SIGN, SIZE AND DISTANCE EFFECTS: WHAT IS THE EVIDENCE FROM AGGREGATE MODELS?

Mark Wardman, Institute for Transport Studies, University of Leeds. Email: m.r.wardman@its.leeds.ac.uk. Tel: (0)113-3435349

Joyce Dargay, Institute for Transport Studies, University of Leeds, Email: j.m.dargay@leeds.ac.uk. Tel: (0)113-3431795

ABSTRACT

The disaggregate choice modelling literature contains extensive evidence that individuals making choices in the context of stated preference (SP) experiments exhibit a stronger response to increases than to reductions in the cost of travel and also, per unit of change, to larger than smaller changes. These are commonly termed size and sign effects.

As far as we are aware, there is very little corroboration in disaggregate revealed preference (RP) data of such patterns of behavioural response. This is unfortunate since we might postulate that the extent of any size or sign effect might well be influenced by the artificial nature of SP exercises. For example, respondents might be expected to register stronger protest responses towards deteriorations than exaggerated responses towards improvements on the grounds that it is easier and more urgent to influence a policy anticipating a cost increase than encourage one that might be considering a cost reduction. Similarly, respondents might wish to send a particular encouragement to large improvements and to protest disproportionately to large deteriorations. SP exercises which present the attributes as changes on the current situation could, through emphasising the change, induce size or sign effects when in fact none exist. Nonetheless, regardless of what we might hypothesise, it would be reassuring to have confirmation of the SP derived size and sign effects in actual behavioural response.

We here present what we believe is novel research that exploits aggregate data to examine whether, in real world settings, these effects exist in the context of rail fare elasticities.

Four weekly ticket sales data is used and various models in 'first difference' form are estimated to data sets involving hundreds of flows and numerous time periods. The fare elasticities estimated to these very large data sets for 'standard' models are generally very

plausible and highly precise, which thus provides a solid basis for more detailed investigation.

We find little support for sign or size effects which contrasts with the evidence from disaggregate models. However, rail travel is generally a rare event and the concept of a reference point may not then be sensible. Hence it is possible that sign and size effects do genuinely exist in SP responses but are not apparent to anything like the same extent in real world behaviour.

Key Words: Aggregate demand models, railways, size and sign effects, stated preference, revealed preference.

INTRODUCTION

There has over many years been a considerable amount of interest in whether travellers' behavioural responses to changes in the features and prices of transport services depend upon:

- whether the change is an improvement or deterioration on some reference point, typically the current situation;
- the magnitude of the change on the reference point
- the actual context in which the change is experienced.

The empirical research has focussed on individuals' responses to stimuli presented in Stated Preference (SP) experiments. It is a relatively straightforward matter to design such experiments to offer both gains and losses on the currently experienced situation and to vary the size this change whilst, through appropriate sampling, the can be readily applied to a wide range of different actual travel contexts.

The extent to which such disaggregate choice analysis, based at the level of the individual decision maker, could be conducted on actual choices depends upon the extent to which the market throws up the relevant changes. Even where such market conditions exist, the costs of purpose specific data collection to support robust estimation could well be prohibitive.

Given that the size and sign effects, and to an extent the distance related effects, detected in SP models could be an artefact of that method, such as small changes being ignored, protests against deteriorations and scale differences that confound with size, sign or distance, it is a pity that there is little RP based evidence of a disaggregate nature to provide useful corroboration of the findings from SP models.

There is, however, another source of RP data which has the potential to provide valuable insights in this area. Aggregate data represents collective behavioural response, being a record of the net outcome of individual behavioural responses in a particular context. This secondary data, typically comprising records of sales and revenue or counts of transport behaviour, and often collected for purposes other than modelling, has supported empirical investigation of a wide range of travel issues, and in particular the estimation of how the demand for travel responds to changes in its costs and availability and to variations in socio-economic factors. However, we contend that its analytical opportunities in this context of sign, size and duration effects have been very much neglected.

The research reported here exploits the contribution that can be made by the analysis of aggregate RP data, in the form of rail ticket sales data, to shed light on whether the demand for rail travel exhibits different response patterns according to the sign and size of price changes and the price levels to which these changes are applied. It is therefore original in analysing such issues in the context of actual, as opposed to stated, behavioural response.

This paper is structured as follows. Section 2 provides useful background by summarising briefly relevant research in this area. Section 3 outlines the rail ticket sales data and section 4 discusses the modelling approach. The models to investigate size, sign and distance effects are reported in section 5 and concluding remarks are provided in Table 5.

