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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 leading to a kinked demand curve. This kink is often invoked in explaining why prices are sticky, especially in the downward direction. 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 0.5 to 1.0 percentage points). We also find that loss aversion contributes to this asymmetry at least on the intensive margin of transport demand.

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 in Kahneman and Tversky (1979), then they will react more strongly to a price increase than they do to an equivalent price decrease. Alternatively, a lag in information dissemination can also lead to asymmetric demand responses. 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).

A more straightforward explanation of asymmetric price elasticities is that demand is simply not iso-elastic. However, loss aversion and asymmetric information have the additional appeal of potentially explaining why fare revisions occur

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infrequently (once a year in the current case). Both loss aversion and asymmetric information lead to a 'kink' in demand, which can be invoked to explain infrequent and discontinuous price adjustments (Dupraz, 2017). Blinder (1991) offers some support for a psychological explanation by reporting that business people prefer to keep prices fixed so as not to antagonize customers. The idea of kinked demand goes back to Sweezy (1939) who shows how it can arise in oligopolies, leading to a discontinuity in marginal revenue, and thus a range of marginal costs for which an oligopolist does not adjust their price. Heidhues and Koszegi (2004) present a model with loss-averse consumers and resulting price stickiness in a monopoly model.

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 (a price decrease) and stock it. After the promotion ends (a price increase) 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. Finally, public transport fares are not subject to price volatility, unlike, for example, gasoline prices (Chi, 2022; Kwon and Lee, 2014) as they change at predictable times and by predictable magnitudes. 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 public transport authorities to understand how their price policies affect demand and the choice of travel mode.

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 0.25 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

2.1. 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

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

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). In transport the focus has mostly been on demand asymmetries with respect to gasoline prices (Chi, 2022; Hymel and Small, 2015; Kwon and Lee, 2014). Interestingly, Chi (2022) is the only study which proposes loss aversion as one potential explanation for the presence of demand asymmetries.

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 studies that we are aware of that look at the asymmetric response of public transport demand to changes in price are Chen et al. (2011) and Li et al. (2020). 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. Li et al. (2020) analyze a panel of Canadian transit agencies and find higher elasticities for fare increases than for decreases. However, the result is not statistically conclusive, and their identification of fare decreases seems likely to be driven by decreases in real fares due to inflation (the study deflates fares to constant prices – it is not clear if there are any instances of nominal fare decreases). 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.

The transport literature has paid more attention to demand asymmetries in the context of gasoline prices, perhaps because price changes and in particular price decreases are more readily observed. Chi (2022) finds higher elasticities of gasoline price increases compared to price decreases on public transit ridership in five of the six U.S. cities included in her study. Hymel and Small (2015) find stronger responses of gasoline price increases compared to decreases on vehicle travel. They explore the channels of price volatility and media attention in explaining this asymmetry and conclude that these channels explain around half of the observed asymmetry. The media coverage channel is very close in spirit to the information asymmetry argument that we explore in this paper. Li et al. (2020) find that transit demand in Canada reacts more strongly to rising than to falling gasoline prices. The emerging consensus here is that demand for road travel as well as public transport responds more strongly when gasoline prices rise than when they fall.

Our paper, to the best of our knowledge, differs from any existing work on asymmetry because the data present a nominal reduction in fares which allows for a unique and rare empirical quantification of the response of demand to a reduction in public transport fares. While we use gasoline prices as a control variable our focus are asymmetries in own-price elasticities of travel demand on the London Underground.

2.2. 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. Wardman (2014) provides a meta-analysis of surface travel elasticities and shows that elasticity estimates vary widely by travel mode, area, travel purpose, and time dimension (short or long run). Schimek (2015) reports a short run elasticity of −0.3 and a long-run elasticity of −0.7 for a large cross-section of U.S. transit agencies. 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. Fig. 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.

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

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

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

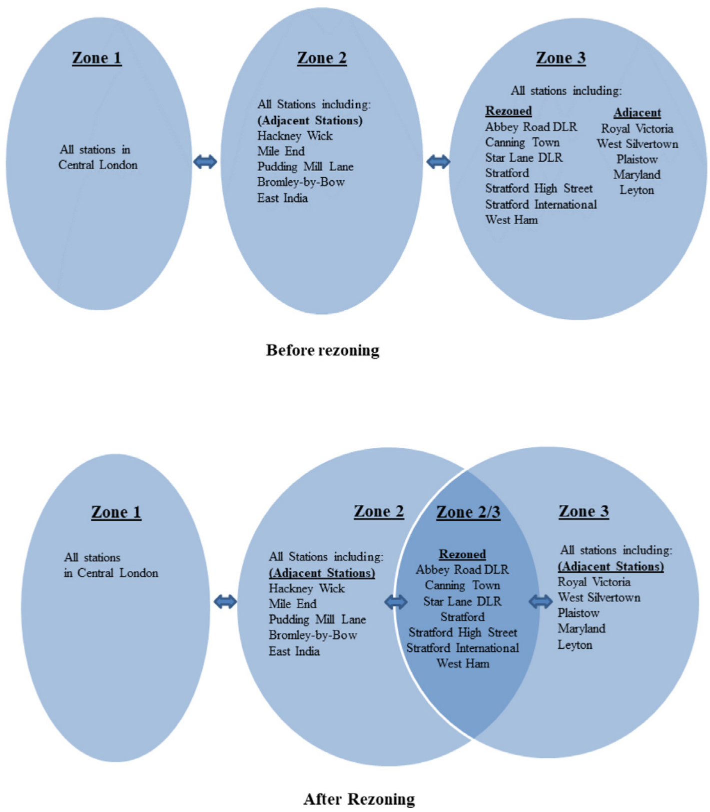

Fig. 1. Rezoned and adjacent stations.
Note: Before rezoning in 2016, the stations under Rezoned were in zone 3 (upper panel). After rezoning, they became boundary stations on the boundary between zones 2 and 3 (lower panel). Adjacent stations are stations which directly connect to one of the rezoned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

