the following equations:

$$Y_t = \alpha + \beta Post_t + \gamma D2017_t + \delta(Post_t \cdot D2017_t) + \rho X_t + \varepsilon_t$$

where the sample is restricted to trains on the Victoria line at King's Cross station. X is a vector of station and service line characteristics as described in section 4.3 and contains a linear time trend. A negative δ indicates a decrease in dwell times at the southbound Victoria line at Kings Cross in 2017 compared to the same time period in the preceding year when no Green Lanes were in place. To see this, take the difference in expected dwell time conditional on X between the post- and pre-treatment in 2017 ($D2017_t$=1) to obtain

$$\Delta_{2017} = E(Y_t|Post_t = 1, X_t) - E(Y_t|Post_t = 0, X_t) = \beta + \delta$$

while the same difference in 2016 would simply be β. The difference in the two differences is thus

$$\Delta_{2017} - \Delta_{2016} = \delta$$

Note that this result depends critically on assuming the time-of-year effect to be the same in both years – β has the same value in both years. Without this assumption, the 2D estimate would only identify the joint effect of the Green Lanes (δ) and the difference in the time-of-year effects between 2017 and 2016 (e.g. $\beta_{2017} - \beta_{2016}$).

Next, we restrict the sample to observations in 2017 and on the Victoria line to estimate

$$Y_{ts} = \alpha + \beta Post_t + \gamma Kings_s + \delta(Post_t \cdot Kings_s) + \rho X_{ts} + \varepsilon_{ts}$$

By the same argument as above, for King's Cross Station we obtain

$$\Delta_{Kings=1} = E(Y_{ts}|Post_t = 1, X_{ts}) - E(Y_{ts}|Post_t = 0, X_{ts}) = \beta + \delta$$

And for other stations

$$\Delta_{Kings=0} = E(Y_{ts}|Post_t = 1, X_{ts}) - E(Y_{ts}|Post_t = 0, X_{ts}) = \beta$$

The resulting 2D estimate is

$$\Delta_{Kings=1} - \Delta_{Kings=0} = \delta$$

The last 2D estimator only considers observations in King's Cross station in 2017:

$$Y_{tl} = \alpha + \beta Post_t + \gamma Victoria_l + \delta(Post_t \cdot Victoria_l) + \rho X_{tl} + \varepsilon_{tl}$$

The change in dwell times for observations on the Victoria line is

$$\Delta_{Victoria=1} = E(Y_{tl}|Post_t = 1, X_{tl}) - E(Y_{tl}|Post_t = 0, X_{tl}) = \beta + \delta$$

The change in dwell times for observations on other service lines is

$$\Delta_{Victoria=0} = E(Y_{tl}|Post_t = 1, X_{tl}) - E(Y_{tl}|Post_t = 0, X_{tl}) = \beta$$

The resulting 2D estimate is

$$\Delta_{Victoria=1} - \Delta_{Victoria=0} = \delta$$

The triple difference estimator

The first 3D estimator considers time-of-the-year and station specific effects and is restricted to observations on the Victoria line. We can obtain a 3D estimate with a model that is saturated in its interactions of the key variables, *Post*, *Kings*, and *D2017*.

$$Y_{ts} = \alpha + \beta Post_t + \gamma Kings_s + \zeta D2017_t + \delta(Post_t \cdot Kings_s) + \upsilon(Post_t \cdot D2017_t)$$
$$+ \iota(D2017_t \cdot Kings_s) + \eta(Post_t \cdot D2017_t \cdot Kings_s) + \rho X_{ts} + \varepsilon_{ts}$$

We obtain dwell time changes (between fall and summer) for King's Cross station, separately for 2017 and 2016:

$$\Delta_{Kings,2017} = \beta + \delta + \upsilon + \eta$$

$$\Delta_{Kings,2016} = \beta + \delta$$

With the resulting difference

$$\Delta_{Kings,2017} - \Delta_{Kings,2016} = \upsilon + \eta \qquad \text{(A1)}$$

Repeating this for other stations, we obtain

$$\Delta_{\text{other},2017} - \Delta_{\text{other},2016} = \upsilon \qquad \text{(A2)}$$

Thus, under the assumption that the year to year change in the dwell time difference between fall and summer is the same at King's Cross station as in other stations which serve the Victoria line, the difference between equations (A2) and (A1) identify the effect of the Green Lanes. The remaining two triple difference models can be constructed in analogous fashion.