Keywords: keyword 1, keyword 2, keyword 3… (Use Keywords style to insert your keywords)

BACKGROUND

The aim here is not to provide a comprehensive account of the extensive literature relating to size, sign and distance effects, not only because it is so vast and because a review is not the purpose of this paper, but also because much of it lies outside the transport market. Instead, the intention is to provide an account of what we perceive the current evidence base to be in the transport market.

Sign, Size and Duration Effects and Evidence from Disaggregate Studies

Sign Effects

A sign effect denotes an asymmetry between the response to improvements and deteriorations. There have been numerous attempts to identify such effects in the transport literature and elsewhere (Steer Davies Gleave, 1982; Hague Consulting Group, 1988; Ampt et al., 1995; Dillen and Algers, 1999; Hague Consulting Group and Accent, 1999; Gunn, 2001; Arsenio, 2002; Horowitz and McConnell, 2002; Mackie et al., 2003; Wardman and Bristow, 2004; Fosgerau et al., 2006; Tapley et al., 2006; Hess et al., 2008). Although under-reporting of their absence is likely, the disaggregate literature clearly points to losses having a larger impact than an equivalent gain.

Sign effects are implied by diminishing marginal utility, whereupon losses will have higher unit values than gains, although these may well be little different for modest changes given an underlying utility function that is not strongly non-linear. The concept of loss aversion was apparent in the early developments of economic theory. Smith (1790) states *"We suffer more…when we fall from a better to a worse situation, than we ever enjoy when we rise from a worse to a better."*

The reference dependent preference theory of Tversky and Kahneman (1991) contains loss aversion which is generally regarded as intuitive by psychologists. Kahneman (2002) states that *"The carriers of utility are likely to be gains and losses rather than states of wealth, and this suggestion is amply supported by the evidence of both experimental and observational studies of choice.*"

If individuals possess non-compensatory choice rules, gains and losses could be valued differently, for example, because journey time is required to achieve a specific standard. The differential could also result from bias in response to SP questions; if gains and losses are not perceived to be equally likely, there is an incentive to bias responses relating to the more likely occurring event.

Size Effects

The response to a change in an attribute might vary with the size of its variation. Studies have tested for such effects in transport and elsewhere (Hague Consulting Group 1988; Ramjerdi et al., 1997; Hague Consulting Group and Accent, 1999; Gunn, 2001; Hultkrantz and Mortazavi, 2001; Arsenio, 2002; Mackie et al., 2003; Fosgerau et al., 2006; Tapley, 2008) and, although we might again suspect under-reporting of their absence, the consensus is that larger changes have a larger unit effect.

Size effects are consistent with diminishing marginal utility, whereby larger gains (losses) will have lower (higher) unit values, although the utility function might have to be strongly non-linear. Tversky and Kahneman's reference dependence theory posits that the unit values of both losses and gains will decrease as their levels increase, assuming that the sensitivity to a difference is smaller when the reference point is more remote.

There are, however, other reasons for size effects such as: a preference for the status quo due to psychological commitment, habit and thinking/transaction costs (Samuelson and Zeckhauser, 1988); and endowment effects, protest responses, mistrust of implementation and response simplifying procedures (Adamowicz et al., 1998). Size effects might stem from the artificial nature of SP exercises since changes which are unrealistically large could be discounted and small variations ignored whilst the concept of 'just-noticeable difference' between options (Tversky, 1969) may reflect behaviour more generally.

Duration Effects

How travellers respond to variation in cost, or indeed any other variable, as journey distance increases is essentially an empirical matter. With regard to cost, it could be argued that as cost increases, and given the implied income effect, there will be greater sensitivity to cost. On the other hand, arguments of 'proportionality' would imply a lesser sensitivity to a given cost variation for longer distances.

Research in this area and relating to cost sensitivity is usefully summarised by Daly (2008). He concludes that, "Cost damping has been found to give an improved explanation of behaviour in both large-scale forecasting studies and value-of-time studies". Other studies (Wardman et al., 1997; Gunn, 2001; Axhausen et al., 2008; Hess et al., 2009) also draw this conclusion.

Evidence from Aggregate Models

On sign effects, Dargay and Gately (1997) report analysis of asymmetries in how the demand for transport fuel responds to increases and reductions in price. This involved specifying separate series of cumulating price increases and price reductions in time series based models. The same method was used to examine differential car ownership income elasticities (Dargay, 2001) and asymmetries in rail fare, generalised journey time and delay elasticities (Jevons et al., 2005).

We are not aware of aggregate studies that have explicitly tested for size effects, although some forms of demand function imply such an effect but possibly confounded with other effects (Wardman, 1997).

