WHAT IS AFFECTING SEASON TICKET ELASTICITIES IN LONDON?

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INTRODUCTION

The market for rail travel using season tickets in London was worth approximately £1.1 billion in 2007/08, or approximately 27.7% of total revenue on the national rail network in the UK.[1] Understanding how passengers in this market respond to changes in the price of tickets is of considerable importance. For example, it is important to:

– the government, when planning how to structure services or assessing the likely level of premium payments from franchised train operators;
– train operating companies (TOCs), when assessing pricing strategy and putting together franchise bids;
– the infrastructure manager (Network Rail), when predicting required capacity.

As another illustration of the importance of this market, the Initial Industry Plan put together by Network Rail, the Association of Train Operating Companies, and the Rail Freight Association provides plans for £3.2 billion of investment by the industry in the rail network in London and south-east England by 2019.[2]

The importance of this market has made it the focus of extensive studies into how passengers respond to changes in the price of fares—ie, estimating the price elasticity of demand in the market.[3] This research is summarised in the Passenger Demand Forecasting Handbook (PDFH), of which the most recent version is version 5.[4] This document contains a large number of elasticities, the relevant ones of which are reproduced in Table 1.[5]

[1] Oxera Arup Dataset (TOAD) and Office of Rail Regulation, National Rail Trends Portal.

[2] Network Rail (2011), 'PR13 Initial Industry Plan Supporting Document', September, p. 12.

[3] Formally, a price elasticity of demand is defined as the percentage change in quantity demand following a one percent change in price. More detail is contained in Appendix A.

[4] Passenger Demand Forecasting Council (2009), 'Passenger Demand Forecasting Handbook', Version 5.0, August.

[5] Oxera acknowledges the permission of the Passenger Demand Forecasting Council for permission to reproduce these elasticities.

Table 1 PDFH elasticities (season tickets)

	Elasticity
London Travelcard Area	–0.45
London Travelcard Area and South East	
To London	–0.50
From London	–0.60
Non-London within South East	–0.9

Source: Passenger Demand Forecasting Council (2009), Passenger Demand Forecasting Handbook, Version 5.0, August, Chapter B3, pp. 7–8.

Oxera has undertaken a number of studies in this market over the last five years, including the 'Revisiting the elasticity-based framework' study—hereafter, 'Revisiting'—for the Department for Transport, Transport Scotland and the Passenger Demand Forecasting Council; and commercial work for TOCs.[6] These studies have suggested that passengers may be more responsive to changes in price than is suggested by the elasticities contained within the PDFH. By way of illustration, the estimated three-year elasticity from the 'Revisiting' study for London, the South East and East of England (LSEE) is –0.73, which is substantially larger (in absolute magnitude) than the price elasticity for travel to/from/within the London Travelcard Area.[7]

These studies suggest that passengers respond in substantially different ways to the received industry wisdom. Given the importance of the market, it is important to investigate whether the findings of these studies are the result of the statistical methodology employed, whether there has been a change in the market that may explain the changes, or whether there is another factor at play.

This paper further investigates these findings by considering a range of alternative approaches to estimating price elasticities and then considering the extent to which changes to the London market might explain the apparent change.

The next section outlines the data that has been used.

DATA

The 'Revisiting' study covered the entirety of Great Britain. However, this paper focuses on travel within the LSEE area.[8] It uses the dataset that was created for the 'Revisiting' study—The Oxera Arup Dataset (TOAD). The use of the same data means that the results presented in this paper are directly

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[6] The 'Revisiting' reports are available from: http://www.dft.gov.uk/publications/revisiting-elasticity-based-framework/.

[7] Arup and Oxera (2010), 'What are the findings from the econometric analysis?', March, p. 10.

[8] The London, South East and East of England area is defined as those stations that fall within the Government Office Regions of London, the South East and East of England.

comparable with those presented for the LSEE area in the ‘Revisiting’ study. It should be noted that the dataset ends in March 2008.

TOAD contains information on 6,753 rail flows in LSEE between 1994/95 and 2007/08.[9] It contains data on passenger journeys; yield; specific flow characteristics such as Generalised Journey Time (GJT) and performance;[10] a range of macroeconomic demand drivers such as income, population and employment; and an improved representation of the costs and time of making an equivalent journey by car.[11] Table 2 below provides summary statistics of some of the key variables, while Figure 1 demonstrates how demand and average yield have changed over the period of the dataset.