Quadruple difference estimator

The 4D estimator naturally extends the 3D estimator. Now, all three scenarios need to be taken into account, and we have to distinguish observations by year, station, and service line. The model to be estimated is

$$
\begin{aligned}
Y_{tsl} = {} & \alpha + \beta_0 Post_t + \beta_1 D2017_t + \beta_2 Kings_s + \beta_3 Victoria_l + \gamma_0 (Post_t \cdot D2017_t) \\
& + \gamma_1 (Post_t \cdot Kings_s) + \gamma_2 (Post_t \cdot Victoria_l) + \gamma_3 (D2017_t \cdot Kings_s) \\
& + \gamma_4 (D2017_t \cdot Victoria_l) + \gamma_5 (Kings_s \cdot Victoria_l) \\
& + \delta_0 (Post_t \cdot D2017_t \cdot Kings_s) + \delta_1 (Post_t \cdot D2017_t \cdot Victoria_l) \\
& + \delta_2 (Post_t \cdot Kings_s \cdot Victoria_l) + \delta_3 (D2017_t \cdot Kings_s \cdot Victoria_l) + \eta (Post_t \\
& \cdot D2017_t \cdot Kings_s \cdot Victoria_l) + \rho X_{tsl} + \varepsilon_{tsl}
\end{aligned}
$$

We verify that η is the 4D estimator. If we considered only observations on the Victoria line, we would obtain

$$\Delta_{\text{Kings,2017}} - \Delta_{\text{Kings,2016}} = \gamma_0 + \delta_0 + \delta_1 + \eta \qquad \text{(A3)}$$

$$\Delta_{\text{other,2017}} - \Delta_{\text{other,2016}} = \gamma_0 + \delta_1 \qquad \text{(A4)}$$

And the resulting difference between (A3) and (A4) is

$$\Delta\Delta_{Victoria} = \delta_0 + \eta$$

Repeating this now for observations which are not on the Victoria line we would obtain simply $\Delta\Delta_{\text{not Victoria}} = \delta_0$. Thus, the resulting quadruple difference is:

$$\Delta\Delta_{\text{Victoria}} - \Delta\Delta_{\text{not Victoria}} = \eta$$

Appendix A2 – Results for complete sample period

Tables A1 to A3 correspond to tables 1 to 3 in the main text, but they are based on the entire sample, whereas the results in the main text exclude all observations which fall into the installation period of the Green Lanes. The 18th July marks the first day of the treatment period (that is, the variable Post is 1 for observations from the 18th of July to the 30th of November). While quantitative differences to the main results exist, the general conclusions about the effectiveness of the Green Lanes hold for this alternative sample selection as well.

Table A1: Treatment effect estimates of Green Lanes

Model	Dwell Analysis	Delay Analysis	
	Effect on dwell time	Effect on dwell time	Effect on delay time
Simple difference	1.4**	4.7*	-4.3**
	(0.3)	(2.1)	(1.6)
Difference-in-differences (1)	0.2	3.9*	-7.2**
	(0.3)	(1.7)	(1.4)
Difference-in-differences (2)	-0.8**	0.4	-2.0
	(0.2)	(1.5)	(1.3)
Difference-in-differences (3)	-0.3	3.1	-5.2**
	(0.3)	(1.9)	(1.0)
Triple difference (1, 2)	-1.9**	0.4	-7.6**
	(0.3)	(2.0)	(2.0)
Triple difference (1, 3)	-5.3**	-0.3	-10.1**
	(0.4)	(2.4)	(1.5)
Triple difference (2, 3)	-1.9**	1.9	-0.4
	(0.3)	(2.1)	(1.4)
Quadruple difference (1, 2, 3)	-7.6**	-1.7	-12.4**
	(0.5)	(2.9)	(2.1)

