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The Sensitivity of Rail Demand to Variations in Motoring Costs: Findings from a Comparison of Methods.

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1. INTRODUCTION

The objective of the research reported here was to explore how rail demand is influenced by motoring costs with a view to informing the official forecasting recommendations of the railway industry in Great Britain and, importantly, contributing more broadly to understanding in this area.

Set against the background of car almost always being the main competitor to rail, this is an important research topic for a number of reasons. Firstly, significant reductions in car costs are expected over the coming years as a result of improved fuel efficiency and this has clear implications for strategic rail demand forecasting. Secondly, cross-elasticities are not easy to estimate in rail demand models, because they are relatively small, context specific and the historic data necessary for estimation is often correlated with other influential variables. Thirdly, there is not only uncertainty surrounding cross-elasticities of rail demand with respect to car costs in Great Britain, which provides the background to this research, but there is generally a lack of up-to-date, robust evidence in this area. Last, but not least, given that cross-elasticities are inherently variable parameters, forecasting practice might consider moving towards methods which support greater disaggregation and 'locally relevant' parameters.

Given the challenges of estimating robust cross-elasticities, we report insights from a number of methods[1]. These are:

- Econometric analysis of very large amounts of rail ticket sales data;
- Econometric analysis of National Travel Survey (NTS) data;
- Evidence from a survey of motorists;
- Reviews of existing evidence;
- Deducing cross-elasticities using relationships of economic theory.

This provides us with a unique opportunity to compare and contrast the cross-elasticities of rail demand with respect to motoring costs obtained from a number of different methods.

The structure of this paper is a follows. Section 2 provides context, in terms of the long-established UK forecasting practice and the broader review evidence. Section 3 sets out the methods we have here employed in estimating cross-elasticities along with the data that supports this analysis. Sections 4 to 8 report the findings from our five approaches listed above. A synthesis is provided in section 9 with concluding remarks in section 10.

[1] Whilst choice models are well suited to providing cross-elasticities, their estimation was beyond the scope of this study.

2. BACKGROUND

We first discuss what is in our understanding the longest-established forecasting practice in this area before considering the status of review evidence.

2.1 The Great Britain Context

The Passenger Demand Forecasting Handbook (PDFH) is unique amongst railway administrations worldwide in that, since 1986, it has provided a framework and recommended parameters for forecasting rail demand and is regularly updated on the basis of emerging evidence (RDG, 2018)[2].

But it is only since 2002 (PDFH v4) that it has contained cross elasticities with regard to car costs. Prior to that, all external factors other than GDP and employment were represented by a negative time trend estimated to the experiences of the 1970s and 1980s. However, the unprecedented rail demand growth from the mid-1990s could not be explained by PDFH's recommended time trends, not least because motoring costs were no longer falling, congestion was increasing and there was a slowing in car ownership growth and new road construction.

In response to this poor forecasting performance, the National Passenger Demand Forecasting Framework study (Steer Davies Gleave, 1999) was commissioned. It provided a significantly enhanced framework that included, amongst other things, explicit cross-elasticities between rail and car. The recommended fuel price cross-elasticities were largely drawn from two review studies of mode choice evidence (Wardman, 1997a, 1997b) and are set out in Table 1. It was, though, acknowledged that this was only a starting point and much further research was required to refine these cross-elasticities.

Table 1. Car Fuel Cost Cross-Elasticities Recommended by National Passenger Demand Forecasting Framework Study

PURPOSE	WITHIN LONDON	SE TO/FROM LONDON[1]	URBAN NON-LONDON	INTER-URBAN
Commute		0.25		0.25
Commute to London		0.0		
Business		0.10		0.10
Leisure		0.30		0.30
All	0.20		0.40	0.25

PDFHv4 in 2002 adopted this enhanced framework and its recommended cross-elasticities. PDFH v4.1 in 2005 made use of the (Dodgson, 1986) relationship to enable cross-elasticities to be deduced as follows:

[2] The document is not openly available but can be sourced through subscription to the Passenger Demand Forecasting Council (https://www.raildeliverygroup.com/pdfc.html) who do though provide access to the document for research purposes where appropriate.

$$\eta_{RC} = |\eta_{CC}| \frac{V_C}{V_R} \delta_{CR} \quad (1)$$

η_{RC} is the cross-elasticity of rail demand with respect to car cost, η_{CC} is the car own-price elasticity, V_C and V_R denote the volumes of car and rail demand and δ_{CR} is the diversion factor that denotes the proportion of car users who when changing behaviour transfer to rail. It recommended η_{CC} and δ_{CR} to operationalise the method. Equation 1 demonstrates the context dependence of cross-elasticities and in particular the influence that rail's competitive position will have on its cross-elasticities.

No changes were made to PDFH v5 in 2009 but PDFH v5.1[3] in 2013 increased the fuel cost cross-elasticities in almost all segments to 0.5, based on the findings of ARUP and OXERA (2010). This generally doubled the recommended cross-elasticities. Whilst the study that provided the revised PDFH v5.1 cross-elasticities was funded by the Department for Transport, it has not accepted them and instead recommends that the cross-elasticities in PDFH v5 are used (Department for Transport, 2014). Indeed, a figure of 0.5 would seem large when compared with the available evidence and particularly where rail is relatively competitive.

2.2 Cross-Elasticity Review Evidence

There are many notable reviews and indeed meta-analyses covering own price elasticities (Webster and Bly, 1980; Goodwin, 1992; Oum et al., 1992, Goodwin et al., 2004; Graham and Glaister, 2004; Jevons et al., 2005; TRB, 2004; TRL et al., 2004; Hensher, 2008; Litman, 2010; Wardman, 2014). In contrast, cross elasticities have received far less attention.

Goodwin (1992) covers five cross-elasticities of public transport demand with respect to petrol prices. These ranged from 0.08 to 0.80 and averaged 0.34. Some of the earliest reviews of cross-elasticities, obtained from UK choice models, were reported by Wardman (1997a, 1997b) and contributed to the recommendations reproduced in Table 1.

De Jong and Gunn (2001) provide a review of European cross-elasticity evidence obtained from choice models. The long run cross elasticity of public transport trips with respect to fuel price in the reviewed literature was found to be 0.12 for commuting, 0.03 for business, 0.07 for leisure and 0.14 for education.

The pioneering Webster and Bly (1980)[4] review of international demand elasticity evidence was updated by TRL et al. (2004)[5]. The latter though provides only a very limited amount of evidence relating to the cross-elasticity of rail demand with respect to fuel price and does not provide any summary guidance in this area.

Wallis (2004) provides a review of public transport demand elasticities. In terms of cross-elasticities, these were for public transport demand with respect to fuel prices and vehicle operating costs. The former averaged 0.07 to 0.30, with a typical value around 0.15, whilst the latter covered a wide range with 0.3 to 0.4 typical. No cross-elasticity recommendations were made and instead diversion factors were provided to support the Dodgson (1986) equation.

[3] At the time of writing, this was the most recent version although PDFHv6 was in preparation.
[4] Traditionally referred to as the 'Black Book', because of its covers.
[5] Sometimes referred to as the 'White Book', because of its covers.

More recently, Fearnley et al. (2017) reviewed a large amount of inter-modal cross-elasticity evidence, although rail demand cross-elasticities were not separately identified, and whilst Fearnley et al. (2018) do separate out rail demand, they do not cover cross-elasticities with regard to fuel costs and the focus is very much on local trips. We here make use of a dataset, reported in section 7.2, which is an extension of that used in the latter study.

2.3 Summary

It is clear from this discussion that further research in this area was warranted. There is little up-to-date and reliable summary evidence that can be drawn upon, and indeed some of the evidence that does exist relates to public transport in general, and then mainly for urban trips, rather than rail in particular[6]. Current PDFH recommendations seem large and are not universally accepted. Moreover, cross-elasticities are inherently variable and recommendations for real-world forecasting should accommodate this.

3. APPROACHES TO ESTIMATING CROSS-ELASTICITIES

Given that the estimation of cross-elasticities is challenging, we have used a range of methods in this research study. We have exploited a mixture of: primary data, through an online survey; secondary data, in the form of records of rail ticket sales and National Travel Survey (NTS) data; deducing cross-elasticities using economic theory; and insights from previous studies. We here discuss the data and evidence base underpinning each of these approaches.

3.1 Ticket Sales Analysis

The Demand Data

Rail ticket sales data, at the level of station-to-station movements, has long been used in Great Britain to support econometric analysis that has provided the 'backbone' of PDFH recommendations covering many influential factors (RDG, 2018).

The analysis reported here is based on annual data covering 1995/96 through to 2016/17. The number of flows available and related observations for the key flow types are set out in Table 2. These are very large datasets.

[6] We do though return to recent British evidence in more detail in section 7.1 and international evidence in section 7.2.