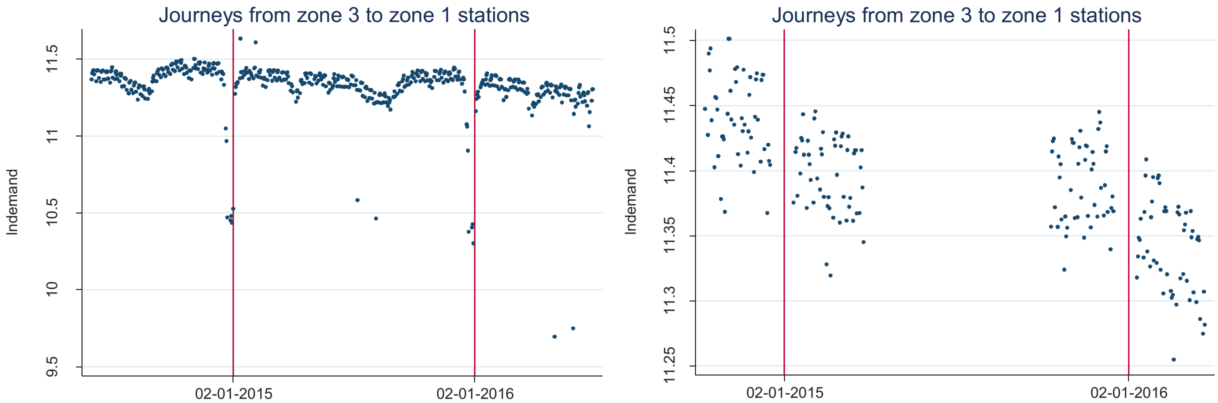

Fig. 2. Daily demand from zone 3 stations to zone 1 stations.
Note: Log of daily demand during peak times and at full fare from zone 3 to zone 1. Left: all observations. Right: after removing troughs and outliers.

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 Fig. 2.

Daily travel demand is influenced by additional factors such as the weather, the cost of alternative modes of transport, and disruptions to the public transport system. To control for weather related factors we use daily data on rainfall, temperature, and other weather characteristics.[3] We obtain weekly petrol price information (price paid at pump station) from the UK Department for Business, Energy, and Industrial Strategy. Monthly data on unemployment and average house prices were obtained from the London Datastore. Finally, we complement TfL's travel data with TfL's internal daily information on lost customer hours as a measure of service reliability.

In projecting monthly data (such as unemployment) onto days we have followed two approaches. The first is to use the unemployment rate reported for a month for all the days which fall into that month. Alternatively, we have used the reported unemployment rate only for the 15th day of each month and filled in the remaining points by linear interpolation. Both calculations yielded nearly identical results for our elasticity estimations. The results reported below are based on the interpolated series. Complete results can be requested by the corresponding author.

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*. Hymel and Small (2015) explore a similar channel by looking at whether elasticities are higher during periods of media coverage of gasoline prices. If media attention is greater to price increases, then this could potentially explain why price increase elasticities are greater than price decrease elasticities.

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:

$$\ln D_{jt} = \alpha_D + \beta_D \ln P_{jt} \tag{1}$$

$$\ln N_{jt} = \alpha_N + \beta_N \ln P_{jt} \tag{2}$$

$$\ln d_{jt} = \alpha_d + \beta_d \ln P_{jt} \tag{3}$$

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

$$\beta_D = \beta_N + \beta_d$$

[3] We obtained rainfall data for London from the London Datastore (data.london.gov.uk) run by the Greater London Authority. We downloaded data on average temperatures, humidity, wind speed and dew point from the Weather Underground website (wunderground.com).

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

Fig. 3. Example daily and weekly travel demand.
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.

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 Fig. 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.

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 other control variables which affect demand for public transport. These are petrol prices, economic conditions, weather characteristics, and service reliability proxied by lost customer hours as described above. For our model in weekly observations, we computed the averages of these data for the corresponding weeks. 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:

$$ln(Y)_{it} = \boldsymbol{\alpha_i} + \boldsymbol{\beta_1} t + \boldsymbol{\beta_2} t^2 + D_t\left(t > January\ 2^{nd}\right) + \gamma'_2 X_{it} + \boldsymbol{\delta_1} ln(fare)_{it} + \boldsymbol{\delta_2} D_i(Rezone) \times ln(fare)_{it} + \kappa\, ln(Y)_{i,t-1} + u_{it} \tag{4}$$

The subscript i refers to journey type, and t to time. Observations are daily or weekly. Y is demand, $D_t(t > January\ 2nd)$ 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. Finally, X is a column vector of control variables including the price of petrol, daily weather characteristics, economic conditions, and daily lost customer hours due to disruptions to the Underground service, and *fare* is the fare in pounds.

