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

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Abstract

Demand is frequently found to react differently to price increases than to price decreases. 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. We analyse 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 that we study 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, we find that demand is more sensitive to price increases than to decreases (by 0.3 to 0.9 percentage points). We also find that loss aversion contributes to this asymmetry at least on the intensive margin of transport demand.

JEL classifications: C23, D91, R41

Keywords: Price elasticity, public transport, loss aversion

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[*] We would like to thank Andrew Hyman, Graeme Fairnie, and Vasiliki Bampi, all from Transport for London, for their help and support in carrying out this work.

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1 Introduction

Demand for many products is frequently found to react differently in magnitude to price increases than it does for price decreases (Cornelsen et al., 2018; Gately, 1992; Gately and Huntington, 2002; Kalyanaram and Winer, 1995). 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 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.

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

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

public transport authorities to understand how their price policies affect demand and the choice of travel mode.

There is an expansive literature which analyses the elasticity of demand for public transport, both theoretical and empirical, and with respect to different factors. This literature forms the basis for transport policy formulation and implementation. Public transport providers may need to estimate the effects of a proposed fare or revenue policy on the level of demand.

Our paper exploits a rare opportunity to observe demand for public transport 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 sets our paper 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.

Our results suggest that demand both in terms of journeys and passengers reacts asymmetrically between fare increases and fare decreases. Our estimates of the difference between price-increase and price-decrease elasticities range from 0.18 to 1.00 percentage points. We can further shed some light on the underlying reasons for these asymmetries by looking at different measures of demand (journeys, passengers, and frequent passengers). While not conclusive, our results suggest that at least some of this asymmetry is attributable to loss aversion.

2 Literature Review

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.

Our paper, to the best of our knowledge, 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.

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., 2004; Bresson et al., 2003; 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., 2006). 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.

3 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 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 1 approximately here]

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 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.

4 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 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

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

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. 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 2 approximately here]

We distinguish between a journey, which is any trip undertaken on the Underground, 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. We caution that we can identify only separate payment sources (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.

5 Model specification and estimation

We look 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.

We complement our analysis based on daily demand 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. 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 approximately here]

Our 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 2nd of January, and petrol prices. Our 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:

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

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

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 2^{nd}, and 0 else. $D_i(Rezone)$ is 1 if the journey type is between zone 1 and a rezoned station. 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]

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 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.[2] For comparison purposes we also estimate our model under the restrictions $\delta_2 = 0$ and $\kappa = 0$.

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[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.

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

6 Results

Table 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.

[Table 1 approximately here]

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 -0.17 in 2014/15 to -0.88 in 2015/16), while demand for journeys affected by re-zoning (which saw fare decreases in 2015/16) became less elastic (from -0.77 in 2014/15 to -0.57 in 2015/16). The difference in these elasticity changes between rezoned and non-rezoned journey types is 0.91 and significant at 1% (see also table 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. -0.17 for non-rezoned, and -0.77 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.

[Table 2 approximately here]

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 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. 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 0.91 – the same as for the complete sample.

[Table 3 approximately here]

Table 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 0.91 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). 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.

[Table 4 approximately here]

We report results for weekly data in table 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.

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 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

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

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.

Did fare decreases crowd out demand for different journey types?

We now investigate whether the fare changes in 2016 have affected demand for journey types whose fares have not changed. Figure 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.

[Figure 4 approximately here]

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. 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 5 approximately here]

7 Conclusion

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 an insignificant 0.31 to a highly significant 0.91 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.