Notes: The coefficients are percentage changes in dwell/delay times. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$. (1) uses the treatment platform in 2016 as control observations, (2) uses adjacent stations on the Victoria line as control observations, (3) uses other service line platforms at King's Cross station as control observations. All regressions control for *Demand*, *Lines*, *DemandPerLine*, *ServiceLevel*, *ServiceLevelDemand,* day of the week dummies, dummies for each 15-minute interval of the day, as well as a linear time trend. See also methodology section.

Table A2: Treatment effect estimates of Green Lanes - Heterogenous trends

Model	Dwell Analysis Effect on dwell time	Delay Analysis Effect on dwell time	Effect on delay time
Difference-in-differences (1)	0.1	4.8	-9.6**
	(0.4)	(2.7)	(2.2)
Difference-in-differences (2)	0.8*	3.3	-1.9
	(0.4)	(2.5)	(2.1)
Difference-in-differences (3)	2.3**	8.1**	-6.7**
	(0.4)	(3.1)	(1.6)
Triple difference (1, 2)	-3.1**	1.1	-13.8**
	(0.5)	(3.3)	(2.7)
Triple difference (1, 3)	-4.5**	0.7	-11.1**
	(0.6)	(3.8)	(2.5)
Triple difference (2, 3)	-1.7**	2.5	-19.0**
	(0.5)	(3.4)	(2.2)
Quadruple difference (1, 2, 3)	-10.2**	-1.7	-46.9**
	(0.8)	(4.6)	(3.3)

Notes: The coefficients are percentage changes in dwell/delay times. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$. (1) uses the treatment platform in 2016 as control observations, (2) uses adjacent stations on the Victoria line as control observations, (3) uses other service line platforms at King's Cross station as control observations.All regressions control for Demand, Lines, DemandPerLine, ServiceLevel, ServiceLevelDemand, day of the week dummies, dummies for each 15-minute interval of the day, as well as linear time trends for each combination of treatment and control platforms. See also methodology section.

Table A3: Treatment effect estimates of Green Lanes - outbound direction

Model	Dwell Analysis	Delay Analysis	
	Effect on dwell time	Effect on dwell time	Effect on delay time
Simple difference	0.6	4.7	-2.9*
	(0.3)	(2.6)	(1.4)
Difference-in-differences (1)	-0.3	1.6	-0.4
	(0.3)	(1.9)	(1.3)
Difference-in-differences (2)	-0.5*	-0.2	0.8
	(0.2)	(1.8)	(1.1)
Difference-in-differences (3)	0.3	3.0	-2.8**
	(0.3)	(2.1)	(1.0)
Triple difference (1, 2)	-1.4**	-1.7	-0.2
	(0.4)	(2.2)	(1.8)
Triple difference (1, 3)	-2.2**	-1.2	3.1*
	(0.4)	(2.5)	(1.6)
Triple difference (2, 3)	-1.2**	-3.0	-0.3
	(0.3)	(2.4)	(1.2)
Quadruple difference (1, 2, 3)	-3.2**	-6.9*	0.8
	(0.5)	(3.1)	(2.0)

Notes: The coefficients are percentage changes in dwell/delay times. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$. (1) uses the treatment platform in 2016 as control observations, (2) uses adjacent stations on the Victoria line as control observations, (3) uses other service line platforms at King's Cross station as control observations. All regressions control for Demand, Lines, DemandPerLine, ServiceLevel, ServiceLevelDemand, day of the week dummies, dummies for each 15-minute interval of the day, as well as a linear time trend. See also methodology section.