5.1. Model validity

The main parameters of interest are δ_1 and δ_2. These parameters can be consistently estimated since fare changes, both in incidence and magnitude, can reasonably be treated as exogenous, especially in the short time window which we observe. In the long-term fares and demand are more likely to be co-determined and endogeneity of fares is a more serious matter in longer time series. Note that for any journey type the fare changes only once (on January 2nd). The variable *ln(fare)* is therefore akin to a treatment variable which allows before and after comparisons on treated observations. The dummy variable $D_t(t > January\ 2nd)$ will absorb any other factors which change on the same threshold day and which affect transport demand. If the fares of all journey types changed by the same proportion, then a fare effect could not be separately identified from the effect of this dummy. However, different journey types change by different rates. This allows us to interpret δ_1 as a pure fare effect. To check whether fare changes affect journeys involving rezoned stations differently compared to the remaining journeys we allow the two journey types to have different elasticities. This is achieved by including the interaction term $D_i(Rezone) \times ln(fare)_{it}$ in our model. The change in travel demand for a 1% fare increase for journeys involving rezoned stations is given by $(\delta_1 + \delta_2)$%, while for the remaining journeys it is δ_1%. The difference between the two is then δ_2 percentage points. The parameter δ_2 estimated for the 2014/15 sample ($\delta_2^{2014/15}$) thus gives us a good indication of the 'natural' difference in elasticities between journeys with and without rezoned stations and absorbs any unobserved differences between journeys with and without rezoned stations.

In the following year (2015/16) the fares for journeys involving rezoned stations have *dropped*. If there are no asymmetric responses between price increases and decreases then we should expect to obtain a comparable value for δ_2 ($\delta_2^{2015/16} = \delta_2^{2014/15}$). A significant difference will support the hypothesis that demand reacts differently in magnitude to price increases than to price decreases. Our empirical strategy thus combines a regression discontinuity (RD) approach (in

Table 1
Price elasticities trips - full sample.

Year	2014/15				2015/16			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Short term ε	−0.12		−0.12		−0.71***		−0.58***	
	(0.20)		(0.17)		(0.07)		(0.06)	
Short term ε - not rezoned		−0.15		−0.13		−0.89***		−0.73***
		(0.20)		(0.17)		(0.07)		(0.07)
Short term ε - rezoned		−0.73**		−0.63**		−0.56***		−0.44***
		(0.35)		(0.29)		(0.08)		(0.06)
Long term ε			−0.14				−0.75***	
			(0.20)				(0.08)	
Long term ε - not rezoned				−0.16				−0.94***
				(0.20)				(0.07)
Long term ε - rezoned				−0.76**				−0.57***
				(0.35)				(0.08)
Petrol price ε	0.53***	0.53***	0.46***	0.46***	1.26***	1.27***	1.03**	1.03**
	(0.22)	(0.15)	(0.14)	(0.14)	(0.17)	(0.17)	(0.16)	(0.16)
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	8163	8163	8163	8163	7981	7981	7981	7981

Note: Results are price elasticities of demand. Further controls are weather characteristics, economic conditions, and lost customer hours (see Section 4 for a detailed description of variables). Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

estimating elasticities exploiting discontinuous changes in fares around the start of a new calendar year) and a difference-in-differences (DiD) model in comparing these elasticities between journeys with and without rezoned stations on the one hand, and between a year with and without re-zoning on the other. The DiD model assumes that *in the absence of treatment* the outcome of treated observations would have evolved parallel to the outcome of the control observations. This is the well-known parallel trend assumptions needed for the causal interpretation of the DiD estimator. The assumption is not testable since we do not observe the evolution of treated observations under a no-treatment scenario.

Given the exogeneity of fares it is unlikely that omitted variables will bias our elasticity estimates. Even if other variables explain day-to-day fluctuations in public transport demand, these variables are likely to be orthogonal to prices, especially given that we control for time effects. This is confirmed by inspecting the correlation of ln(fare) with the remaining control variables (see Table A1 in the appendix). The highest correlation is with ln(petrol) – a correlation coefficient of merely −0.04. However, control variables may help in reducing the remaining noise in our model and lead to more precise estimates.

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%. We caution the reader that short and long run in the current context are quite distinct from their use in the literature due to the high frequency of our data. There is probably more day-to-day variation in demand than would be the case for monthly data which would explain the relatively small coefficients on lagged demand. 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.[4] 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 2nd)*.

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

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 ($\kappa = 0$),

[4] 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 $p_{1t} = (\sum_{j=1}^{J} p_{j1}) - (\sum_{j=2}^{J} p_{jt}) + D_{t=2}(\sum_{j=1}^{J} \Delta p_j)$, 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.

[5] We also considered Newey-West standard errors, but this did not generally change the inference. Significance levels for results in Table 4 were reduced.

Table 2
Selected studies on public transport demand.

Study	*Cross section*	*Time*	*Fare metric*	*Price elasticity*
Chen et al. (2011)	Commuter rail trips between New Jersey and New York City	1996–2009 (monthly)	Average fares charged	−0.4
Wardman (2014)	Meta analysis of rail travel in the UK			−0.4 to −1.0
Schimek (2015)	198 US transit agencies (all modes)	1991–2012	Revenue/passengers	−0.34
Daldoul et al. (2016)	12 Regional Transport Companies in Tunisia (mostly buses)	1997–2010	Revenue/passengers	−0.46
Li et al. (2020)	99 Canadian transit authorities	2002–2016	Actual fares charged	−0.24
This study	81 journey type dyads on the London Underground	2014–2016 (daily and weekly)	Actual fares charged	−0.12

Note: Comparison of this study with recent estimates of own fare elasticities for public transport.

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. The weather characteristics are jointly highly significant, unemployment correlates negatively and service reliability positively with travel demand as expected.[6] 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.