Table 2. Ticket Sales Data Flows and Observations

FLOW TYPE	FLOWS	OBS
London Long Distance (Non-Season) Tickets **(LL)**	803	17666
Non-London Long Distance (Non-Season) Tickets **(NLL)**	6184	136048
London and South East Season Tickets **(LSES)**	838	18436
London and South East Non-Season Tickets **(LSENS)**	838	18436
Non-London Short Distance Season Tickets **(NLSS)**	1898	41756
Non-London Short Distance Non-Season Tickets **(NLSNS)**	3685	81070

The Motoring Cost Data

The primary focus of this research is to determine the impact of car costs on rail demand and we constructed four historic cost indices as follows[7]:

- Fuel cost based on Department for Transport WebTAG guidance;
- Car operating cost based on Department for Transport WebTAG guidance;
- Pump price;
- Pump price with allowance for car fuel efficiency.

The WebTAG guidance on car costs is based upon car speeds to accommodate fuel efficiency. We do not have historic data on car speeds to operationalise the WebTAG cost functions. However, a study by Leigh Fisher et al. (2016) conducted analysis of historic NTS data over the period 1995 through to 2013 and came up with equations that related car speed to year, origin region, destination region and distance band to enable the WebTAG fuel and total costs functions.

As might be expected, there is a strong degree of correlation, exceeding 0.9, between the various indices. This will make it difficult to discern which provides the best explanation of the impact of car costs on rail demand.

We explored two possibilities for populating our dataset with historic parking cost data. One was from Parkopedia, which provides information on parking availability and costs. Historic data was available but the costs of acquiring it were beyond the scope of this study. The other avenue we explored was historic data in the NTS. Whilst the NTS asks relevant questions on parking costs, it became apparent that this information was not included in the available dataset even though NTS staff confirmed that it should have been.

[7] The historic indices were provided by the Department for Transport using the same methodology relating to fleet mixes and fuel cost curves as used in official WebTAG guidance for future car costs (Department for Transport, 2017a).

3.2 Analysis of National Travel Survey (NTS) Data

The NTS is the primary source of information on personal travel in the Great Britain, although since 2013 the survey covers only residents of England (Department for Transport, 2018). The survey acquires weekly travel diary data from around 16,000 individuals in 7,000 households each year in a representative sample of the population. Official government statistics make much use of the data collected.

The NTS data at our disposal covered 2002 to 2015, and included 223,245 adults of whom 135,373 were employed. Table 3 presents summary statistics for key variables in addition to the 48% of the sample that is male. The age and employment distributions are in line with official statistics based on census data and discussed in section 3.3. This is not surprising given that the NTS goes to great lengths to obtain a nationally representative sample. The annual household income figures are in 2015 prices but cover the entire period. We therefore provide figures in brackets for the most recent three years which indicate relatively little growth in incomes over the period, reflecting the 2008 financial crisis and subsequent low economic growth and austerity.

Table 3. Distribution of Key Variables of the NTS Data 2002-2015

AGE	%	HOUSEHOLD INCOME	%	EMPLOYMENT	%
17-24	11.3	Less than £13k	19.4 (15.4)	Employed full time	38.2
25-34	15.2	£13k to £24k	16.0 (22.0)	Employed part time	12.5
35-44	18.1	£25k to £49k	30.1 (32.0)	Self-employed	7.9
45-54	17.1	£50k to £74k	16.8 (17.4)	Homemaker/Carer	5.9
55-64	15.9	£75k +	17.7 (13.2)	Full time education	3.2
65+	22.4			Unemployed	2.5
				Retired	24.1
				Other	5.7

3.3 Survey Methods

We conducted an Online Panel Survey to complement other aspects of the study, particularly with respect to establishing the costs that were most important to motorists and quantifying behavioural changes as a result of fuel cost changes. We do not set out the questions here since they are clear in the discussion of the analysis of the data in Section 6.

Data collection was undertaken by Research Now (www.researchnow.com) who maintain the U.K.'s largest online panel. In-scope were those who made at least one car journey per week and who had some responsibility for car costs. We obtained a sample of 1,713 respondents, although discarded 70 (4%) on the grounds that they reported car costs that were much too large for the journeys being undertaken. We took such responses to indicate those who had not taken the survey seriously.

Table 4 reports summary data for the sample collected. Given that the sample is based upon car users, it will not be representative of the population at large. Even so, the 47% of the sample who were male reflects the national proportion. In terms of age profile, the two younger age groups are under-represented when compared to national statistics (21% vs 29%) and the NTS sample (27%) which, given this is a survey focussed on car users, might be expected. The two middle age categories are broadly similar (32% vs 34%) and in line with the NTS sample (35%) , whilst the two oldest categories are strongly over represented (47% vs 37%) with the NTS being 38%. This will be partly due to the emphasis on car users but also because older people tend to be more inclined to participate in panel surveys. Whilst this could introduce a bias, we found that weighting the sample had a negligible impact on the results of our analysis.

National Statistics indicate that around 75% of the adult population are employed, compared to 61% here, with 4% unemployed which is a little larger than the 2% here, and economically inactive at 21% compared to the 37% here. Again this reflects retired people having a greater tendency to be involved in survey panels. Nonetheless, when we compare the employment distribution in Table 4 with the equivalent NTS figures in Table 3 we find them to be broadly similar.

Re-apportioning those who did not want to provide their household income, and comparing with the most recent three years of NTS data, the online panel contains a lower proportion with annual household incomes less than £25k (26% vs 37%) which is offset by a greater proportion in the range £25k to £49k (43% vs 32%). The selection criteria based around car users may well have contributed to the somewhat lower proportion of the online panel in the lowest income group. The two surveys provide very similar proportions with incomes in the range £50k-£75k (18% vs 17%) and over £75k (13% vs 13%) where we can assume car ownership and use levels are high.

Table 4. Key Characteristics of the Online Panel Survey

AGE	%	HOUSEHOLD INCOME	%	EMPLOYMENT	%
17-24	7.0	Less than £25k	24.0	Employed full time	40.5
25-34	14.0	£25k to £49k	39.0	Employed part time	14.2
35-44	15.6	£50k to £74k	16.2	Self-employed	5.7
45-54	16.3	£75k to £99k	8.5	Homemaker/Carer	6.3
55-64	24.5	£100k +	3.7	Full time education	1.6
65+	22.6	Prefer not to say	8.6	Unemployed	1.9
				Retired	28.8
				Other	1.0

3.4 Making Use of Cross-Elasticity Evidence

There are two aspects to the car cost cross-elasticity evidence reported here:

- A review of relevant UK studies;

- Insights provided by a review of international evidence.

The review of relevant studies focusses on econometric analysis of rail ticket sales data where some measure of fuel price has been included in the estimated model. In addition, Fearnley et al. (2017, 2018) report an extensive review of international cross-elasticity evidence. We here make use of that dataset with some additions made to it.

3.5 Deducing Cross Elasticities

Equation 1 illustrates how the cross-elasticity of rail demand with respect to motoring costs can be deduced from evidence on car cost own-elasticities, relative market shares and diversion factors. We here provide a robust basis for this approach through interrogation of the NTS with regard to relative market shares and by making use of a major review of diversion factor evidence (RAND Europe and SYSTRA, 2018).

4. ANALYSIS OF TICKET SALES DATA

4.1 Modelling Approach

We have estimated fixed effects regression models to our data pooled across routes and the 22 years of data between 1995/96 and 2016/17 available to us. These take the form:

$$V_{ijt} = \tau \prod_{k=1}^{n} X_{ijkt}^{\alpha_k} e^{\sum_{l=1}^{m} \beta_l X_{ijlt}} e^{\sum_{r=1}^{s} \gamma_r D_{ijrt}} \quad (2)$$

V_{ijt} is the demand for rail travel between stations i and j in time period t. It is a function of n continuous variables (X_{ijkt}) entered so that their coefficients (α_k) are interpreted as elasticities and m categorical variables (X_{ijlt}) entered so that their coefficients (β_l) denote the proportionate change in demand after a unit change in the variable. In addition, there are s categorical variables denoted by the dummy variables (D_{ijrt}) and their coefficients (γ_r) denote the proportionate effect on demand of a particularly category of a variable relative to an arbitrarily selected base category. The 'fixed effects' for p-1 of the p station-to-station movements are covered by the D_{ijrt} term without any variation by time period t. These represent unaccounted for characteristics that are specific to each flow and do not vary over time, essentially allowing flow specific intercepts. The estimated models are logarithmic transformations of equation 2.

We have estimated separate models for the six flow types set out in Table 2, but additionally splitting the very large Non London long distance data set into flows greater or less than 100 miles. The models based on long distance flows pool data across directions[8] whilst all other models retain the two directions as separate observations.

The variables we have used, in addition to motoring cost indicators, to explain rail demand are:

- Fare represented by revenue per trip and converted to real terms using the CPI;

[8] So whilst data is supplied for, say, Manchester to London and London to Manchester separately, we pool across directions because the prevalence of single leg tickets on long distance flows means that we do not have a good way of distinguishing within Manchester to London tickets those who are residents of Manchester travelling to London and those who are residents of London returning home from Manchester.

- Generalised Journey Time (GJT), an industry standard composite term representing journey time, service frequency and interchange;
- Gross Value Add per Capita at NUTS3 level for non-season tickets;
- Employment at the destination for season tickets. This is either Central London Employment or district level;
- Population and the proportion of the population without a car at district level;
- Time trend.