There is literature on distance effects, although in contrast to the disaggregate work the emphasis is on elasticities rather than the 'marginal utilities' of choice models (Fowkes et al., 1985; Wardman, 1994; AEAT, 1999; Wardman and Whelan, 2004).

THE DATA SETS

The railway industry in Great Britain has available large amounts of ticket sales data which provides a reasonably accurate account of rail travel demand between a very large number of stations with varying degrees of historic availability depending upon, amongst other things, the level of detail required.

This data has for many years supported analysis of a wide range of factors that influence rail demand, including economic activity and external factors, fares, timetable related service quality, accessibility to the rail network, reliability and rolling stock. Much evidence is contained in the Passenger Demand Forecasting Handbook (PDFH) which not only contains the forecasting framework and demand parameters widely used in the railways industry in Great Britain but also serves as a repository for much rail research (ATOC, 2005).

Rail ticket sales are recorded on an ongoing four-weekly basis, although historic data are often available over a longer period but at the expense of being at a more aggregate level which is typically annual. We here use four weekly data since annual data could include multiple changes and indeed both gains and losses.

Service Quality Data Set

This data set was initially assembled specifically for the purpose of examining the influence of changes in the timetable related service quality attributes of journey time, headway and interchange (Wardman and Whelan, 2004). The four weekly data covers the financial years 1995/6 through to 2000/1 for 814 flows.

Scottish Flows

This data set was assembled as part of research into fares regulation for Transport Scotland (Wardman et al., 2006). It covers the four weekly periods from financial year 1994/5 through to 2004/5 period 5 for 128 flows.

THE MODELLING APPROACH

Suppose we have a rail demand function that specifies the volume of demand (V) between origin station i and destination station j in any time period t as:

$$V_{ijt} = \kappa e^{\sum_{i=1}^{K}\sum_{j=1}^{L}\mu_{ij}} F_{ijt}^{\alpha} GJT_{ijt}^{\beta} GVA_{it}^{\gamma} EMP_{jt}^{\delta} e^{\sum_{p=2}^{13}\tau_p P_p} \quad (1)$$

The μ_{ij} terms in this fixed effects pooled cross-sectional time-series model represent the basic size of each flow, around which demand varies according to the levels of the other variables. The two principal rail variables that drive demand are fare (F) and generalised journey time (GJT) which is a composite term containing the timetable related service quality variables of journey time, service frequency and interchange. We here simply represent the generating potential of the origin in terms of income level, as represented by gross valued added (GVA), and the attracting potential of the destination in terms of employment levels

(EMP). The terms enter in constant elasticity form. Given the data is four weekly, period effects are discerned by the specification of 12 period specific dummy variables (P_p)

This representation is standard practice in the railway industry in Great Britain for both estimation and forecasting (ATOC, 2005), although additional terms, such as representing competition from other modes, can be added when necessary.

Given that we are here concerned with changes in demand, and in particular whether they are positive or negative and their magnitude, we specify the model as a period-on-period change. The resulting model takes the form:

$$\frac{V_{ijt}}{V_{ijt-1}} = \left(\frac{F_{ijt}}{F_{ijt-1}}\right)^{\alpha} \left(\frac{GJT_{ijt}}{GJT_{ijt-1}}\right)^{\beta} \left(\frac{GVA_{it}}{GVA_{it-1}}\right)^{\gamma} \left(\frac{EMP_{jt}}{EMP_{jt-1}}\right)^{\delta} e^{\sum_{p=2}^{13}\tau_p \Delta P_p} \qquad (2)$$

where ΔP denotes successive difference in the period dummies. It is assumed that the fixed effects cancel out when taking ratios; that is, there is no variation in the volume of demand period-on-period other than that attributable to the included independent variables and the period dummies.

The parameters of this function can be estimated by ordinary least squares of a logarithmic transformation:

$$In\left(\frac{V_{ijt}}{V_{ijt-1}}\right) = \alpha In\frac{F_{ijt}}{F_{ijt-1}} + \beta In\frac{GJT_{ijt}}{GJT_{ijt-1}} + \gamma In\frac{GVA_{it}}{GVA_{it-1}} + \delta In\frac{EMP_{jt}}{EMP_{jt-1}} + \sum_{p=2}^{13}\tau_p \Delta P_p \qquad (3)$$

The fare elasticity is simply α. However, we can generalise the model to examine size, sign and duration effects. A fairly general specification would take the form:

$$In\left(\frac{V_{ijt}}{V_{ijt-1}}\right) = \alpha In\frac{F_{ijt}}{F_{ijt-1}} + \sum_{m=1}^{M}\lambda_m d_m In\frac{F_{ijt}}{F_{ijt-1}} + \ldots\ldots\ldots \qquad (4)$$