How do our estimates compare to recent findings in the literature? Table 2 compiles a selected list of recent studies which have estimated price elasticities for public transport demand. The estimates of original studies range from −0.24 to −0.46 – a remarkably narrow range given the diversity of regions and transport modes considered. The most typical elasticity from our investigation is −0.12. This is the elasticity for non-rezoned journeys – by far the more common type of journey undertaken on the London Underground – in 2014/15 when travel fares increased for all journey types. A number of factors contribute to a lower elasticity estimate compared to the literature. First, we look at journey types within one mode of travel and one city. Different journey types are less substitutable than different modes of travel. Second, TfL increased fares in 2015 for all journey types and travel modes. For example, pay as you go bus fares increased from £1.45 to £1.50, reducing the relative benefit of changing transport modes. As a result, travelling became more expensive, but the cost of travelling relative to another mode changed less. Third, structural features of London (population density, the congestion charge of driving into the inner city, commuting distances) might contribute to a lower elasticity in London compared to other cities. We thus think that our elasticity estimates fall in a reasonable range given these features. Only two of the papers have explored demand asymmetries (Chen et al. (2011) and Li et al. (2020)). Both fail to find a significant effect of price decreases on demand but they do find a significant effect of price increases. We suspect that the failure to find effects of price decreases is due to the fact that price decreases are only identified in terms of real prices which fall due to inflation. In contrast, in our context we can observe the change of demand after a nominal price decrease.

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 −0.89 in 2015/16), while demand for journeys affected by re-zoning (which saw fare decreases in 2015/16) became less elastic (from −0.73 in 2014/15 to −0.56 in 2015/16). The difference in these elasticity changes between rezoned and non-rezoned journey types is 0.90 and significant at 1% (see also Table 4).

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 which 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 −0.73 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 DiD estimator.

[6] We omit the results from the table to avoid clutter and to focus attention on fare elasticities. Full results are available upon request from the corresponding author.

Table 3
Price elasticities trips - small sample.

Year	2014/15				2015/16			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Short term ε	-1.85^{***} (0.47)		-1.56^{***} (0.44)		-0.65^{***} (0.05)		-0.52^{***} (0.05)	
Short term ε - not rezoned		-2.11^{***} (0.54)		-1.78^{***} (0.52)		-0.69^{***} (0.13)		-0.57^{***} (0.10)
Short term ε - rezoned		-2.80^{***} (0.80)		-2.39^{***} (0.75)		-0.62^{***} (0.09)		-0.49^{***} (0.07)
Long term ε			-1.79^{***} (0.48)				-0.68^{***} (0.06)	
Long term ε - not rezoned				-2.04^{***} (0.56)				-0.74^{***} (0.12)
Long term ε - rezoned				-2.73^{***} (0.82)				-0.63^{***} (0.09)
Petrol price ε	0.34 (0.24)	0.34 (0.24)	0.31 (0.24)	0.31 (0.24)	1.27^{***} (0.24)	1.27^{***} (0.24)	1.16^{***} (0.22)	1.16^{***} (0.22)
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	911	911	898	898	898	898

Note: Results are price elasticities of demand. The small sample consists only of journey types which have had their fare changed in both fare revision rounds (at the beginning of 2015 and again in 2016). Further controls are weather characteristics, economic conditions, and lost customer hours (see Section 4 for a detailed description of variables). Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Table 4
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 (0.20)	-0.88^{***} (0.07)	-0.74^{***} (0.21)	0.13 (0.23)	-0.82^{***} (0.06)	-0.96^{***} (0.24)	−0.15 (0.19)	-0.16^{***} (0.05)	−0.01 (0.19)
Short term ε - rezoned	-0.73^{**} (0.35)	-0.57^{***} (0.08)	0.16 (0.36)	−0.46 (0.43)	-0.59^{***} (0.03)	−0.13 (0.43)	-0.76^{*} (0.42)	-0.52^{***} (0.02)	0.24 (0.42)
Difference	-0.58^{***} (0.22)	0.32^{***} (0.12)	0.90^{***} (0.25)	-0.59^{**} (0.28)	0.23^{**} (0.09)	0.83^{***} (0.29)	-0.61^{*} (0.33)	-0.37^{***} (0.06)	0.25 (0.34)
Number of observations	8163	7981		8121	8195		8263	8203	
Small sample									
Short term ε - not rezoned	-2.11^{***} (0.53)	-0.70^{***} (0.12)	1.41^{**} (0.54)	-2.19^{***} (0.70)	-0.69^{***} (0.11)	1.50^{**} (0.69)	-2.86^{***} (0.75)	-0.15^{*} (0.09)	2.71^{***} (0.76)
Short term ε - rezoned	-2.81^{***} (0.79)	-0.62^{***} (0.09)	2.18^{***} (0.79)	-2.87^{***} (1.00)	-0.64^{***} (0.04)	2.23^{**} (1.00)	-3.79^{***} (1.12)	-0.53^{***} (0.03)	3.26^{***} (1.12)
Difference	-0.70^{**} (0.29)	0.07 (0.18)	0.77^{**} (0.34)	-0.70^{*} (0.37)	0.05 (0.15)	0.73^{*} (0.40)	-0.93^{**} (0.45)	-0.38^{***} (0.11)	0.55 (0.46)
Number of observations	911	898		912	913		936	919	

Note: Results are price elasticities of demand and their differences over time and between stations which were and were not rezoned. Further controls are weather characteristics, economic conditions, and lost customer hours (see Section 4 for a detailed description of variables). 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.

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. 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 0.77 which is in the ballpark of the 0.90 estimated for the complete sample.