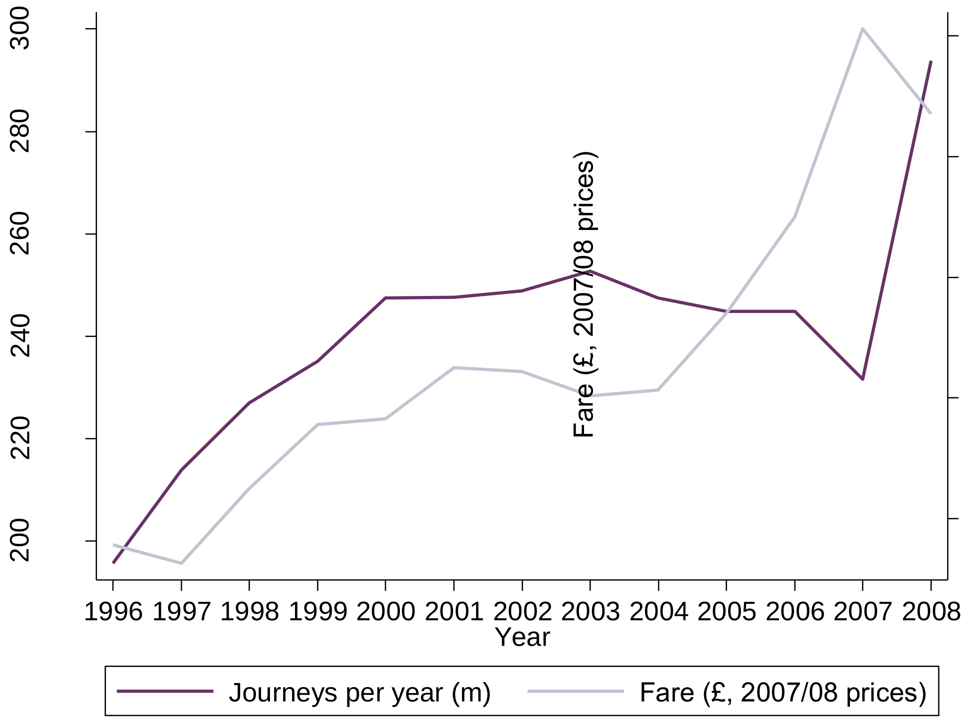
[9] The study also contains data from 1990/91 to 1994/95, but this data displays considerable volatility and is not considered reliable.
[10] GJT consists of in-vehicle time, an interchange penalty if appropriate, and a frequency penalty. Performance is measured by the Public Performance Measure (PPM).
[11] For full details of the dataset, see Arup and Oxera (2010), ‘Is the data capable of meeting the study objectives?’, March.

Table 2 Summary statistics

Variables	N	Mean	Standard deviation	Maximum	Minimum	P5	P95
Demand (million journeys)	75,744	1.280	3.410	19.63	0	0.0100	3.620
Fares (£)	75,744	3.460	1.970	2,154.46	0.0100	1.130	6.980
Flow length (miles)	75,744	17.95	15.76	198.9	0	1.600	50.60
GJT (minutes)	75,744	43.25	22.74	364.9	–1	12	84.10
Performance (PPM)	64,468	84.53	4.560	91.60	68	77.70	89.60
Real disposable income per capita (£)	69,962	17,380	3,925	29,162	10,597	13,288	27,848
Employment ('000)	75,744	4,024	706	4,692	2,453	2,566	4,663
Car ownership (% without cars)	75,744	0.290	0.130	0.620	0.0500	0.120	0.570
Car cost (£)	74,621	282	174	1,810	10	76	619

Note: All monetary values are in constant 2007/08 prices.
Source: The Oxera Arup Dataset (TOAD).

Figure 1 Demand and fares in LSEE



Source: TOAD.

Table 2 shows that the average fare per journey in the sample was £3.46, although this price varied significantly, as indicated by a standard deviation of £1.97. The average flow length was approximately 18 miles, with average GJT being approximately 43 minutes. 29% of households in this area did not have immediate access to a car. The total number of journeys had approximately doubled from 141m in 1995 to 294m in 2008.

This dataset provides a substantial volume of data that can be analysed using alternative econometric techniques to estimate the price elasticity of demand for passengers in the market.

EMPIRICAL ANALYSIS

As mentioned above, there are a number of alternative econometric approaches for estimating price elasticities. Before discussing the results of these approaches, we discuss the general methodology for econometric analysis of this type. There are a number of steps:

– developing the appropriate economic model;
– specifying that economic model in a way that is amenable to statistical estimation;
– determining the most appropriate econometric technique to estimate the model.

The economic model is developed from microeconomic theory and industry knowledge. There is a well-developed literature on the factors that can affect the demand for passenger rail travel, as summarised in the PDFH. The economic model is specified as:

Journeys = f(fare, population, income, employment, prop. no car, car cost, car journey time, GJT, performance, SQI)