4.2 Selecting a Preferred Model

We have removed observations where the standardised residual is outside the range ±2 and which might be deemed to reflect the 5% of cases where the recorded data is of poorest quality or where there were significant unexplained impacts on demand. Only in the case of the LSES[9] flows did this materially impact on the estimated car cost cross-elasticity, which for fuel cost increased by around 30%.

We are aware that elasticity estimates can exhibit high volatility when obtained from rail demand models which attempt to estimate the effects of a range of external factors (Leigh Fisher et al., 2016; Mott Macdonald and University of Southampton, 2014, Wardman, 2006). This is also the case here when we freely estimated all the parameters above.

The GJT elasticity estimates varied enormously across models, from -0.09 to -2.61, even though they were all highly statistically significant! Measured GJT can exhibit minor but largely unperceived changes given that the railway industry in Britain is continually striving to improve its offering. If correlated with the trend increases in rail demand witnessed in Britain over many years, this could result in exaggerated GJT elasticities. On the other hand, GJT variations tend to be slight on most routes and in most years, which is not conducive to robust elasticity estimation. Whilst we therefore isolated the GJT effect by constraining its elasticity to PDFH recommendations, this had little effect on other coefficient estimates.

Although all of the five estimated GVA elasticities for Non-Season flows were highly significant, three were very low at less than 0.4 whilst that for LL was 2.30. Moreover, the employment elasticity was negative for LSES and the population elasticities for LL was 0.29 and for NLL under 100 miles was 1.44. The fuel cost cross-elasticities were all highly significant but across the seven models estimated varied from 0.38 on LL flows to 3.67 on NLL flows less than a 100 miles. Six of the seven cross-elasticities exceeded 1.0, with an overall average of 1.97 which is simply not credible. In five of the seven models, the coefficient estimated to the proportion of households without a car was wrong sign despite being highly significant in all cases.

These implausible results are the result of large correlations amongst variables over time and are unsurprising on the basis of previous research findings. We therefore constrained the population and employment elasticities and the proportion without a car parameter to PDFH recommendations to isolate their effects.

The constraints tended to reduce the estimated fare elasticities, but only a little, and led to more credible GVA elasticity estimates with less variation. Most importantly, the fuel cost cross elasticities

[9] Flow acronyms defined in Table 2.

were much more plausible. Before discussing these models, we consider the different representations of motoring cost.

The estimated motoring cost cross-elasticities varied little across the three representations based around fuel costs but, as expected, were much lower than the car operating cost cross-elasticity estimates. Across the seven flow types, the cross-elasticities estimated to the various fuel based terms ranged from around 35% to 70% of the total cost cross-elasticity, with an average around 62%, very much in line with fuel cost forming around 60% of operating cost. But given that the operating cost cross-elasticity provided the worst fit to the data in five of the seven models, and that our survey, discussed below, indicates that sometimes even fuel cost is not always considered and is anyway much more important than operating cost, we rule out operating cost as the preferred index.

As for the fuel based measures, the estimated webTAG fuel cost and pump price cross-elasticities differed in absolute by an average of only 0.11 across the seven flow types, with the corresponding figure being 0.06 for the fuel cost and pump price with efficiency indices. These findings are not surprising given the very high correlations between these indices and they are essentially representing the same effect. Whilst in six out of the seven cases the pump price index provided the best fit to the data, which is unsurprising given that pump price is a headline figure that motorists observe, we have opted for the webTAG fuel cost measure in our econometric models. This is because we are reluctant to use a motoring cost measure going forward that would not allow for anticipated large reductions in fuel costs due to improved fuel efficiency whilst the two pump price indices recovered wrong sign cross-elasticities for the LL flows. Moreover, using the WebTAG fuel measure has the attraction of being consistent with Department for Transport guidance in investment and policy appraisal[10].

4.3 Results

The preferred models for the seven sets of flow are reported in Table 5. These models do not contain any dynamic effects. Despite extensive investigation (Stead and Wheat, 2017), the models indicated that the long run effect was generally between 5 and 15 years which we do not regard to be credible because five of the seven flows contain very few commuters who have to await the process of moving house or changing job which implies longer periods of adjustment. Indeed, several recent rail studies have found the long run to be less than 5 years, and sometimes much less, and even for commuting trips (Jevons et al., 2005; ARUP and OXERA, 2010; Batley et al., 2011; Wheat and Wardman, 2017). We therefore here report static models which will represent a one year effect and might be less than the long run effect[11].

[10] Having said all this, whilst the precise index used will impact on forecasts, our models essentially obtain the same cross-elasticities for the different fuel based indices and hence the issue here is not the estimate but which index should be used in forecasting. Readers, and forecasters, can make up their own minds!
[11] PDFH recommends that almost all adjustment to changes are achieved within one year, except for commuting where it is two years.

Table 5. Preferred Econometric Models of Ticket Sales Data

VARIABLE	LL	NLL<100	NLL>100	NLSS	NLSNS	LSES	LSENS
Fare	-0.832 (32.1)	-0.817 (81.7)	-0.733 (91.6)	-1.038 (79.8)	-1.167 (145.8)	-0.803 (32.1)	-0.772 (40.6)
GJT	*	*	*	*	*	*	*
GVA	2.845 (142.2)	1.032 (93.8)	0.789 (52.6)	n.a.	0.467 (47.6)	n.a.	-0.203 (6.8)
Trend	-0.027 (0.3)	0.020 (0.14)	0.007 (25.5)	0.036 (17.5)	0.031 (61.3)	-0.005 (4.5)	0.044 (43.8)
EMP	n.a.	n.a.	n.a.	*	n.a.	*	n.a.
Pop	*	*	*	n.a.	*	n.a.	*
Fuel	0.117 (2.3)	0.558 (32.8)	0.300 (33.3)	0.685 (34.3)	0.315 (26.3)	0.532 (10.55)	0.188 (5.7)
No Car	*	*	*	*	*	*	*
Adj R^2	0.979	0.976	0.968	0.856	0.968	0.948	0.980
Observations	16804	62725	67101	39724	77743	17244	17700

Note: * denotes constrained to PDFH (version 5.1) recommendations. Flow acronyms set out in Table 2.

The estimated fare elasticities are all correct sign and highly significant. Whilst those for seasons (LSES and NLSS) are somewhat larger than expected, in general the results accord with previous evidence (Wardman, 2014) and PDFH recommendations in this area.

We enter time trends because there are a host of unaccounted for improvements over the period that might have impacted on rail demand growth. These include the digital revolution, which can be expected to have had a disproportionately large impact on the demand for rail travel (Wardman and Lyons, 2016), whilst there have been trend improvements in reliability, rolling stock quality, information provision, purchasing arrangements and marketing more generally, along with trend increases in road journey times. Indeed, there must have been other factors at work to explain why rail demand continued to grow during the serious economic downturn of the late 2000s.

Nonetheless, time trends can be highly correlated with GVA, which might account for the unexpected negative sign for LL flows, which just so happens to be associated with a GVA elasticity which is clearly too large, and the negative GVA elasticity for LSENS flows. Overall though the estimated time trends indicate the expected effect; the negative for LSES could stem from people moving out of season tickets given much greater flexibility in the employment market.

The reported fuel price cross-elasticities are all correct sign and significant, and almost all are estimated with a very high degree of precision. As might be expected, the fuel price elasticity for LL is low, given this is where rail is in one of its strongest competitive positions. However, on such grounds we might expect the LSES and NLSS cross-elasticities to be somewhat very much lower than estimated.

The cross-elasticity for NLL flows less than 100 miles is relatively large, which might be expected given the strength of competition here from car and to some extent inter-urban bus services, and it falls on such flows for journeys over 100 miles where rail is then more competitive. The two remaining cross-elasticities for non-season tickets (NLSNS and LSENS) are, as would be expected, relatively low given that rail is in a stronger competitive position than for the former flows.

4.4 Variations in Fuel Cost Cross-Elasticities

We examined whether the estimated fuel cost cross-elasticity varied with the size and sign of the fuel cost variation, whether pump price thresholds were crossed, and with the level of car ownership. We also explored whether cross-elasticities on London flows differed after the London congestion charge was introduced in 2003 which would have strengthened rail's competitive position[12]. The only statistically significant and correct sign effects related to car ownership, where on many flows the fuel price cross-elasticities were lower where car ownership levels were lower, but the variations were slight and would not warrant variations in recommended cross-elasticities on this account.

5. ANALYSIS OF NATIONAL TRAVEL SURVEY DATA

5.1 Modelling Approach

The estimated trip rate models take the form:

$$RT_{jpt} = \tau + \alpha I_j + \beta_1 C_{1j} + \beta_2 C_{2j} + \gamma T + \lambda P_t + \theta F_t + f\left(X_{1j,} X_{2j,\ldots\ldots,} X_{nj}\right) \qquad (3)$$

where RT is the number of rail trips in the surveyed week made by individual j for purpose p in some time period t. These are a function of the individual's income (I), whether they have one (C_1) or two or more cars (C_2) in their household, a time trend (T), and the price (P_t) and fuel cost (F_t) indices for year t. In addition, this model contains a set of n other socio-economic variables (X_1, X_2, …… X_n) relating to individual j that might explain variations in the propensity to make rail trips but which cannot be entered into the ticket sales models previously discussed.