Table 4 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 0.90 percentage points in the full sample and by 0.77 percentage points in the small sample. This holds both

Table 5
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	0.17	-0.60^{***}	-0.78^{***}	0.58^{***}	-0.64^{***}	-1.21^{***}	0.23^{**}	-0.18^{***}	-0.40^{***}
	(0.23)	(0.06)	(0.23)	(0.13)	(0.05)	(0.14)	(0.11)	(0.02)	(0.11)
Short term ε - rezoned	−0.32	-0.61^{***}	−0.29	0.09	-0.17^{***}	−0.26	-0.49^{***}	-0.18^{***}	0.31
	(0.38)	(0.11)	(0.40)	(0.26)	(0.02)	(0.27)	(0.27)	(0.01)	(0.27)
Difference	-0.49^{**}	−0.01	0.49^{*}	-0.49^{**}	0.47^{***}	0.96^{***}	-0.72^{***}	−0.01	0.71^{***}
	(0.24)	(0.13)	(0.27)	(0.19)	(0.06)	(0.20)	(0.23)	(0.03)	(0.23)
Number of observations	1548	1485		1563	1556		1611	1596	
Small sample									
Short term ε - not rezoned	-2.90^{***}	-0.48^{***}	2.43^{***}	−0.46	-0.52^{***}	−0.06	-2.21^{***}	-0.17^{***}	2.04^{***}
	(0.52)	(0.09)	(0.52)	(0.35)	(0.07)	(0.35)	(0.29)	(0.04)	(0.30)
Short term ε - rezoned	-3.74^{***}	-0.64^{***}	3.11^{***}	-0.96^{*}	-0.21^{***}	0.75	-3.23^{***}	-0.19^{***}	3.04^{***}
	(0.73)	(0.11)	(0.73)	(0.54)	(0.03)	(0.54)	(0.48)	(0.01)	(0.47)
Difference	-0.84^{***}	−0.16	0.68^{**}	-0.51^{**}	0.30^{***}	0.81^{***}	-1.02^{**}	−0.02	1.00^{***}
	(0.27)	(0.16)	(0.32)	(0.24)	(0.09)	(0.25)	(0.26)	(0.05)	(0.27)
Number of observations	177	167		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. Further controls are weather characteristics, economic conditions, and lost customer hours (see Section 4 for a detailed description of variables). 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 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 −0.46 to −0.59 (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 0.13 to −0.82, resulting in a significant difference in differences of 0.83 (0.73 in the smaller sample). The implied difference in differences estimates for journeys per passenger (the intensive margin) are 0.07 in the full, and 0.04 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 (0.25 for the full, 0.55 for the small sample) but they are not significantly different from zero.

We report results for weekly data in Table 5. 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 0.17 to −0.60 and from −0.32 to −0.61 respectively). However, the estimates from the small sample suggest that elasticities have decreased (from −2.90 to −0.48 and from −3.74 to −0.64). In either case, the resulting difference in elasticity changes is estimated as 0.49 for the full, and 0.68, with the latter being significant at 5%.

For passengers, we do observe statistically significant differences, and the asymmetry is close to one percentage point (0.96 and 0.81). 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.[7] 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 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.

6.1. 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. Fig. 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

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

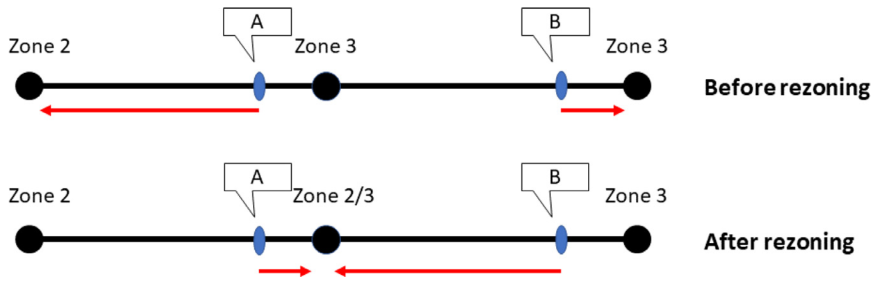

Fig. 4. Optimal departure station before and after rezoning.
Note: Person A walks to the zone 2 station before (to pay a lower fare), and to the boundary station after rezoning. Person B walks to the zone 3 station before, and to the boundary station after rezoning (to pay a lower fare).

Table 6
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	0.07	0.11	0.09	−0.05	0.04
	(0.12)	(0.12)	(0.11)	(0.13)	(0.15)	(0.07)
Short term ε - rezoned	0.05	0.09	0.13	0.04	0.16^{***}	0.17^{***}
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
Small sample						
Short term ε - not rezoned	0.23	0.18	0.15^{**}	0.15	0.08	0.06
	(0.15)	(0.16)	(0.07)	(0.15)	(0.16)	(0.08)
Short term ε - rezoned	0.01	0.06	0.12	0.03	0.13	0.15^{**}
	(0.07)	(0.07)	(0.14)	(0.08)	(0.06)	(0.06)

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. Further controls are weather characteristics, economic conditions, and lost customer hours (see Section 4 for a detailed description of variables). Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

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 6. In both the full and the small 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

7. Robustness

The methods applied in this paper all rely on certain assumptions to either consistently estimate the parameters or to give them a causal interpretation. We discuss below the following potential threats to the validity of our results: The potential correlation of error terms across journey types (cross-sectional dependence), the parallel trends assumption and heterogeneity in elasticities, and the possibility of a structural break in the coefficients of our control variables. In this section we briefly discuss these issues and our remedies. Corresponding results can be found in the appendix.