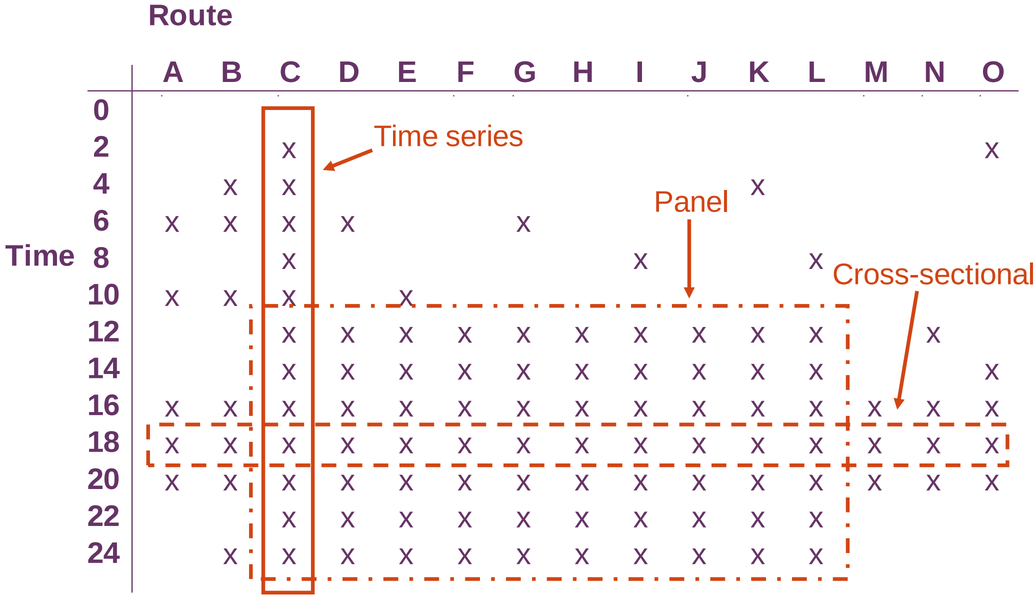
where journeys are the factor of interest; population is the population at the origin of the flow; income can be measured in a number of ways, depending on whether it aims to explain business activity or personal wealth; employment is typically measured at the destination of the flow; prop. no car is the proportion of households without access to a car; car cost is the cost of making an equivalent journey by car, accounting for both fuel prices and wear and tear; car journey time is the time taken to make an equivalent journey by car; GJT is in-vehicle time, an interchange and frequency penalty; performance is measured by the Passenger Performance Measure (PPM); and SQI is a service quality index.[12]

The purpose of the economic model is not to say that all of these factors will be important, but to say that they are important factors to consider based on economic theory and industry knowledge. The econometric analysis will suggest which factors from the data are important.

The next step is to consider the structure of the available data and to specify the econometric model in such a way that it can be estimated using statistical tools. In this case, the dataset is a large panel dataset. Panel datasets contain both a time dimension and a cross-sectional dimension—ie, observations of the same flows over time. This has important implications for the types of econometric model that can be used. To clarify, Figure 2 provides an illustration of panel data.

[12] More details of the SQI are provided in Arup and Oxera (2010), 'How can a quality of service index be created?', March.

Figure 2 Illustration of types of data



Source: Oxera (example data).

Another important question that will determine the appropriate statistical formulation of the model is whether it is necessary to allow the model to account for passenger dynamics. There is considerable evidence that passengers take time to respond to changes in demand drivers, and it is therefore important to allow for this when conducting econometric analyses.[13] To test this hypothesis, both static (ie, models that assume that all changes in passenger demand in response to a change in a demand driver, such as fares, occur in the same year as the change in the demand driver) and dynamic models (which relax this assumption and allow changes in passenger demand to occur over a number of years) are considered below.

When the form of the data and the importance of dynamics have been considered, the econometric model can be specified, as in the equation below:

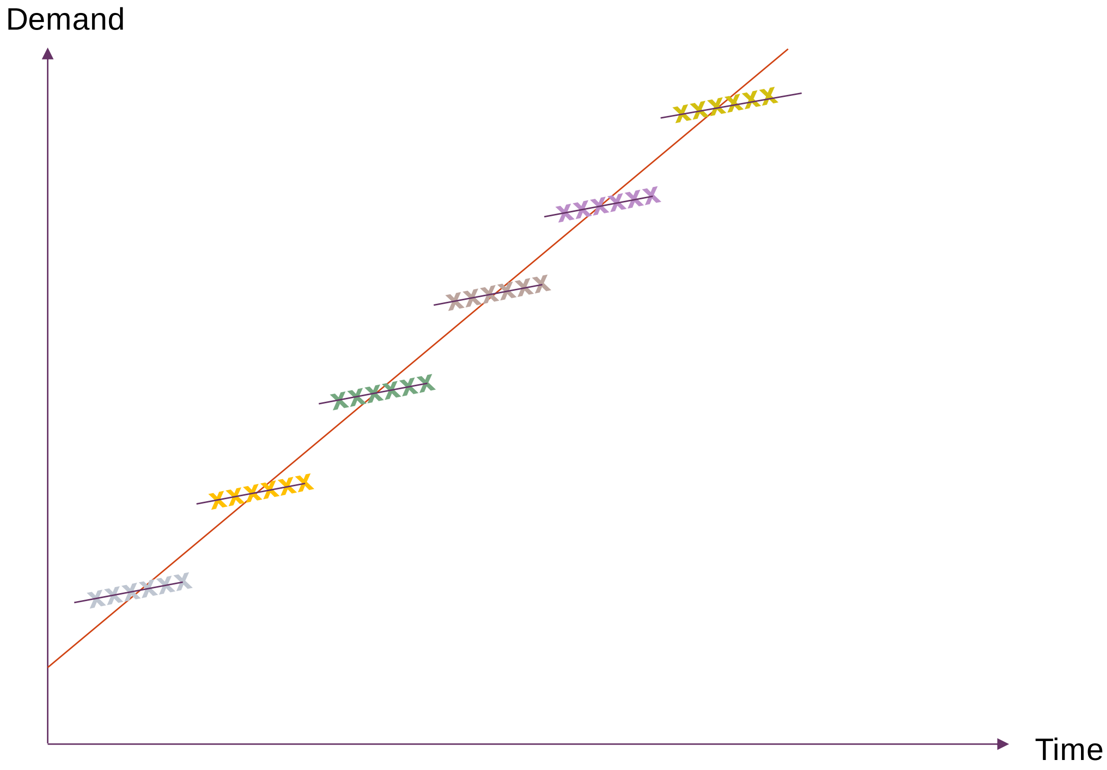
$$
\begin{aligned}
lnJ_{i,t} = \beta_{0,i} &+ \sum_{k=1}^{m} \beta_k \ln \mathrm{J}_{i,t-k} + \sum_{k=0}^{m} \xi_k \ln \mathrm{F}_{i,t-k} + \sum_{k=0}^{m} \gamma_k \ln \mathrm{P}_{i,t-k} + \sum_{k=0}^{m} \delta_k \ln \mathrm{Y}_{i,t-k} \\
&+ \sum_{k=0}^{m} \zeta_k \ln \mathrm{Emp}_{i,t-k} + \sum_{k=0}^{m} \eta_k \mathrm{Prop}_{i,t-k} \\
&+ \sum_{k=0}^{m} \theta_k \ln \mathrm{CC}_{i,t-k} + \sum_{k=0}^{m} \rho_k \ln \mathrm{CJT}_{i,t-k} + \sum_{k=0}^{m} \alpha_k \ln \mathrm{Freq}_{i,t-k} \\
&+ \sum_{k=0}^{m} \mu_k \ln \mathrm{Punct}_{i,t-k} + \varepsilon_{i,t}
\end{aligned}
$$

13 See, for example, 'How do Rail Passengers Respond to Change?', with D. Jevons, N. Robins, J. Dargay, P. Goodwin, J. Preston and M. Wardman, *Papers and Proceedings of the European Transport Conference*, Strasbourg, October 3rd–5th 2005.

where subscript $_i$ denotes a particular route, and subscript $_t$ denotes the time; $J_{i,t}$ represents the number of passenger journeys for route i at time t; F represents fare; P represents population; Y represents income; Emp represents employment; Prop represents the proportion of households without a car; CC represents the cost of running a car; CJT represents the time required to make the journey by car; Freq represents frequency; Punct represents punctuality; and $\varepsilon_{i,t}$ is the error term.

Once the model is specified, attention can turn to the econometric techniques that can be used to estimate the model. To assist with this discussion, Figure 3 illustrates one potential structure of a panel dataset with a number of flows.

Figure 3 Panel dataset structure



Source: Oxera analysis.

As can be seen from Figure 3, while each set of observations has the same slope, when a model is estimated that assumes a constant intercept, the slope of the estimated line might not be appropriate for any particular set of observations.

Depending on the model, there are a number of techniques for estimating models using panel data:[14]

– pooled Ordinary Least Squares (OLS)—the most commonly used econometric approach, which assumes that both the intercept and the slope are constant for all flows;

[14] More details on all of these techniques are available from a range of econometrics textbooks, including Wooldridge, J.M. (2002), *Econometric Analysis of Cross Section and Panel Data*, The MIT Press.

– approaches designed specifically for panel data, such as Fixed Effects (FE) or Random Effects (RE), which allow each flow to have a different intercept but slopes that are constant for all flows;
– dynamic panel data models, such as the Arellano & Bond or Blundell & Bond estimators, which allow for both FE or RE and are unbiased when estimating panel data models with dynamics.

The potential options are summarised in Table 3 below.

Table 3 Possible econometric approaches

	Same intercept	Varying intercepts
Static	Pooled OLS	FE or RE
Dynamic	Pooled OLS	Arellano & Bond or Blundell & Bond

Source: Oxera.

These approaches are considered in more detail in the 'Revisiting' study.[15] Regardless of the choice of estimator, common econometric practice is to specify a 'general' model where all factors of interest are represented; to estimate this model using the estimator of choice; to remove a statistically insignificant variable, re-estimate the model and repeat until all variables that remain in the model are statistically significant and correspond to both economic theory and industry knowledge. The resulting model is known as the 'specific' model, and the overall process is known as 'general-to-specific modelling'.[16] This process has been shown to result in models that are well specified, and minimises the probability of omitting relevant variables.[17] All of the results presented in the 'Revisiting' study are the output from this process.