The model takes this form given that RT_{jpt} can be zero. The implied fuel cost elasticity for purpose p in year t can be calculated as:

$$\eta_{Fpt} = \theta \frac{F_t}{\overline{RT}_{pt}} \qquad (4)$$

where $\overline{RT}_{pt}$ is the mean number of rail trips per person for purpose p in period t.

5.2 Results

Given that it is a key distinction in railway demand forecasting, we estimated ten separate models for rail trips according to whether they were to or from London or were Non-London, the three journey

[12] We also examined whether the congestion charge had any effect on rail demand itself, as opposed to the fuel price cross-elasticity, but none was detected. However, it is worth pointing out that we have not here analysed flows within the London Travelcard Area which is where we might expect the impacts of the congestion charge on rail demand and cross-elasticities to be greatest.

purposes of commuting, business and other trips and with the latter two purposes distinguishing between shorter (≤20 miles) and longer (>20 miles) trips. Space precludes us from reporting all ten models each with around 17 independent variables each[13], and we here summarise the key findings.

Fuel cost had the correct positive sign in 9 out of the 10 models. However, only that for short other trips was significant on London flows. On Non London flows, the fuel cost coefficient was significant for commuting and both short and long other trips but not for business trips.

Household income was highly significant in all 10 models. We evaluated the implied income elasticities at the mean levels of income and trip rate. For London flows these were 0.91 for commuting, 0.35 and 0.74 for other short and long, and 0.67 and 1.20 for business short and long. The corresponding figures for Non London trips were 0.35, 0.16, 0.27, 0.54 and 0.89. These figures seem broadly credible, and demonstrate the expected stronger effect of income on longer distance trips.

Car ownership had a statistically significant impact on rail demand in all models. One car per household reduced London trips by between 12% for commuting and 37% for other short trips, with two cars per household reducing demand by between 50% and 70% except for short business trips which were reduced by 90%. The effects on Non-London trips were, as expected, generally larger. One car per household reduced rail trips by around 40% to 70% except for short business trips which were effectively eliminated. Two cars per household reduced rail trips for business long and other trips by around 80%, with virtually no trips for commuting.

The annual time trend was significant in all 10 models and positive in all but one. On the London flows, they were all around 5% per annum whilst the positive trends on Non London flows ranged from 4% for commuting and business long to 8% per annum for other short and business short. These are large but reflect the strong rail demand growth over the period. The rail fare index was only significant in two models, and then it was wrong sign in one.

As for the socio-demographic variables, females tend to make fewer trips for business and commuting and those in the 18-35 category generally made more rail trips except for business travel. Part time workers make, as expected, fewer commuting and business trips, but were also found to make more other trips. Those in professional/managerial occupations did not make significantly more other rail trips but made around 60% more commuting rail trips with double the amount of business trips on London flows, and 75% (140%) more short (long) business trips on Non-London flows.

Across all ten models, there was a strong and highly significant effect from walk time to the rail station, but there may well be an element of endogeneity here since those who want to make journeys by train will tend to locate nearer to railways stations. There were also variations in the propensity to make trips rates by location and according to urban density.

Table 6 reports the implied fuel cost cross-elasticities for the five journey purpose and distance combinations for London and Non-London flows. These are obtained using equation 4 and are averages across years. Those obtained from fuel cost coefficients that were significant are

[13] Detailed results are reported in SYSTRA and ITS University of Leeds (2017) and are available from the corresponding author upon request.

highlighted bold. The implied elasticities from models that removed the time trend were not greatly different. Whilst the cross-elasticities are large, and we will return to this below, they exhibit a number of interesting relativities.

London travellers are less sensitive to fuel costs than Non-London. This may be because rail is generally in a much stronger position on London based flows.

In none of the four cases does fuel price have a significant effect on rail trips made by business travellers. We might expect a lesser effect given that the company bears the cost. Other trips tend to have larger cross-elasticities than commuting, which may reflect rail's weaker position in the off-peak and higher incomes amongst commuters.

Where the fuel coefficients are significant, there is evidence that they increase with journey distance. This may be because car costs are more likely to be considered for longer trips which are made less routinely and are more expensive.

Table 6. Implied Cross Elasticities

FLOW TYPE	COMMUTE	OTHER SHORT	OTHER LONG	BUSINESS SHORT	BUSINESS LONG
London	0.24	**0.39**	0.09	0.40	0.06
Non London	**0.62**	**0.90**	**1.10**	-0.16	0.22

Whilst we cannot claim that this analysis of NTS has been entirely successful with regard to estimating the impact of fuel costs on rail demand, the variations in the estimated cross-elasticities across categories are in line with expectations. As for the absolute values, whilst they can generally be regarded to be large, it is important to bear in mind that NTS provides a representative account of all travel in Great Britain whereas ticket sales analysis covers movements where at a minimum rail is available extending to situations where it is in a strong competitive position.

For example, for Non-London long distance flows, the share of rail amongst rail and car is around 6% for business and 10% for leisure trips in NTS. Restricting this to movements between what NTS defines as urban areas, which is where the main rail networks are, increases these figures to around 11% and 30% respectively. Hence the V_C/V_R ratio of equation 1 falls very appreciably from 15.2 and 9.3 in the former case to 7.8 and 2.3 in the latter. As such, the absolute cross-elasticities here can be expected to be larger than those estimated to the rail demand data.

6. ANALYSIS OF ONLINE PANEL SURVEY

The online panel survey provided insights into which costs are considered by motorists and behavioural responses to changes in motoring costs.

6.1 Which Costs are Considered?

Whilst the railway industry does account for the impacts of fuel cost on rail demand, there might be other motoring costs that should be taken into account in its forecasting procedures. We therefore asked motorists whether a 'significant' increase in a range of costs would impact on car use. The reasoning behind using the term significant, as opposed to whether it was 'considered', was to distinguish a cost term having no effect because it is perceived to vary little from a cost term being irrelevant to changes in car use. We accept though that such phrasing could well have led to exaggerated responses.

We distinguished between local trips, specified to be up to 20 miles, and less routine longer distance trips. The results for a wide range of types of cost are reported in Table 7[14]. As might be expected, fuel cost has the largest impact on behaviour, and is the only cost type with more than a third stating it would have a large impact and less than 20% stating that it is irrelevant. The costs of oil and tyres has a large number stating that it would have some effect, as is the case with insurance, depreciation and service and labour. Hence exploring broader operating costs as we did would seem justified. Even though motorists do not always pay to park, parking has the second largest proportions indicating a strong effect and almost a half indicating some effect. Tolls and congestion charge have very little effect 'on average' as they are rarely faced. The other costs are essentially fixed and as expected would have relatively little impact on car use.

We note that there is here very little difference in impact between local and longer journeys. This might have been a function of the use of the term significant cost increase.

Table 7. How Important is a Significant Increase in Motoring Costs?

	YES – A LOT (%)		YES – A LITTLE (%)		NO RELEVANCE (%)	
TYPES OF COST	**LOCAL**	**LONGER**	**LOCAL**	**LONGER**	**LOCAL**	**LONGER**
Fuel	36	35	48	49	17	16
Oil and Tyres	11	14	57	55	32	31
Parking	18	16	45	44	37	40
Tolls/congestion charges	14	17	27	34	60	49
Car Tax	12	10	47	48	41	42
Depreciation	6	6	44	44	49	50
Insurance	17	14	48	50	36	36
Breakdown Cover	7	8	46	42	48	50
Service and Labour	10	11	51	49	39	39
Fines (Speeding or Parking)	9	11	27	28	64	61
Garage Hire	6	5	15	18	79	77
Cleaning/Valeting	5	4	24	25	71	71

[14] The list of variables was intentionally as comprehensive as we could make it, even though several might not be expected to impact on car use at the margin.

6.2 Fuel and Parking Costs

Given that fuel and parking costs were expected to be key variable costs, we explored these in further detail.

The comment is sometimes made that just as electricity is needed to power consumer goods, so fuel is needed to power a car; in each case the latter is useless without the former. Do consumers really consider the running costs of their washing machines and cookers? Perhaps motorists simply fill their car with fuel because that is what is needed to use it, particularly if for most activities there are no feasible alternatives. We therefore asked motorists whether they "normally filled the tank up to full and did not think about the costs of driving", and 59% agreed with this statement.

We might hypothesise that motorists are more likely to consider fuel costs for longer distance journeys, partly on the grounds that they are less routine and partly because the monetary amounts per trip can be very much larger. For those who do consider fuel costs, we asked them at what length of journey they generally consider fuel cost. The cumulative proportions for any journey, up to 50 miles, up to 100 miles and over 100 miles were 14%, 35%, 62% and 100%.

As for parking costs, only 17% stated that they generally paid for parking for local trips with 44% paying for longer trips, although as we shall see these figures vary by journey purpose. Of those who generally paid, even then there was a reluctance to pay: for local (longer) journeys 18% (21%) stated that they would not mind parking some way from their destination if it meant cheaper or free parking whilst 47% (51%) stated that they try to park close to their destination but would check for the cheapest parking in that area.