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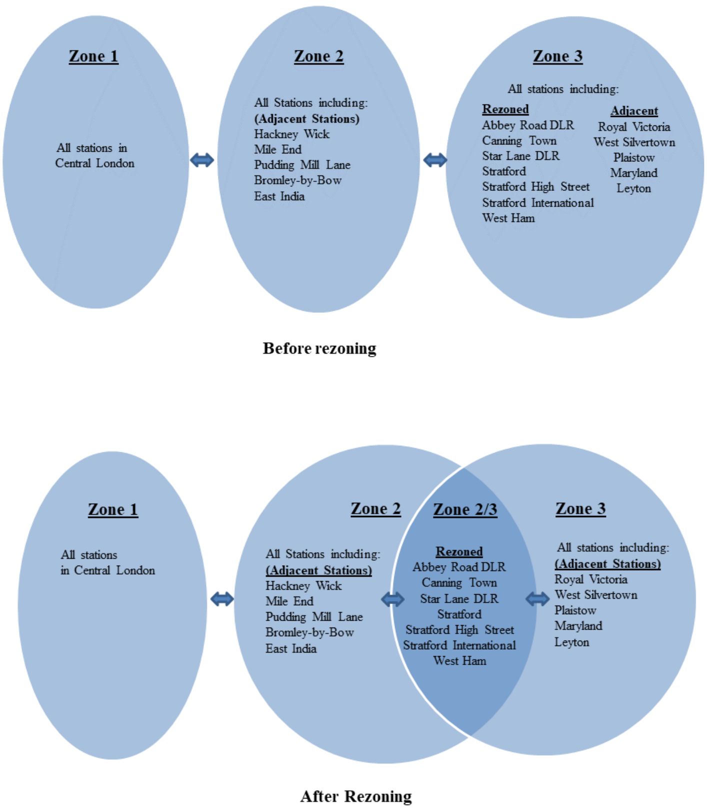
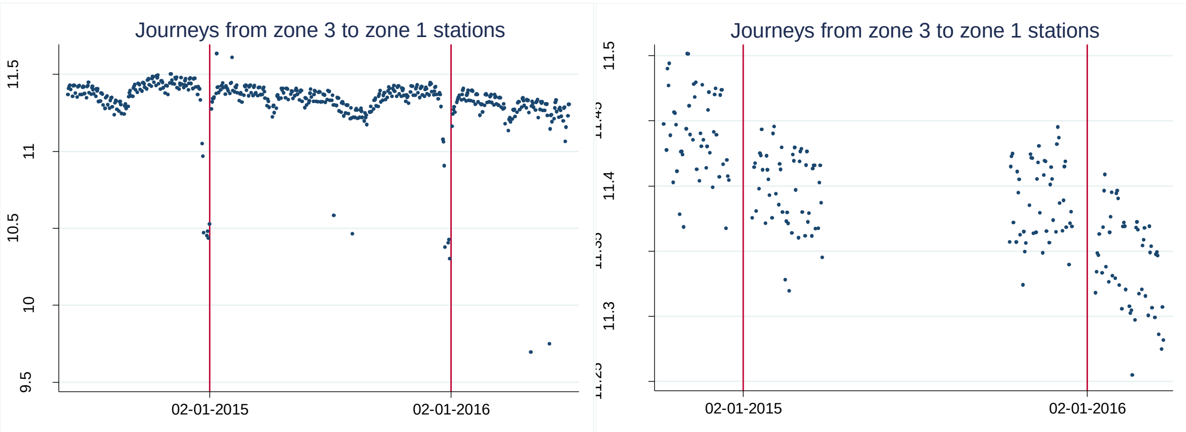
Figures and tables

Figure 1



Note: Before rezoning in 2016, the 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.

Figure 2



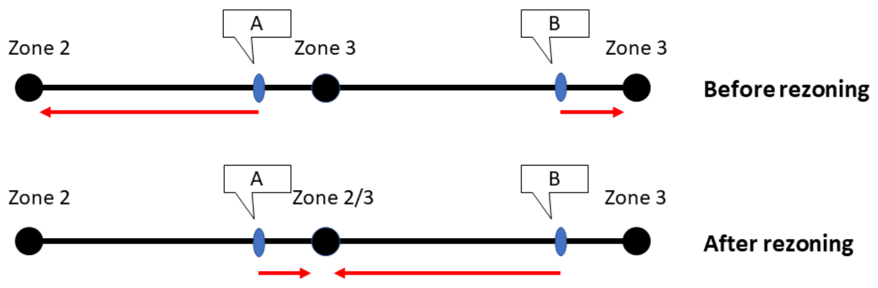
Note: Log of daily demand during peak times and at full fare from zone 3 to zone 1. Left: all observations. Right: after removing troughs and outliers.

Figure 3

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.

Figure 4



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).