Having discussed the overall approach, we now turn to the results of models estimated using a number of estimators. In order to provide comparability between the results, we have not fully pursued the general-to-specific approach, and present models with the same explanatory variables.

The model that is used in subsequent examples is:

journeys=f(fare, jobs at destination, car cost, GJT, performance)

Full results of all models are provided in Appendix 1.

As much of the PDFH is underpinned by elasticities estimated using pooled OLS in a static framework, this was the model estimated first. As outlined above, this model assumes that all passenger responses to changes in

[15] Arup and Oxera (2010), 'How has the preferred econometric model been derived?', March.

[16] For the benefits of a general-to-specific modelling approach, see Campos, J., Ericsson, N.R. and Hendry, D.F. (2005), 'General-to-specific Modeling: An Overview and Selected Bibliography', *Board of Governors of the Federal Reserve System International Finance Discussion Papers*, **838**, August.

[17] For more detail on the benefits of general-to-specific modelling, see the literature survey contained in Campos, J., Ericsson, N.R. and Hendry, D.F. (2005), 'General-to-specific Modeling: An Overview and Selected Bibliography', *Board of Governors of the Federal Reserve System International Finance Discussion Papers*, **838**, August.

demand drivers take place within the same year as the changes in the driver of demand, and that all flows have a common intercept.

This model results in an estimate of the fare elasticity of –0.9, which is considerably greater than the PDFH estimate of –0.45.

However, given that the data is in the form of a panel and there is a substantial range in the sizes of flows in the dataset—with the largest being Clapham Junction to London BR with 4,661,000 journeys in 2007/08, and 24 of the smallest flows having only ten recorded journeys in 2007/08—it would seem sensible to test whether the assumption that all flows have a common intercept is justified.

We therefore estimate a static fixed effects model, and test whether the fixed effects explain a significant amount of the variation in the dataset. The result of this model is that the fixed effects do explain a substantial proportion of the variation in the dataset. The model suggests a fare elasticity of –1.2, which is significantly larger than the fare elasticity estimated using static pooled OLS.

Having established that accounting for the panel nature of the dataset is important, the next consideration is whether it is important to allow for dynamics within the analysis. From an intuitive perspective, it seems sensible to at least allow for the possibility and let the data inform our decision.

Following this decision, there are two possible options for estimating dynamic panel data models: the Arellano & Bond estimator and the Blundell & Bond estimator. The differences between the two are technical and, as there are advantages and disadvantages to both approaches, we have estimated the model outlined above using both estimators. The Arellano-Bond estimator produces a long-run price elasticity estimate of –1.3, while the Blundell-Bond estimator produces a long-run price elasticity estimate of –1.7.

For ease of comparison, Table 4 summarises the results from the different models.

Table 4 Long-run price elasticities

	Same intercept	Varying intercepts
Static	–0.9	–1.2
Dynamic	n/a	–1.3/–1.7

Note: These elasticities do not precisely match those from ‘Revisiting’, because they are long-run rather than three-year elasticities, and the model specification is not precisely the same.
Source: Oxera.

These results suggest that the main difference arises from a) updating the dataset; and b) allowing for the panel nature of that dataset, with all panel data estimators providing price elasticities that are significantly larger (in absolute magnitude) than those produced by the static OLS model. The analysis presented above therefore suggests that the key factor that has resulted in an increase in the price elasticity of demand is not the change in the choice of econometric estimator, but rather that the structure of the market may have changed.

CHANGES IN THE MARKET

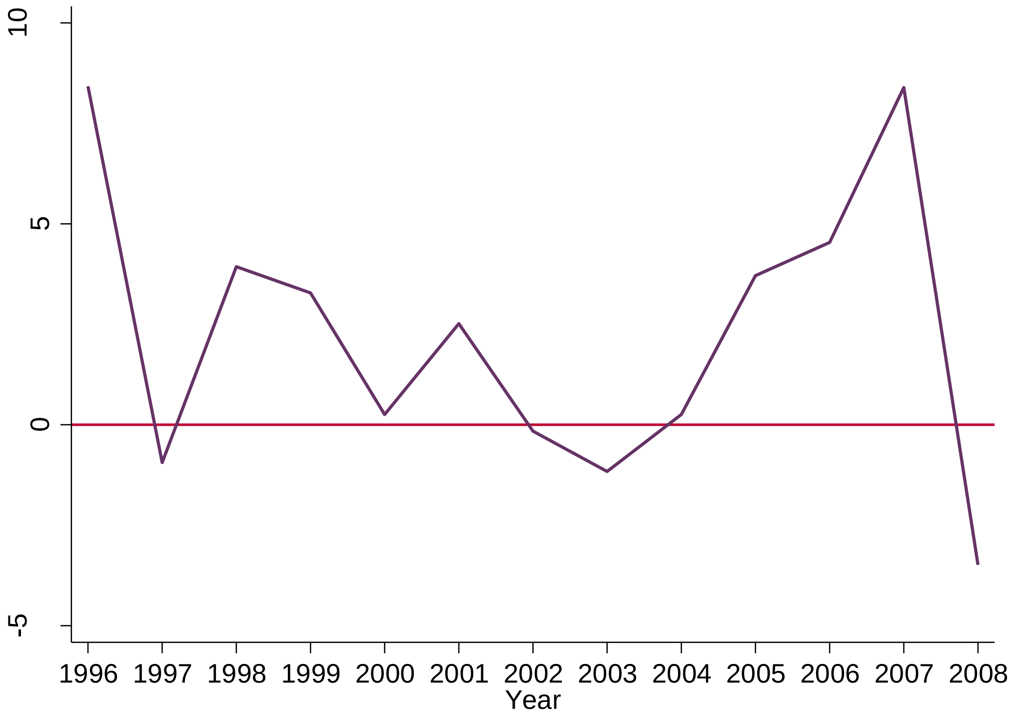
We then consider whether there have been any changes in the market that might explain this observed increase. Two of the key changes in the market since 1994/95 are:

- continued increases above inflation in the level of fares;
- the introduction of Pay As You Go (Oyster) in 2003.[18]

We look at these in turn below.

Figure 4 provides a plot of the average fare in this market against the rate of retail price inflation between 1994/95 and 2007/08.

Figure 4 Average fare (real terms)



Source: TOAD.

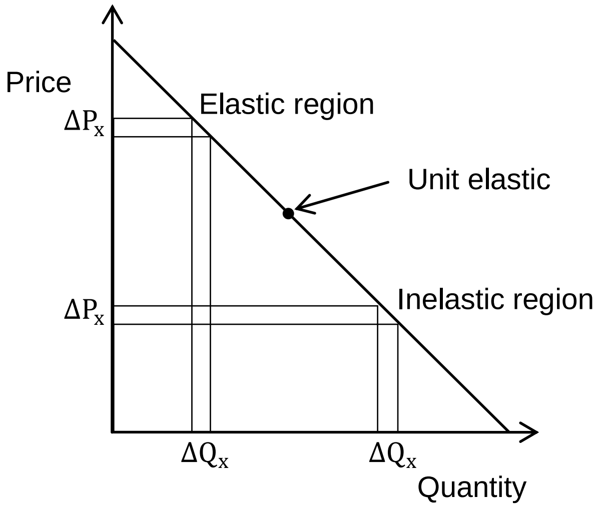
As can be seen from Figure 4, average fares increased by significantly above inflation over this period. This is due to government policy, which has resulted in fare increases at the rate of RPI inflation plus one percentage point since

[18] These are just two of the possible explanations; there are alternative explanations, such as increased churn in the job market.

2004.[19] Economic theory provides some predictions for what might happen to the observed price elasticity of demand in such an event, as outlined below.

For an ordinary good, the own-price elasticity of demand will be negative—ie, an increase in price results in a decline in demand. If a linear demand curve is assumed then there are areas of the curve that are own-price inelastic—ie, where the elasticity is less than one in absolute magnitude—and elastic—ie, where the elasticity is greater than one in absolute magnitude—separated by a midpoint where the own-price elasticity of demand equals minus one. Figure 5 provides an illustration.

Figure 5 Linear demand curve



Source: Oxera.

The impact of continued real price increases

According to the analysis above, for the linear demand curve, the elasticity becomes more and more negative—ie, passengers respond more to changes in fares—for a given percentage change in price. Therefore, with continued real price increases (if the price of season tickets increases faster than the rate of inflation in the economy), there is likely to be movement along the demand curve and we would expect the own-price elasticity of demand to increase over time, if all other things are held equal.

The other noticeable change in the market between 1994/95 and 2007/08 is the introduction of the Oyster card.

What is Oyster?

The Oyster card is a 'contactless' smartcard for use in travelling around London, introduced by Transport for London (TfL) in 2003.[20] There are two main types of Oyster card: a season ticket, and Pay As You Go (PAYG).

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[19] Following a review of the fares structure conducted by the Strategic Rail Authority. Strategic Rail Authority (2003), 'Fares Review Conclusions 2003'.

[20] Transport for London (2010), Oyster Factsheet. [online] Available at: http://www.tfl.gov.uk/assets/downloads/corporate/oyster-factsheet.pdf [Accessed: 18th Sept 2012].

PAYG is an alternative to paying cash for single or return fares and offers cheaper single fares, daily price capping and ticket extensions automatically.[21] The Oyster card can be used for travel on buses, the London Underground, Docklands Light Railway (DLR), London Overground, London Tramlink, Thames Clipper river services, and National Rail services in Greater London.