These results indicate that variations in these most marginal of car costs might not impact greatly on rail demand.

6.3 Stated Behavioural Impacts

In the context of their last reported local and longer distance car journey, motorists were asked to state whether they would still make that car journey in the event of a 25% increase in the cost of fuel and, for those who paid it, of parking charge. The specific aim of these questions was not to return car own-elasticities per se, since these are not of primary interest to us. Rather they provide a means of translating fuel cost cross-elasticity estimates into parking charge cross-elasticity estimates in anticipation of not having other evidence on motorists' responses to parking charges.

Table 8 reports the implied elasticities for local and longer journeys split by journey purpose. The Parking Overall column is the parking elasticity across all respondents including those who did not pay and hence would have no behavioural response. The ratio column denotes the overall parking cost elasticity relative to the fuel cost elasticity which we subsequently use in translating fuel cross-elasticities into parking charge cross-elasticities.

Table 8. Fuel and Parking Price Elasticities if Faced with a 25% Increase

PURPOSE	FUEL	PAY FOR PARKING	PARKING OVERALL	RATIO
	LOCAL TRIPS (<20 miles)			
Commuting	-0.71 [240]	-1.06 [57]	-0.23 [240]	0.32
Business	-0.73 [40]	-1.00 [15]	-0.35 [40]	0.48
Other	-0.33 [1,363]	-0.75 [214]	-0.11 [1,363]	0.33
Total	-0.39 [1,643]	-0.82 [286]	-0.13 [1,643]	0.33
	LONGER TRIPS (20+ MILES)			
Commuting	-0.42 [144]	-1.36 [84]	-0.74 [144]	1.76
Business	-0.64 [98]	-0.82 [6]	-0.05 [98]	0.08
Other	-0.49 [1,180]	-0.84 [545]	-0.37 [1,180]	0.76
Total	-0.49 [1,422]	-0.90 [635]	-0.38 [1,422]	0.78

Note: Figures are Elasticities and [observations].

The fuel price elasticities are generally larger than the conventional wisdom, discussed in section 8 below, presumably because stated intentions to cost increases are influenced by strategic bias. However, a contributory factor could have been that a 25% fuel price increase is large.

The parking charge elasticities for those who pay for parking are larger than the fuel price elasticities, which is to be expected given that, as we have seen, not everyone considers fuel costs.
It can be seen that after accounting for those who do not pay to park, and hence will have zero parking cost elasticity, the ratio of the overall parking charge elasticity to the fuel price elasticity is almost always less than one.

For local trips, the ratios are consistent whilst in contrast the ratios for longer distance trips are highly variable. The ratio for longer distance commuting is very large, as a result of the large parking elasticity for those who pay and the relatively large proportion who do pay, but this forms a very small proportion of commuters. In contrast, the ratio is very low for business travel where few pay to park presumably because they park for free in branch or client offices.

Motorists were also asked which rail trips in the past year would have been made by car in the event of ‘significantly cheaper’ fuel costs. No distinction was made by journey length and the results for the 1,161 respondents who provided relevant information are presented in Table 9.

The proportionate reductions in commuting, business and other trips are 25%, 33% and 13%. It is surprising that leisure has the lowest proportion and business trips the highest.

Whilst respondents were not asked what constituted a significant reduction in fuel price, and indeed this could vary by journey purpose which might explain the differential behavioural responses by purpose, we consider that reductions in the range 25% to 50% might be deemed to constitute significantly cheaper fuel costs. The implied cross-elasticities for these two reductions are provided in Table 9. The cross-elasticities are large for commuting and particularly for business travel. However, elasticities from Stated Intention data should very much be regarded as upper bounds.

Table 9. Intentions to Switch from Rail Due to 'Significant' Reduction in Fuel Prices

	COMMUTING	BUSINESS	OTHER
Current Annual Rail Journeys	33,028	2,034	8,371
Switched Rail Journeys	8,142	679	1,080
Cross Elasticity 25% Fuel Price Reduction	0.98	1.41	0.48
Cross Elasticity 50% Fuel Price Reduction	0.41	0.59	0.20

6.4 Actual Behavioural Impacts

We asked the sample of motorists who had perceived fuel price reductions in the past two years whether they had changed behaviour and switched rail journeys to car. Despite the fact that there had been fuel price reductions in real terms over the period, only 136 (8%) respondents perceived these to be so.

Of the 136, only 10 (7%) switched some of their 52 trips per year. The 126 who did not switch rail trips made 2137 current rail journeys per year. Even in the unlikely event that the former stopped making all of their rail trips, the reduction in demand would only be 2.4%. Given that the perceived fuel price reduction was a little over 12%, the maximum implied cross-elasticity would be 0.19.

We can explore these figures in a little more detail but only for the other trips since the samples for commuting and business were far too small. We have 84 respondents who made 598 other trips by rail in the past year and reported making 10 fewer rail trips as a result of fuel price reductions. Given the perceived fuel price reduction of 12%, the implied cross-elasticity is 0.13.

These cross-elasticities based on recollection of actual behaviour and perceived price changes are low, and not surprisingly less than those implied by Stated Intentions responses.

7. MAKING USE OF AVAILABLE EVIDENCE

7.1 Great Britain Econometric Evidence

Table 10 provides a summary of studies in Great Britain that have conducted econometric analysis of rail demand data and recovered statistically significant estimates of car cost cross-elasticities[15].

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[15] We are also aware of Dargay (2010) which provides a large range of cross-elasticity estimates. However, these were deduced using relationships of economic theory which we here do on a more comprehensive basis. Moreover, the cross-elasticities related to total operating costs and covered very long trips including those where air competes.

However, some of this evidence should be discounted in attempting to summarise the insights of these studies. A justification of this is that in some periods car costs can be highly correlated with other external factors, such as GDP, population, car ownership and car journey times, and endogenous factors, such as rail fares, so that the results are not credible.

Table 10. Existing Econometric Car-Cost Cross Elasticity Evidence

STUDY		FUEL CROSS-ELASTICITY
1	Steer Davies Gleave (1999) National Passenger Demand Forecasting Framework	0.11 to 1.29
2	Steer Davies Gleave (2004) Effect of Road Congestion on Rail Demand	0.14 to 0.58
3	Wardman and Dargay (2007) External Factors Data Extension and Modelling	< 0.26
4	MVA Consultancy (2008) Econometric Analysis of Long Time Series	0.14 to 0.65
5	MVA Consultancy (2009) Regional Flows	0.25
6	ARUP and OXERA (2010) Revisiting the Elasticity Framework	0.20 to 2.35
7	Meaney and Shepherd (2012) What is Affecting Season Ticket Elasticities in London?	0.42 to 0.48
8	SYSTRA (2014) Rail in the North Demand and Revenue Model	0.28 to 0.95 Gen Cost[16]
9	Mott MacDonald (2014) PDFC Rail Demand and External Impacts	0.05 to 1.38 (and numerous negative)

We discounted study 1, on the grounds that the estimated cross-elasticities related to trips from the South East into London, where rail has a large share and cross-elasticities can hardly be expected to be large, and the study returned a large range of different values. Moreover, the study itself essentially favoured other evidence in arriving at its cross-elasticity recommendations.

The results of Study 6 should be ignored because of the very large range of the estimated cross-elasticities and what seem to be some very large values. Indeed, the Department for Transport who funded this research did not accept its cross-elasticity values for official forecasting purposes.

We find the car cost cross-elasticities in study 7 to be far too large given that the market under consideration here was commuting into London where rail has a very high share and there are few situations worldwide where rail is in a stronger competitive position[17]. Finally, we discount study 9 given there was considerable volatility in the car cost cross-elasticity estimates across the very many models reported.

We examined the remaining five studies which together provided 24 cross-elasticities covering a range of different circumstances. Whilst the results do not paint an entirely consistent picture, and there is volatility in cross-elasticity estimates which is not surprising given their market dependency and the challenges of estimation, we arrived at the summary figures reported in Table 11[18]. These cross-elasticities are relatively low, and lowest for season tickets and long distance flows to and from

[16] Fuel costs might be taken as a third of generalised costs whereupon the implied fuel price cross-elasticities would be a third of these.

[17] Not only is car parking notoriously difficult in London, alongside heavy peak-period congestion, but it is one of the few cities in the world where there is a charge for cars to enter the central area.

[18] Detailed results of the process involved are reported in SYSTRA and ITS University of Leeds (2017) and are available from the corresponding author upon request.

London where rail is in its strongest position. Whilst studies might not report models which contain very large cross-elasticities that are deemed implausible, offsetting this is that some low elasticities will be insignificant and hence are excluded from reported models.

Table 11. Car Cost Cross-Elasticities Implied by Econometric Studies

FLOW	CROSS ELASTICITY
London Long Non-Seasons	0.25
Non London Long Non-Seasons	0.40
Non London Short Non-Seasons	0.40
South East Non-Seasons	0.40
Seasons	< 0.10

7.2 International Cross-Elasticity Evidence

As pointed out in section 2.2, we here make use of a dataset that extends considerably upon those used in Fearnley et al. (2017, 2018).