7.1. Cross-sectional dependence

Panel data methods typically rely on independence across panel units for inference. When the time dimension of a panel is long then this assumption is less tenable as the likelihood of events which affect all panel units increases. These events may affect both observable and unobservable characteristics. The ensuing dependence between units is known as cross-sectional dependence (CSD) and has spurned an entire literature on how to treat it in estimation (see Chudik (2013) for a survey). Note that CSD which affects both observable and unobservable characteristics is akin to omitted variable bias and as such causes endogeneity. In the current setting, we do not think that our model is subject to this bias. All our control variables are exogenous to consumer behavior (the weather, the aggregate economy, and service levels) and vary only across time but not across journey types. Equally, fares are exogenous and we cannot think of any factor which might have affected fares and travel behaviour at the same time, at least not within the six month period which we consider here. Still, one can object to the assumption of independence across journey types on efficiency grounds. We therefore re-estimated our model using the Common Correlated Effects estimator developed by Chudik and Pesaran (2015). The estimator's intuition is simple: if all units at a given point of time are affected by unobserved common factors, then the average values of observed variables absorb the common factor effects and can serve as proxies for the common factors. All our independent variables other than fares vary over time but not across journey types. Fares are set by TfL and there is no room for any other factor or variable to affect them. We therefore only use average demand as a proxy for common factors. Our model is thus an augmented version of Eq. (4) which also includes average (across journey types) demand as an independent variable. We estimated the model using the xtdcce2 Stata package by Ditzen (2018). The results can be found in Table A2. We expected results to be similar to the benchmark model, and this was in general the case: The change in elasticities among journey types affected by rezoning is around one percentage point higher than the change for the remaining journey types, although we fail to find any sizeable effect among frequent passengers. While point estimates between the benchmark and CCE model are comparable, we note that standard errors in the CCE model are higher and that none of the elasticity differences are significantly different from zero.

Table A3 shows the results from the dynamic version of this model. The model includes lagged demand as well as a number of lagged cross-sectional averages of demand. For convenience we only report the DiD estimate. The results are a 1 to 1.5 percentage point difference in elasticities for daily data. Consistent with previous results, the estimates are smaller for frequent passengers. The model performs less robustly when using weekly data, perhaps due to leaving very little variation in demand after controlling for several lagged variable.

7.2. Parallel trends and heterogeneous elasticities

Recall that our estimate of the asymmetry in price elasticities derives from a DiD design. We observe elasticities for rezoned and non-rezoned journey types before the rezoning, and again after the rezoning. If we assume that elasticities for rezoned journey types had changed by the same proportion as the remaining journey types, then the DiD estimate delivers a treatment effect on the treated (here: the effect of rezoning on journey types involving rezoned stations; see discussion in Section 4). While this assumption cannot be tested, the customary approach in the literature is to compare whether treatment and control observations were moving on similar trajectories before the treatment. In our case this is not possible since we have only one elasticity estimate for both types of journeys before the rezoning – we can identify level but not trend differences.

A related issue is one of slope heterogeneity. Models with panels often restrict the effect of most variables to be the same across panel units. Short panels typically do not contain enough information to estimate the effects separately even if the researcher were interested in slope heterogeneity. Since we have a panel with comparable cross-sectional and time dimensions, we can gauge the heterogeneity in elasticities. This also serves as a check to what extent baseline differences exist between rezoned and non-rezoned journeys.

We therefore explore baseline differences in elasticities across journey types. We cannot separately identify all individual elasticities since they would be collinear with the dummy for the new year. However, we can estimate the *difference* between the elasticity of rezoned journeys and the elasticities of non-rezoned journeys in 2014/15. Fig. A1 in the appendix plots the histogram of these elasticity differences. We see that the elasticity of rezoned journeys in 2014/15 was greater than the elasticity of most other journey types – 86% of elasticity differences are positive.[8] This reflects the estimated elasticity differences in Table 1 and casts some doubt on the comparability between rezoned and non-rezoned journey types at baseline.

Fig. A2 looks at the position of the rezoned journeys compared to the remaining journeys. The histogram depicts the changes in log demand across all journey types identified around the beginning of the new year. That is, we estimate

$$ln(Y)_{it} = \boldsymbol{\alpha}_\mathbf{i} + \boldsymbol{\beta}_\mathbf{1i} t + \boldsymbol{\beta}_\mathbf{2i} t^2 + \gamma_i D_t\left(t > January\ 2^{nd}\right) + u_{it}$$

for all journey types i. We then calculate $d\gamma_j = \gamma_j - \gamma_{rezoned}$ for all $j \neq rezoned$, and where $\gamma_{rezoned}$ is the average change in log demand for the rezoned journeys. We do this separately for the 2014/15 and 2015/16 sample. The histograms depict the distributions of these $d\gamma_j$. In 2014/15 (before the rezoning) demand for most journey types increased relative to rezoned journeys – or equivalently, demand for rezoned journeys dropped more compared to the remaining journeys. Rezoned journeys are at the 10th percentile of the distribution. In 2015/16 however the demand change for rezoned journeys exceeded the demand change of most other journey types and was at the 90th percentile of the distribution. We cannot translate these numbers into elasticities because most fares did not change in 2015/16. However, the results suggest that the fare decrease through rezoning has moved rezoned journey types from the bottom to the top of the distribution of demand changes.

7.3. Structural breaks

We considered the possibility that our control variables might affect demand differently after the fare revision on the 2nd of January. We therefore allowed for the control variables (weather characteristics, economic conditions, petrol prices and service reliability) to carry different coefficients before and after the 2nd of January. Table A4 in the appendix compares results from the benchmark models and the more flexible specifications. The results remain virtually unchanged.

[8] Note that the elasticity is typically a negative number. A difference between -0.5 (inelastic) and -1.5 (elastic) would be +1.

8. 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 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.

Our findings constitute a considerable challenge to TfL and to public transport authorities in general. Demand for journeys on the LU peaked in November 2018 with 118 million journeys undertaken over a 28-day period. Patronage dropped by 95% after the announcement of the first Covid lockdown in the UK in March 2020. The latest figure for journeys on the LU is for May 2022 and stands at 79 million journeys – 67% of the pre-Covid peak (TfL, 2022). Thus, while managing growing demand under capacity constraints was a pressing problem for TfL, it now faces a revenue crunch as demand seems unlikely to recover to pre-Covid levels. Working habits have dramatically changed, and demand has probably become more elastic due to home office and online teamwork arrangements. In light of our findings TfL will find it difficult to use pricing as a policy tool. Increasing fares might fail to raise revenue due to loss aversion. Decreasing fares might fail to increase patronage due to slow information dissemination. Both effects combine with changing working and commuting patterns to reduce the utility of fares as a demand and revenue management tool.