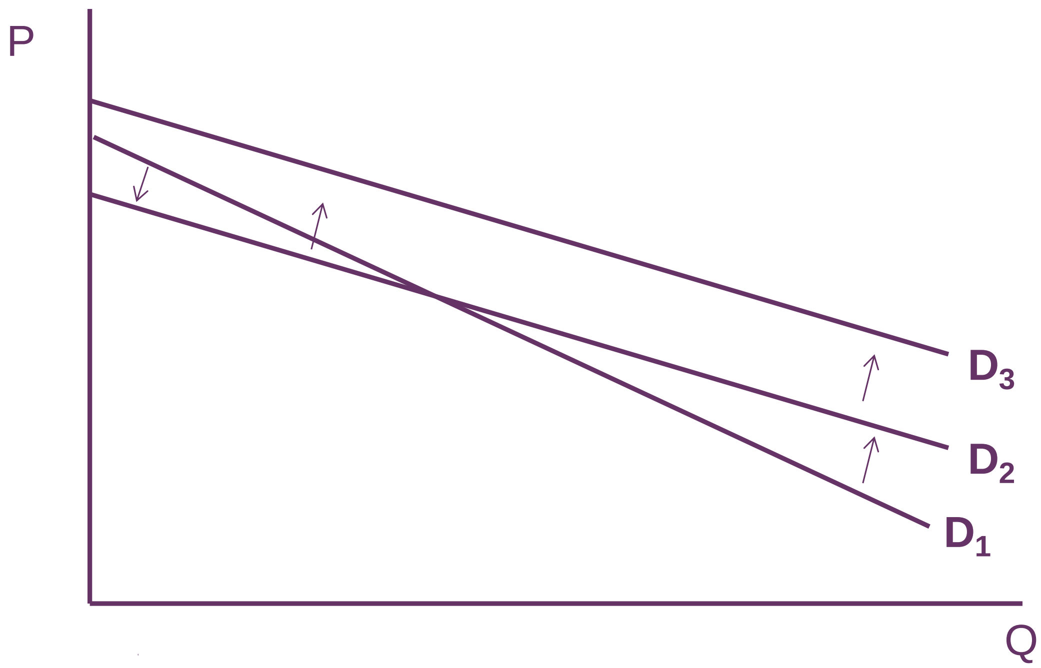
Using economic theory, it is possible to determine the expected impact on observed price elasticities of existing products, such as season tickets, following the introduction of a new product into the market.

The impact of introducing a new product

When there is more competition between products, the demand curve may be 'pivoted', as set out in Figure 6, to a flatter position (ie, it may move from D_1 to D_2), because an increase in competition increases the substitution effect—ie, for any given increase in price, because there is now a new product available for passengers to switch to, the effect on the number of trips made using season tickets decreases by more than would have been the case without the new product.

In addition, it may be possible that the new product is a complement to the existing product, which means that, at any given price, passengers demand a greater volume of the good or service.

Figure 6 Introduction of a new product



Source: Oxera analysis.

[21] Transport for London (2011), 'Travel in London Report 4', Appendix A. [online] Available at: http://www.tfl.gov.uk/assets/downloads/corporate/travel-in-london-report-4.pdf [Accessed: 18th Sept 2012].

Only a pivot of the demand curve implies a higher own-price elasticity of demand at each point—a shift in the demand curve would not affect the price elasticity, but would be reflected in the econometrics by an increase in demand.

It is, however, important to remember the perspective that is being used to consider the price elasticity. For example, the observed price elasticity reflects only the impact of changing the price of season tickets, holding the price of all other tickets constant. If the price of all other tickets (including the Oyster card) were changed at the same time, we would expect the observed price elasticity to be different.

These two events (continued real-terms price increases and the introduction of the Oyster card) both appear to provide some explanation for the increase in the absolute value of the price elasticity in the season ticket market for the LSEE market.

CONCLUSIONS

This paper has examined one of the key findings from the 'Revisiting' study—ie, that the price elasticity of demand for rail travel in LSEE is greater in absolute magnitude than is suggested in current industry guidelines as codified in the PDFH. We began by considering the possibility that the results reported in the 'Revisiting' study were an artefact of the statistical approach, and found that this is not the case—the results of the analysis are broadly consistent, regardless of the choice of econometric approach. Following this finding, we considered whether there have been developments in the market that might explain the observed changes.

It was found that both continued above-inflation increases in the price of season tickets, and the introduction of the Oyster card, are likely to have increased the measured price elasticity of demand in this area.

As outlined above, the responsiveness of passengers to changes in price is of considerable importance to a wide range of industry participants, ranging from the Department for Transport, TfL and Network Rail, which are engaged in strategic planning; TOCs aiming to balance supply and demand of services and negotiating with the Department for Transport on the impact of changes in fares policy; and those engaged in franchise bidding.

The analysis outlined in this paper suggests that price elasticities are indeed larger in absolute magnitude than those suggested by the PDFH. This has a number of policy implications:

– the policy of increasing season ticket prices in this market by RPI + 3 will generate less revenue than suggested by the PDFH;
– continued real-terms fare increases might not generate the revenue expected by franchise bidders and thus increase the likelihood of financial difficulties;
– the government's stated aim of stopping above-inflation fare increases may generate more demand for rail travel than anticipated.