The updated dataset covers 1096 cross-elasticity observations across all modes and variables with 149 cross-elasticities of rail demand with respect to fuel costs from 34 studies. Of these, 105 are from UK studies but using a range of different methods rather than just the direct demand model evidence of the previous section.

The overall mean cross-elasticity with respect to fuel price is 0.30, being slightly larger at 0.32 for the 101 inter-urban observations than the 0.25 for the 48 urban observations. Table 12 provides summary statistics segmented by purpose and whether the journey is urban or inter-urban.

When split by purpose, there is no clear indication of whether inter-urban cross-elasticities are larger than urban or not and the small samples in some categories mean that we cannot draw firm conclusions of variations by journey purpose. Indeed, the results will be confounded by a range of other factors, such as whether the cross-elasticities are short run or long run and the method used to obtain them. For example, the 23 short run cross-elasticities from dynamic regression models averaged 0.31, the 24 long run cross-elasticities averaged 0.44 and the 102 remaining cross-elasticities averaged 0.26. Nonetheless, the cross-elasticities are, on average, relatively low.

Table 12. Car Cost Cross-Elasticities in Cross-Modal Data Set

PURPOSE	DISTANCE	ELASTICITY
Commuting	Urban	0.44 (0.07) [15]
Commuting	Inter	0.27 (0.05) [15]
Other	Urban	0.60 (0.21) [2]
Other	Inter	0.34 (0.04) [42]
Business	Urban	0.06 (0.06) [2]
Business	Inter	0.40 (0.12) [15]
No Distinction	Urban	0.15 (0.03) [29]
No Distinction	Inter	0.27 (0.03) [29]

Note: Figures are mean, (standard error), [number of observations]

8. DEDUCING CROSS ELASTICITIES

As is clear from equation 1, deducing cross-elasticities of rail demand with respect to motoring costs requires evidence on the car own price elasticity, relative car and rail demand, and the diversion factor. We discuss each of these in turn prior to deducing cross-elasticities for a wide range of situations.

8.1 Car Own Elasticities

One source of evidence on car own-elasticities is the meta-analysis of price elasticities reported by Wardman (2014). The meta-model produced the long run car fuel price elasticities set out in Table 13.

Table 13. Car Fuel Price Elasticities Implied by Wardman (2014) Meta-Model

PURPOSE	URBAN TRIPS	INTER-URBAN TRIPS	KM
Commute	-0.21	-0.36	
Business	-0.12	-0.21	
Other	-0.23	-0.41	
All			-0.37

Another recent review (RAND Europe, 2014) of car fuel price elasticities concluded that: "*the fuel cost (price) elasticity falls within a fairly narrow range of -0.1 to -0.5, but some trips may be more elastic, depending on distance and trip purpose*". Whilst no specific recommendations were made, the range covers the figures in Table 13.

The other source of evidence we here use is Department for Transport (2017b) official webTAG guidance which sets out that the aggregate car fuel cost elasticity should lie within the range -0.25 to

-0.35 with figures of -0.1 for business, -0.3 for commuting trips and -0.4 for other trips. Note that these relate to passenger kilometres rather than trips, and hence will be larger, but the differences ought not to be a cause for serious concern as is apparent from the overall passenger kilometre elasticity relative to the trip elasticities reported in Table 13.

8.2 Demand Measures

We obtained demand evidence from the NTS for the years 2010 to 2016. For long Distance flows to and from London we split by trips up to and beyond 150 miles given that rail market shares can be expected to increase with distance and distinguished between Central London and Greater London. We distinguished long distance Non-London flows into 20 to 100 miles and over 100 miles trips. Given the NTS covers movements where there is effectively no viable train service, and hence rail shares will be very low, we have calculated the market shares for flows between origins and destinations that NTS specifies to be in urban areas.

There will be many short distance trips within NTS where the option of using train is not practical. We have calculated the market shares for trips within metropolitan districts, where the main rail networks exist, and for trips over 5 miles. For commuting trips between 25 and 50 miles, they are within or between metropolitan areas. For the London Travelcard Area flows less than five miles have been removed whilst for longer distance trips within the South East we have distinguished Central London and a combined Central and Inner London.

8.3 Diversion Factor Evidence

The RAND Europe and SYSTRA (2018) study provides the most extensive review of diversion factors yet undertaken, covering 1009 diversion factors from 45 studies. The study recommends the following diversion factors from car to rail:

- 0.12 for urban trips
- 0.65 for inter-urban trips

Whilst the study does report some variations by journey purpose, the evidence is not conclusive. We therefore distinguish only by distance band, acknowledging that these will be an average across values that vary with, amongst other things, journey purpose and the relative attractiveness of car and rail travel.

8.4 Occupancy

The car demand elasticity relates to the vehicle and not the number of individuals, and the diversion factors also relate to what a driver would do whilst the demand measures for car represent drivers. We therefore need to allow for car occupancy.

The average car occupancies per trip are 1.18 for commuting, 1.20 for business, and 1.73 for other (Department for Transport, 2017a). Given that the figures for commuting and business are low and not all occupants would switch, along with some of the other approximations involved in the calculations here, we feel that there is little to be gained here by complicating matters and adjusting the deduced business and commuting elasticities by occupancy. In contrast, average occupancy for other trips is high and cannot be ignored, even though not all occupants would necessarily switch, and hence we also provide upper bound deduced cross-elasticities assuming that all other occupants would switch.

8.5 Deduced Cross Elasticities

The deduced cross-elasticities are reported in Table 14 for a wide range of flow types and distances. Rail% denotes the share of rail amongst rail and car and V_C/V_R is the ratio of car and rail demand used in equation 1. We use both sets of purpose specific car cost own-elasticity evidence discussed above, which yield the cross-elasticities denoted DfT Cross and Meta Cross. The average of the two is denoted Mean Fuel and this is then used to derive the parking cost cross-elasticities, denoted Park

Cost, using the Ratio variable of Table 8. Cross-elasticities in brackets are the upper bound estimates for other trips assuming all other occupants switch. We first discuss the deduced fuel price cross-elasticities.

The fuel price cross-elasticities for long distance trips to Central London are, unsurprisingly, very low. The traffic congestion in Greater London, lack of parking spaces and the congestion charge, along with the generally long distances involved and rail services being far better on London routes means that car is an unattractive option for such trips and Rail% (V_C/V_R) is large (low). It is only when we extend coverage to Greater London and then for other trips that the cross-elasticity is non-trivial and even then it remains low.

Non London long distance flows are somewhat different. Whilst the distance element might favour rail, the other features making for a strong rail position on London flows are here missing and Rail% is much lower with some very large V_C/V_R. The cross-elasticities are larger, with some very large, although as might be expected they diminish with distance. We should though point out that we might here expect the diversion factor of 0.65 to be on the large side for such flows, particularly for journeys less than 100 miles, where we might expect not making the trip at all to be an attractive proposition for car drivers and rail to be unattractive or indeed unavailable for some.

The deduced cross-elasticities for the London Travelcard Area are all low, reflecting rail's strong position. Regardless of whether the London employment market is defined to be Central or Central and Inner London, rail's dominance is here so great that the cross-elasticities are effectively zero. The same essentially applies to business trips and largely to other trips from the South East to London.

For Non London short distance trips, the cross-elasticities are low for commuting and business trips although somewhat larger for other trips and particularly when the full occupancy effect is entered for other trips. These would though be expected to vary across specific corridors as rail's attractiveness and V_C/V_R varies.

Turning to the deduced parking cost cross-elasticities, these are almost always low for business travel and commuting; the proportions not paying to park reduce what are already generally low fuel price cross-elasticities. However, the deduced parking cost cross-elasticity can be large for other trips, especially where rail is in a weak competitive position.

Table 14. Deduced Fuel and Parking Cost Cross-Elasticities

FLOW TYPE		PURPOSE	RAIL%	V_C/V_R	DFT CROSS	META CROSS	MEAN FUEL	PARK COST
Long distance to/from London (<150miles)	Central London	Business	0.82	0.21	0.01	0.03	0.02	0.002
	Central London	Other	0.81	0.24	0.06	0.06	0.06 (0.11)	0.047 (0.081)
Long distance to/from London (>150 miles)	Central London	Business	0.85	0.18	0.01	0.02	0.02	0.001
	Central London	Other	0.90	0.11	0.03	0.03	0.03 (0.05)	0.022 (0.037)
Long distance to/from London overall	Central London	Business	0.83	0.21	0.01	0.03	0.02	0.002
	Greater London	Business	0.64	0.56	0.04	0.08	0.06	0.005
	Central London	Other	0.83	0.20	0.05	0.05	0.05 (0.09)	0.040 (0.069)
	Greater London	Other	0.51	0.95	0.25	0.25	0.25 (0.42)	0.190 (0.322)
Non London long < 100 miles		Business	0.09	9.97	0.65	1.36	1.00	0.080
		Other	0.29	2.44	0.63	0.65	0.64 (1.09)	0.488 (0.830)
Non London long > 100 miles		Business	0.21	3.79	0.25	0.52	0.38	0.031
		Other	0.42	1.37	0.36	0.36	0.36 (0.61)	0.273 (0.465)
Overall Non London		Business	0.11	7.75	0.50	1.06	0.78	0.063
		Other	0.30	2.30	0.60	0.61	0.60 (1.03)	0.459 (0.781)