Declaration of Competing Interest

Firat Yaman has no interest to declare.
Kingsley Offiaeli works as a controller for the London Underground at Transport for London.
No financial support has been received or used for the completion of this project.

Data availability

The authors do not have permission to share data.

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Appendix. Further figures and tables

Table A1
Correlation matrix independent variables.

	Log fares	Log petrol	Lost customer hours	Air pressure	Wind speed	Humidity	Dew point	Temperature	Rainfall	House prices	Unemployment
Log fares	1.00										
Log petrol	−0.04	1.00									
Lost customer hours	0.00	0.10	1.00								
Air pressure	0.02	−0.08	0.08	1.00							
Wind speed	0.00	−0.10	−0.05	−0.37	1.00						
Humidity	−0.01	0.30	0.12	0.01	−0.37	1.00					
Dew point	−0.02	0.32	−0.03	−0.09	0.06	0.48	1.00				
Temperature	−0.02	0.24	−0.09	−0.10	0.23	0.10	0.92	1.00			
Rainfall	−0.01	0.05	−0.03	−0.27	0.07	0.16	0.11	0.05	1.00		
House prices	0.04	−0.10	0.27	0.15	0.04	0.03	−0.04	−0.05	−0.10	1.00	
Unemployment	−0.04	0.16	−0.30	−0.20	0.02	0.03	0.41	0.45	0.10	−0.70	1.00

Note: Raw correlations between independent variables.

Table A2
Price elasticities with cross-sectional dependence.

	Journeys			Passengers			Frequent passengers		
	2014/15	2015/16	Difference	2014/15	2015/16	Difference	2014/15	2015/16	Difference
Daily									
Short term ε - not rezoned	−0.06	−0.92	−0.86	−0.05	−0.81	−0.76	−0.35	−0.00	0.35
	(0.80)	(0.76)	(1.10)	(0.44)	(0.91)	(1.01)	(0.46)	(0.35)	(0.58)
Short term ε - rezoned	−0.95	−0.53	0.42	−1.29	−0.56	0.73	−1.19	−0.56	0.63
	(1.86)	(0.31)	(1.91)	(0.84)	(0.38)	(0.92)	(1.00)	(0.48)	(1.11)
Difference	−0.89	0.40	1.29	−1.24**	0.25	1.50	−0.84	−0.56	0.28
	(1.36)	(0.88)	(1.62)	(0.50)	(0.99)	(1.11)	(0.68)	(0.60)	(0.91)
Number of observations	8163	7981		8121	8195		8263	8203	
Weekly									
Short term ε - not rezoned	0.20	−0.78*	−0.98	0.25	−0.66	−0.92	0.22	0.28***	0.06
	(0.66)	(0.44)	(0.79)	(0.46)	(1.41)	(1.49)	(0.46)	(0.09)	(0.47)
Short term ε - rezoned	−0.55	−0.51	0.03	0.14	−0.18***	−0.32	−0.23	−0.20***	0.03
	(1.47)	(0.46)	(1.54)	(1.29)	(0.06)	(1.29)	(1.58)	(0.07)	(1.58)
Difference	−0.75	0.26	1.01	−0.11	0.48	0.59	−0.45	−0.48***	−0.03
	(1.05)	(0.64)	(1.23)	(1.06)	(1.42)	(1.77)	(1.40)	(0.14)	(0.46)
Number of observations	1536	1495		1563	1556		1611	1596	

Note: Results from a Common Correlated Effects estimator - an augmented version of Eq. (4) which also controls for the contemporary cross-sectional average of log(demand). Further controls are weather characteristics, economic conditions, and lost customer hours (see Section 4 for a detailed description of variables). Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Table A3
DiD estimates based on dynamic CCE model.

	Journeys	Passengers	Frequent passengers
Daily			
1 period lag	1.15	1.00	0.22
	(5.53)	(3.26)	(14.90)
2 period lags	1.34	1.12	0.22
	(5.14)	(2.48)	(11.89)
3 period lags	1.47	1.23	0.32
	(7.13)	(2.96)	(11.89)
Weekly			
1 period lag	2.08	−0.32	−0.02
	(4.02)	(3.88)	(8.95)
2 period lags	2.00	−0.83	0.03
	(6.18)	(4.61)	(22.55)
3 period lags	2.82	3.55	2.00
	(151.20)	(18.76)	(70.58)

Note: DiD estimates for a Common Correlated Effects estimator - an augmented version of Eq. (4) which also controls for the contemporary and lagged cross-sectional averages of log(demand). The lags in the table refer to the number of lags of average log(demand) included in the model. Further controls are weather characteristics, economic conditions, and lost customer hours (see Section 4 for a detailed description of variables). Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Table A4
DiD estimates without and with structural breaks.