While this paper has focused on the impact of fares on the demand for passenger rail travel, it is important to remember in all of these discussions that there are many factors that are likely to affect the demand for passenger rail travel in the UK. When assessing how changes in the product offering may affect demand, it is likely to be important to consider all of these factors, rather than focusing on a subset of them.

Appendix 1 Model results

	OLS	FE	AB	BB
ln_fare	–0.903***	–1.212***	–0.918***	–1.089***
	(0.030)	(0.049)	(0.062)	(0.066)
ln_D_totaljobse01	0.673***	7.022***	0.719***	1.397***
	(0.006)	(0.185)	(0.168)	(0.072)
L.ln_jny			0.318***	0.340***
			(0.010)	(0.014)
ln_carcost	1.722***	1.141***	0.290***	0.321***
	(0.027)	(0.082)	(0.041)	(0.050)
ln_gjt	–3.110***	–0.882***	0.034	–0.241**
	(0.029)	(0.106)	(0.082)	(0.108)
ln_PPM	0.767***	0.970***	0.182***	0.316***
	(0.135)	(0.075)	(0.043)	(0.049)
Constant	1.638***	–75.526***	–3.797**	–11.096***
	(0.617)	(2.021)	(1.905)	(0.925)
Observations	58,529	58,529	41,726	50,307

Note: Standard errors are in parantheses. These elasticities are all short-run. Where the models are dynamic—ie, AB and BB—the relevant long-run elasticity can be calculated by dividing the relevant elasticity by (1-L.ln_jny), which is the lagged dependent variable.
Source: Oxera analysis.

Appendix 2 Price elasticity

An individual's demand could be a function of many factors, including tastes, time of the day, and so on. For simplicity, let us consider a simplified demand that is only a function of market prices ($P_x, P_y, \cdots, P_z$) and the individual i's income I^i. Suppose also that we have linear demand, so that the individual demand for good x of agent i is given by:

$$X^i(P_x, P_y, \cdots, P_z, I^i) = a - b_x P_x - b_y P_y \cdots - b_z P_z + I^i$$

where $b_x > 0$ for the ordinary goods, $b_y, b_z < 0$ if goods y and z are substitutes, and $b_y, b_z > 0$ if goods y and z are complements.

Market demand for good x is then given by summing the individual quantity demand functions of all the individuals in the market. The market demand is therefore a function of market prices and the incomes of the n agents in the market. For good x, we can denote market demand by:

$$Q_x(P_x, P_y, \cdots, P_z, I^i, I^j, \cdots, I^n) = \sum_{i=1}^{n} X^i(P_x, P_y, \cdots, P_z, I^i)$$
$$= \sum_{i=1}^{n} (a - b_x P_x - b_y P_y \cdots - b_z P_z + I^i)$$
$$= n(a - b_x P_x - b_y P_y \cdots - b_z P_z) + \sum_{i=1}^{n} I^i$$

Solving for the price as a function of quantity demanded yields the inverse demand curve, which relates the price required the generate the quantity demanded.

The price elasticity of demand gives the percentage change in demand for a good per percentage change in the price of the good. Unlike the derivatives of demand (slopes of the demand curve), elasticities are independent of the units chosen for measuring commodities, and therefore provide a unit-free way of capturing demand responsiveness. The own-price elasticity of demand is denoted by:

$$\varepsilon_D = \frac{\frac{\Delta Q_x}{Q_x}}{\frac{\Delta P_x}{P_x}} = \frac{\Delta Q_x}{\Delta P_x} \frac{P_x}{Q_x}$$

where Q_x is the quantity of the good, and P_x is the price of the good.[22]

According to economic theory, there are several factors that affect the own-price elasticity of a good. It is mainly determined by the availability of substitutes and complements, the proportion of one's budget that the good occupies, and the time horizon considered.

– Substitutes/Complements: demand for a good is more own-price elastic when there are close substitutes for the good. If there are very close substitutes, even a small increase in price might lead consumers to switch to the substitute. On the other hand, demand for a good is more own-price inelastic when there are complements to the good.

– High Need/Addiction: demand is more own-price inelastic when the good is addictive or when there is critical need for the good.

– Portion of Budget: demand is more own-price inelastic when a consumer's expenditure on the good is small relative to income. The consumer does not need to respond very much to price changes because the good makes up only a small part of their entire budget.

– Time Horizon: demand is more own-price inelastic in the short run than in the long run. Consumers might not be able to find suitable substitutes in

[22] If we want to compute 'point elasticity', we need to consider an infinitesimal changes in the price at that point—ie, $\varepsilon_D = \lim_{\Delta P \to 0} \frac{\Delta Q}{\Delta P}\frac{P}{Q} = \frac{\partial Q}{\partial P}\frac{P}{Q}$.

the short run, but in the long run they can respond optimally to price increases by finding substitutes and changing consumption behaviour.