London Travel Card Area		Commute	0.52	0.92	0.03	0.02	0.03	0.009
		Business	0.38	1.63	0.02	0.02	0.02	0.010
		Other	0.28	2.62	0.13	0.07	0.10 (0.17)	0.033 (0.055)
South East to London	Central London	Commute	0.96	0.04	0.01	0.01	0.01	0.017
	Central & Inner London	Commute	0.86	0.16	0.03	0.04	0.04	0.062
South East to/from London	Central London	Business	0.78	0.28	0.02	0.04	0.03	0.002
	Central & Inner London	Business	0.65	0.53	0.03	0.07	0.05	0.004
	Central London	Other	0.86	0.16	0.04	0.04	0.04 (0.07)	0.033 (0.056)
	Central & Inner London	Other	0.68	0.47	0.12	0.12	0.12 (0.21)	0.093 (0.159)
Non London <20 miles	Within Urban Areas	Commute	0.18	4.66	0.17	0.12	0.14	0.046
		Business	0.10	9.00	0.11	0.13	0.12	0.057
		Other	0.09	9.99	0.48	0.28	0.38 (0.64)	0.125 (0.212)
Non London (21-50 miles)	Between Metropolitan Areas	Commute	0.14	5.97	0.22	0.15	0.18	0.058

9. SYNTHESIS AND DISCUSSION

A key feature of the cross-elasticities reported here is that they stem from a variety of sources. They are a mix of journey purpose and sometimes distance segmentations on the one hand and flow and ticket type segmentations on the other, and are estimated to different types of data. It is informative to compare the cross-elasticities obtained from the various means and also to evaluate official recommendations in the light of this evidence, bearing in mind that cross-elasticities are inherently variable parameters.

In terms of the segmentations by trip characteristics and data type, there is evidence that the directly estimated and review based cross-elasticities are lowest for business travel, followed by commuting and other trips. Nonetheless, the deduced cross-elasticities demonstrate that differences in market share have a strong bearing. In terms of the flow and ticket type segmentations, London flows tend to have lower cross-elasticities than Non London flows and cross-elasticities are larger for inter-urban than urban trips, although with a tendency to fall within the former category. Whilst season tickets would be expected to have lower cross-elasticities than Non-Seasons, our directly estimated evidence does not support this although these season ticket cross-elasticities do seem to be far too large. In general, there is some support for the directly estimated and review based elasticities varying in the expected manner with the competitive position and market shares.

Inspecting the evidence in its entirety, we have to place everything on a flow basis given that we can aggregate from purpose to flow type but we cannot disaggregate from flow type to purpose. Table 15 places all our cross-elasticity estimates on a consistent basis of flow type, converting purpose based cross-elasticities to flow specific cross-elasticities according to the average proportions of commuting, business and other travel on each flow type (Leigh Fisher et al., 2016). We also summarise the evidence in the scattergram of Figure 1 which usefully indicates the degree of clustering of the cross-elasticities. Note that in the latter, we use the online stated intention cross-elasticities based on an assumed 25% fuel price reduction, we take 0.05 to represent the <0.10 figures and the overall deduced cross-elasticities are those where all other occupants are assumed to switch. Where cross-elasticities are the same or very similar, we place them alongside each other on the graph.

The resulting cross-elasticities in Table 15 and Figure 1 provide a number of important insights.

- Whilst accepting that cross-elasticities are inherently variable, as is evidenced by the variations across flows and purposes in our evidence, there is a noticeable degree of similarity in the mean values across various methods as reported in the final column of Table 15. Figure 1 demonstrates clearly that the cross-elasticity estimates tend to be clustered in a relatively narrow range and noticeably less than PDFH recommendations. Such similarity can be regarded to be encouraging.
- Generally, the cross-elasticities of rail demand with respect to car fuel costs are relatively low. This is in line with motorists' survey based reporting of their consideration of fuel costs and indeed their awareness of fuel cost changes.
- With the exception of the cross-elasticities for season ticket flows, which are far too high given rail's strong position in these markets, the econometric analysis of tickets sales provides elasticities that seem plausible in absolute and across flow types. Ignoring the

implausibly large estimates for seasons, the mean falls to 0.30. Whilst it should be borne in mind that these cross-elasticity estimates might not represent full long run effects, our view is that the latter are unlikely to be materially larger.

- The analysis of NTS data tended to provide cross-elasticities where significant that were out-of-line with the other evidence. It is the low and insignificant estimates that bring the NTS figures in Table 15 more into line with the estimates of other methods than they would otherwise be. We accept that this method is more suited to explaining how rail trip rates vary with a range of socio-economic and trip characteristics than to variations in the times and costs of different modes. Nonetheless, we have also argued that this method will tend to produce larger cross-elasticities than ticket sales on market share grounds whilst the variations in the cross-elasticities appear sensible.
- The Stated Intention based estimates seem to be on the large side, which is clear from Figure 1, whilst in contrast the Actual Behavioural responses tend to be on the low side. The former might be impacted by strategic bias whereas the accuracy of recall of past behaviour might have a bearing on the latter. Both, but especially the latter, are unable to provide much by way of elasticity variations across routes.
- There is some support for the international review evidence providing larger cross-elasticities than the U.K. review evidence. Whilst this might be because the former contains some SP evidence, we should point out that the NPDFF recommendations were based entirely upon SP findings yet these are relatively low.
- The deduced elasticities are, as would be expected, much more variable than the other estimates.

Turning specifically to the PDFH recommendations, Figure 1 illustrates that they generally appear to be too large and lack the variation that might be expected across flow types that is apparent in our econometrically estimated and deduced cross-elasticities. Indeed, the NPDFF cross-elasticities, which formed the basis of the recommendations of previous versions of PDFH, would seem more appropriate than current recommendations.

Our preference is for deducing cross-elasticities using equation 1 given its flexibility. Although other methods can provide variations across flows and to some extent journey purposes, they tend to be less marked than for the deduced method as can be seen in Figure 1. For example, where rail is in a very strong competitive position, it is only the deduced method that consistently provides low cross-elasticities yet it can also provide amongst the largest cross-elasticities where rail is in a weak competitive position. Nonetheless, broad support for the deduced cross-elasticities from the evidence of other methods would clearly be desirable.

Over and above the general degree of support provided by comparison of the mean cross-elasticities in Table 15, the two sets of econometric estimates provide an encouraging degree of support to the deduced cross-elasticities. If we discount the two season ticket flows where the ticket sales analysis has produced cross-elasticities which in our view are far too high given rail's strong position in these markets and are indeed amongst the largest across methods for those flows, then the mean absolute difference between the deduced and ticket sales cross-elasticities is 0.07 where there is no occupancy effect in the former and 0.20 where there is a full occupancy effect. In both cases, the degree of correlation is 0.96! The corresponding figures for the NTS based cross-elasticities are 0.27 and 0.15 for the mean differences and 0.91 for the correlations.

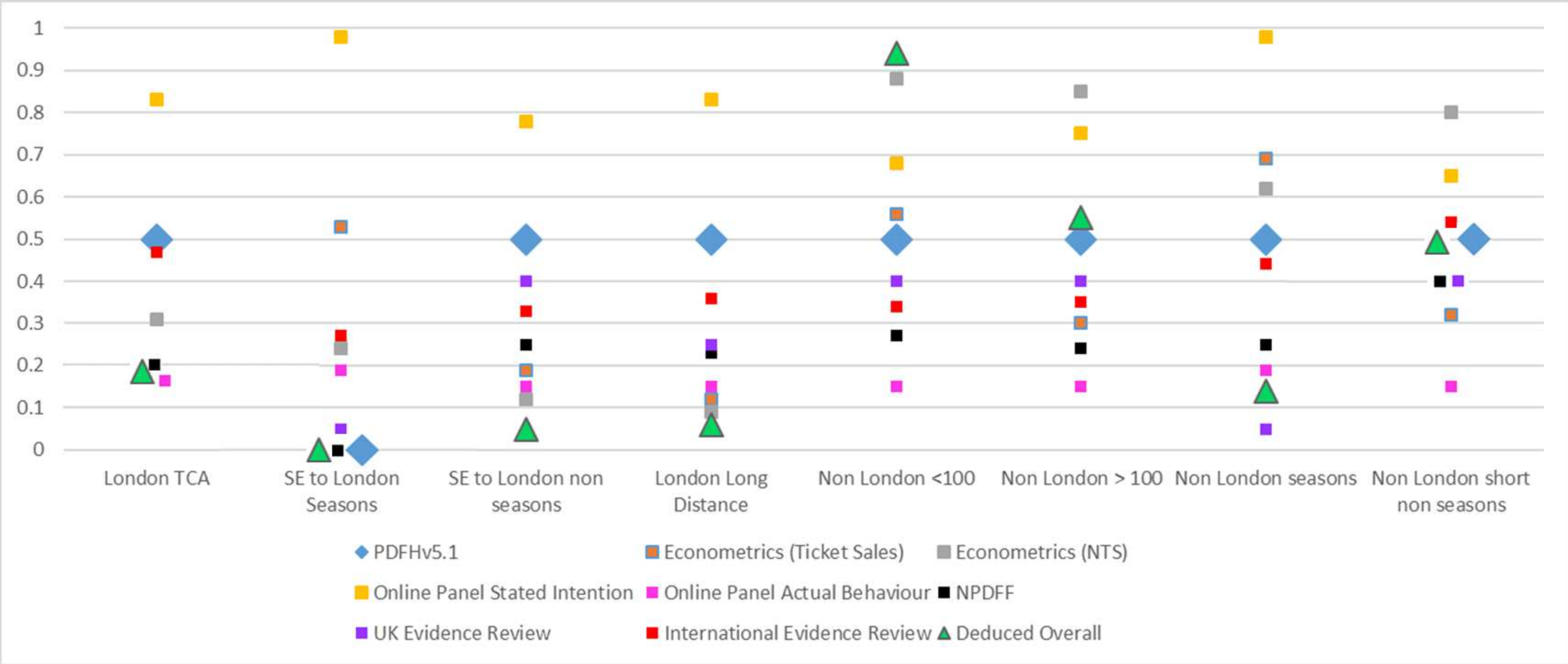
Whilst our econometric models contain time trend terms, there remains the possibility that correlations between increased fuel costs and increased car journey times means that the fuel cost cross-elasticities are to an extent inflated because they are discerning more than just the fuel variation. Offsetting this though is that the deduced cross-elasticities are explicitly long run whereas the econometric estimates here will not represent full long run effects.