Table 1

Table 1: Price elasticities trips - full sample

Year	2014/15				2015/16			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Short term ε	-0.14		-0.09		-0.72***		-0.56***	
	(0.18)		(0.13)		(0.07)		(0.06)	
Short term ε - not rezoned		-0.17		-0.11		-0.88***		-0.70***
		(0.18)		(0.13)		(0.06)		(0.06)
Short term ε - rezoned		-0.77**		-0.57**		-0.57***		-0.44***
		(0.35)		(0.26)		(0.08)		(0.06)
Long term ε			-0.12				-0.74***	
			(0.18)				(0.07)	
Long term ε - not rezoned				-0.15				-0.91***
				(0.18)				(0.06)
Long term ε - rezoned				-0.79**				-0.58***
				(0.35)				(0.08)
Petrol price ε	0.68***	0.68***	0.53***	0.53***	1.06***	1.07***	0.79**	0.80**
	(0.22)	(0.22)	(0.19)	(0.19)	(0.28)	(0.39)	(0.34)	(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%.

Table 2

Table 2: Price elasticities trips - small sample

Year	2014/15				2015/16			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Short term ε	-1.94***		-1.58***		-0.67***		-0.54***	
	(0.47)		(0.40)		(0.05)		(0.05)	
Short term ε - not rezoned		-2.27***		-1.87***		-0.74***		-0.60***
		(0.54)		(0.44)		(0.11)		(0.11)
Short term ε - rezoned		-3.05***		-2.55***		-0.62***		-0.49***
		(0.79)		(0.65)		(0.09)		(0.07)
Long term ε			-1.84***				-0.68***	
			(0.45)				(0.06)	
Long term ε - not rezoned				-2.18***				-0.77***
				(0.51)				(0.13)
Long term ε - rezoned				-2.97***				-0.63***
				(0.75)				(0.09)
Petrol price ε	0.58	0.58	0.53	0.53	1.23	1.23	0.99	0.99
	(0.45)	(0.45)	(0.44)	(0.44)	(0.73)	(0.73)	(0.65)	(0.65)
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%.

Table 3

Table 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	-0.17	-0.88***	-0.71***	0.12	-0.81***	-0.92***	-0.16	-0.13***	0.03
	(0.18)	(0.06)	(0.19)	(0.23)	(0.06)	(0.24)	(0.18)	(0.05)	(0.19)
Short term ε - rezoned	-0.77**	-0.57***	0.20	-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	-0.60***	0.31***	0.91***	-0.58**	0.21**	0.79***	-0.59*	-0.41***	0.18
	(0.23)	(0.11)	(0.26)	(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	-2.27***	-0.74***	1.52***	-2.14***	-0.68***	1.46**	-2.90***	-0.14*	2.76***
	(0.54)	(0.11)	(0.54)	(0.69)	(0.11)	(0.69)	(0.76)	(0.08)	(0.75)
Short term ε - rezoned	-3.05***	-0.62***	2.43***	-2.80**	-0.64***	2.16**	-3.82***	-0.54***	3.28***
	(0.79)	(0.09)	(0.79)	(1.02)	(0.04)	(1.01)	(1.14)	(0.03)	(1.12)
Difference	-0.78***	0.12	0.91***	-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.

Table 4

Table 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***	-0.78***	0.57***	-0.64***	-1.22***	0.23**	-0.18***	-0.41***
	(0.22)	(0.06)	(0.22)	(0.13)	(0.05)	(0.14)	(0.11)	(0.02)	(0.11)
Short term ε - rezoned	-0.35	-0.64***	-0.28	0.09	-0.17***	-0.25	-0.49***	-0.19***	0.30
	(0.41)	(0.09)	(0.42)	(0.27)	(0.02)	(0.27)	(0.27)	(0.01)	(0.27)
Difference	-0.49*	0.01	0.49*	-0.49***	0.48***	0.96***	-0.72***	-0.01	0.71***
	(0.25)	(0.12)	(0.28)	(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***	1.22*	-0.95*	-0.20***	0.75	-3.23***	-0.19***	3.04***
	(0.60)	(0.11)	(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***
	(0.25)	(0.19)	(0.32)	(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.

Table 5

Table 5: Cross price elasticities in 2015/16

	Daily			Weekly		
	Journeys	Passengers	Frequent passengers	Journeys	Passengers	Frequent passengers
Full sample						
Short term ε - not rezoned	0.12	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	0.02	0.08	0.12**	0.03	0.17***	0.17***
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Small sample						
Short term ε - not rezoned	0.97***	0.61*	0.74**	1.71***	1.51***	-1.42
	(0.30)	(0.32)	(0.35)	(0.47)	(0.43)	(0.90)
Short term ε - rezoned	-0.27**	0.09	0.12	-0.38**	-1.53	1.64***
	(0.11)	(0.09)	(0.09)	(0.16)	(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%.