	Journeys	Passengers	Frequent passengers
Daily			
No structural break	0.90***	0.83***	0.25
	(0.25)	(0.29)	(0.34)
Structural break	0.90***	0.83***	0.25
	(0.25)	(0.29)	(0.34)
Weekly			
No structural break	0.48*	0.96***	0.71***
	(0.24)	(0.20)	(0.23)
Structural break	0.31	0.97***	0.71***
	(0.28)	(0.20)	(0.24)

Note: DiD estimates from an augmented version of Eq. (4) which allows for control variables to have a different effect before and after the 2nd of January of a year. Controls are weather characteristics, economic conditions, and lost customer hours (see Section 4 for a detailed description of variables). Standard errors in parentheses. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

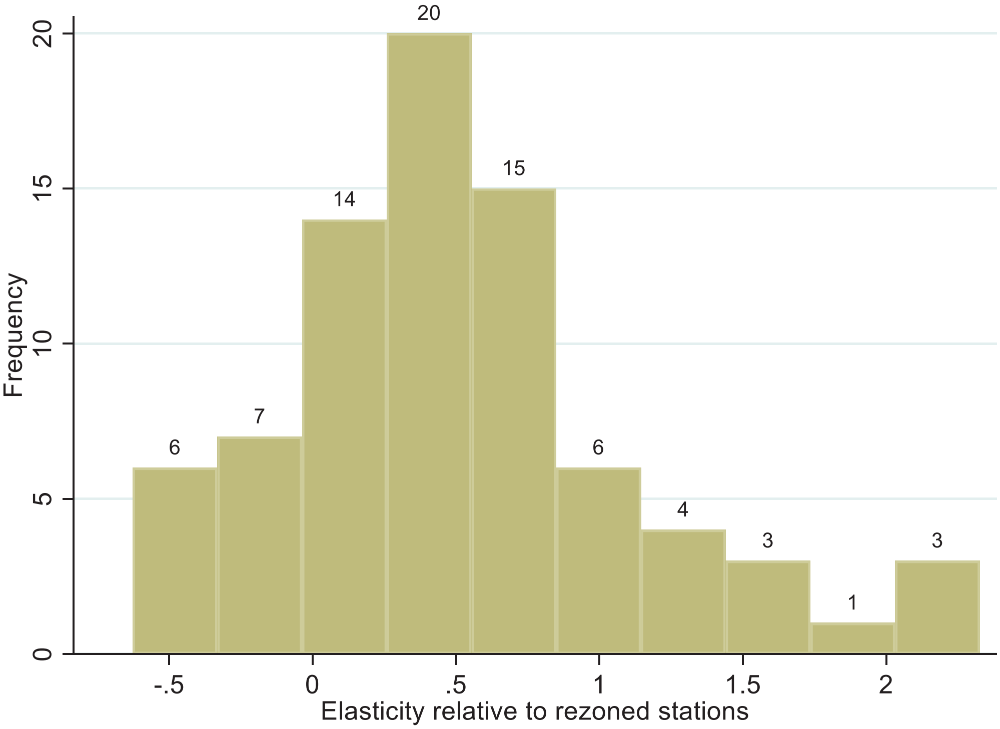

Fig. A1. Distribution of elasticities relative to elasticity of rezoned stations in 2014/15.
Note: The graph depicts the distribution of fare elasticities relative to the elasticity for rezoned journey types. Our elasticity definition is not in absolute value. A positive value on the histogram thus implies a lower elasticity compared to the rezoned journey types.

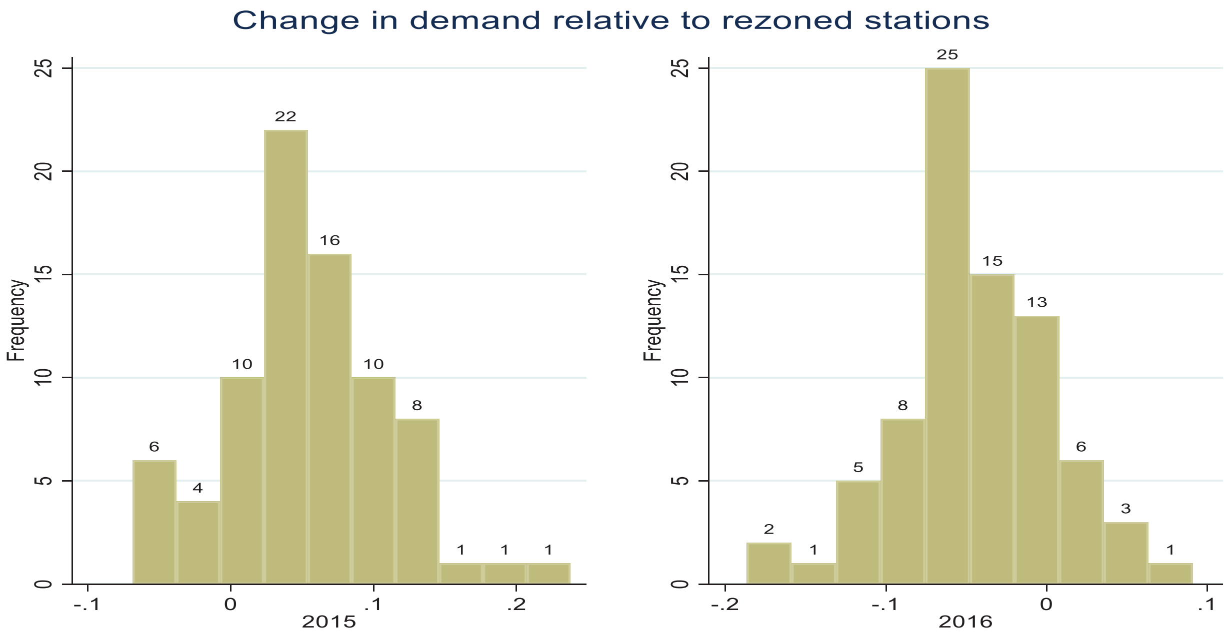

Fig. A2. Change in demand relative to rezoned station after January 2nd.
Note: The distribution of changes in demand (in %) relative to the change in demand for rezoned journeys. Demand for most journey types increased more (decreased less) than demand for rezoned journey in 2015, while the reverse holds in 2016.

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