Table 15. Summary Fuel Price Cross Elasticities

	LONDON TCA	SE TO LONDON SEASONS	SE TO LONDON NON SEASONS	LONDON LONG	NON LONDON < 100	NON LONDON > 100	NON LONDON SEASONS	NON LONDON SHORT NON SEASONS	MEAN
PDFHv5.1[2]	0.50	0.0	0.50	0.50	0.50	0.50	0.50	0.50	0.44
Econometrics (Ticket Sales)	-[A]	0.53	0.19	0.12	0.56	0.30	0.69	0.32	0.39
Econometrics (NTS)[B]	0.31	0.24[C]	0.12	0.09	0.88	0.85	0.62	0.80[D]	0.49
Online Panel Stated Intention[B,E]	0.35-0.83	0.41-0.98	0.32-0.78	0.35-0.83	0.28-0.68	0.31-0.75	0.41-0.98	0.27-0.65	0.34-0.81
Online Panel Actual Behaviour[F]	0.17	0.19	0.15	0.15	0.15	0.15	0.19	0.15	0.16
NPDFF[G]	0.20	0.0	0.25	0.23	0.27	0.24	0.25	0.40	0.23
UK Evidence Review	-[A]	< 0.10	0.40	0.25	0.40	0.40	<0.10	0.40	0.28
International Evidence Review[B]	0.47	0.27	0.33	0.36	0.34	0.35	0.44	0.54	0.39
Deduced Commute Deduced Other Deduce Business	0.03 0.10 (0.17) 0.02	0.01	0.01 0.04 (0.07) 0.03	0.01 0.05 (0.09) 0.02	0.18 0.64 (1.09) 1.00	 0.36 (0.61) 0.38	0.14	0.14 0.38 (0.64) 0.12	
Deduced Overall[B]	0.05 (0.18)	0.01	0.03 (0.05)	0.04 (0.06)	0.62 (0.94)	0.37 (0.55)	0.14	0.32 (0.49)	0.20 (0.30)

Notes: Figures in brackets are for other trips where all other occupants are assumed to switch. [A] Not covered. [B] The estimated values were split by journey purpose. The journey purpose splits by flow type reported by Leigh Fisher et al. (2016) have been used to calculate these flow type cross-elasticities. [C] Not significant. Other non-significant NTS cross-elasticities are used in some flows here. [D] The business short distance cross-elasticity for Non-London was wrong sign so the London cross-elasticity was used instead. [E] The two cross-elasticities reported in Table 9 provide the range here. [F] For other trips, the cross-elasticity of 0.13 for other reported in section 6.4 is used. For commuting and business, we use the 0.19 figure reported in section 6.4. [G] Mix of flow type and purpose cross-elasticities and [B] applies where purpose related.

Figure 1: Scattergram of Cross-Elasticity Values



10. CONCLUSIONS

The research reported here was specifically concerned with addressing how variations in motoring costs impact on rail demand. This was motivated by considerable uncertainty in Great Britain surrounding such cross-elasticities due to the difficulties that sometimes face econometric estimation and the lack of robust up-to-date evidence. The inherent variability of cross-elasticities was also an important driver, coupled with what are expected to be significant reductions in car operating costs in future years. These issues are not unique to the railway industry in Great Britain, where the evidence base is comparatively strong and the Passenger Demand Forecasting Handbook (PDFH) provides a longstanding and what seems to be unique forecasting framework amongst railway and other official organisations worldwide. We point to the lack of notable review studies concerning cross-elasticities in general, let alone relating to motoring costs, compared to own-elasticity evidence. The research reported here therefore contributes more broadly to understanding in this area.

A unique feature of the research reported here is that it deliberately draws upon evidence obtained from a range of sources given that the estimation of cross-elasticities and their variation is challenging. These include: fresh survey evidence, obtained from interviews with motorists; econometric analysis of secondary data, relating to very large amounts of both rail ticket sales and National Travel Survey (NTS) records; reviews of existing evidence, covering both econometric analysis of rail demand in Great Britain and broader international studies; and deducing cross-elasticities using relationships of economic theory.

Survey based insights indicate that fuel cost is the most important motoring cost, although parking and tolls are important where they are incurred. Nonetheless, not all motorists consider fuel costs and many are not aware of the variations that have occurred in recent years. These all point to low cross-elasticities; if motoring costs are not having a large direct impact on motoring behaviour, they cannot be expected to be having a large impact on rail demand! And whilst we find parking costs to have a larger behavioural impact than equivalent fuel price increases, as expected, not everyone pays to park.

Different fuel cost measures yield very similar cross-elasticities, and our preference is for a measure that accounts for fuel efficiency improvements going forward. In line with the survey evidence, the econometric analysis did not support the inclusion of terms additional to fuel cost in the representation of motoring costs.

The evidence indicates that cross-elasticities of rail demand with respect to fuel costs are generally not large, and indeed can be very low where rail is in a strong position. However, several approaches demonstrate large cross-elasticities where rail is in a weak competitive position. In general, and recognising the inherent variability of cross-elasticities, we would conclude that there is an encouraging degree of similarity between the results obtained by different methods.

Our research findings challenge the current PDFH recommendations, both in terms of absolute values and the range of variation, and our preference is for the deduced method because it provides explicitly long-run cross-elasticities and it gives much greater flexibility than other methods in terms of its ability to provide context specific cross-elasticities. A contribution of this paper is in providing empirical support to the theoretical attractions of deducing cross-elasticities using equation 1.

We would recommend that forecasting practice moves towards a more disaggregate approach enabled by equation 1. We also recommend its use for parking, and have provided a set of parking charge cross-elasticities not hitherto covered by PDFH and the main U.K. literature. Indeed, it would be a straightforward matter to replace the car own-price elasticities in Table 14 with car own-time elasticities to obtain a set of deduced cross-elasticities of rail demand with respect to car journey time[19]. Whilst we consider that this would constitute an advance on current forecasting practice, and we have provided much new evidence, there are four of areas of further research we would recommend to provide a more robust and disaggregated basis to the use of equation 1 to deduce cross-elasticities.

Firstly, the diversion factor (δ_{CR}) from car to rail in equation 1 can be expected to vary with a range of factors. Here we felt able to distinguish only between 0.65 for inter-urban trips and 0.12 for urban trips even though evidence from a major review was available. We would expect δ_{CR} to depend upon, amongst other things, journey purpose, distance and, most importantly, the relative attractiveness of at least rail and car and perhaps other modes. Specific survey based research to provide this detail is warranted.

Secondly, the relative demand of car and rail (V_C/V_R) in equation 1 is another key factor. This can be expected to vary strongly according to journey length, journey purpose, car ownership levels and, of course, the relative attractiveness of car and rail. Whilst an advance here was to interrogate NTS data to provide more detail on relative shares, there is scope for quantitative analysis of NTS data to provide greater insight into how V_C/V_R varies with key influential factors.

Thirdly, car occupancy is an important issue for discretionary travel. Whilst average occupancy rates can be used, it would be beneficial to determine how these vary with, say, distance or flow type and to establish the extent to which other occupants have the same diversion factor as the driver.

Finally, it is always desirable to validate forecasts in reliable real-world behaviour. We would recommend that equation 1, ideally enhanced with these more detailed means of populating its parameters, is used to produce expected customised cross-elasticities for a wide range of rail routes and time periods. These expected cross-elasticities would then be entered as independent variables in ticket sales based models and scales estimated to them to determine the extent to which the expected cross-elasticities are consistent with actual demand responses.

[19] The research reported here was funded primarily to inform PDFH. However, its recommendations came too late to influence the most recent update (v6 June 2018) and instead they will be included within the evidence base to be evaluated for the next update.

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