The dm are dummy variables denoting M different categories of interest, such as:

Different categories of proportionate or absolute fare increases
Different categories of proportionate or absolute fare reductions
Different categories of absolute fare, distance or fare per mile

The attraction of such an approach is that it does not impose any particular functional form on the sign, size or duration effects but rather indicates whether any relationship is apparent and the likely form of that relationship. More parsimonious and transferable functions can subsequently be estimated. Such a function might be:

$$In\left(\frac{V_{ijt}}{V_{ijt-1}}\right) = \alpha In\frac{F_{ijt}}{F_{ijt-1}} + \beta_1 d_I \ln\frac{F_{ijt}}{F_{ijt-1}} + \beta_2 d_I \ln\left(\frac{F_{ijt}}{F_{ijt-1}}\right)^2 + \beta_3 d_R \ln\left(\frac{F_{ijt}}{F_{ijt-1}}\right)^2$$
$$+ \beta_4 M_{ij} \ln\frac{F_{ijt}}{F_{ijt-1}} + \beta_5 \frac{F_{ijt-1}}{M_{ij}} \ln\frac{F_{ijt}}{F_{ijt-1}} \quad (5)$$

The dummy variables d_I and d_R denote an increase or reduction in fare and M_{ij} indicates the mileage between stations i and j. Thus the fare elasticity (η) for an increase in price would be:

$$\eta = \alpha + \beta_1 + 2\beta_2 \ln\frac{F_{ijt}}{F_{ijt-1}} + \beta_4 M_{ij} + \beta_5 \frac{F_{ijt}}{M_{ij}} \quad (6)$$

If we are to estimate models in such ratio form, there are advantage for choosing a common base year against which all other periods are compared since this can lead to more variation in the independent variables, and hence more precise estimates, that if successive periods form the basis of the ratios.

However, the aim here is to examine whether changes have a different effect according to whether they are increases or reductions and according to the size of the change. In assessing whether there are any size or sign effects apparent, it would seem sensible to make the reference point the most recent period rather than some more distant and possibly forgotten reference point. Indeed, if we were to specify larger differences, such as annual, the time period could include multiple changes and indeed both gains and losses.

THE RESEARCH FINDINGS

Up to five models have been estimated for each set of flows:

- Model I: Standard model with a single fare elasticity
- Model II: Fare elasticities segmented into proportionate increase bands, proportionate decrease bands and by distance band (eq$^{\underline{n}}$ 4)
- Model III: Fare elasticities segmented into increases, decreases and by fare per mile band (eq$^{\underline{n}}$ 4)
- Model IV: Continuous functions allowing for sign ,size and distance effects (eq$^{\underline{n}}$ 5)
- Model V: Continuous functions allowing for sign, size and fare per mile effects (eq$^{\underline{n}}$ 5)

In all cases, we removed those observations where the standardised residual exceeded 2, thereby reducing the sample size by 5%.

We have distinguished between season ticket sales and non season ticket sales, journey length and whether the flows are London based or not. Season tickets represent largely commuting trips whilst non-season tickets on longer distance flows are dominated by leisure travel on Non London flows and a mixture of leisure and business travel on London flows. Similarly, the shorter distance flows tend to have a mix of all three journey purposes and to experience stronger competition from other modes. We would therefore expect these markets to be fundamentally different and hence segmentation is sensible.

For the shorter distance flows, defined to be up to 30 miles, no distance segmentation is specified and hence Models II and III and Models IV and V become equivalent.

Given that we do not have GVA data by four weekly period to explain variations in non season ticket sales, nor employment data at such a level of detail in order to explain season ticket demand, we have discerned the net effect of changes in external factors and the period effects by specifying dummy variables, fixed across flows, for n-1 of the n time periods.

We report only the fare related terms. The GJT term was never significant in any of the models reported. This is because with only two timetables per year (Summer and Winter) and even then often little or no variation between them, there was very little period-on-period variation in GJT and hence the estimation of a significant effect could not be expected.

The absence of other terms, such as relating to competition from other modes, ought not to material impact on the model. Changes in fuel prices, which tend to be common across routes, will be discerned by the time period specific dummies whilst car journey times vary little between periods. On the routes in question, there were few changes in competition from bus and air.

Service Quality Data Set

Table 1 reports the results for Non Season tickets for longer distance Non London flows. This is a large data set. Although the goodness of fit is low, the overall fare elasticity in Model I is plausible, broadly in line with expectations and estimated with a very high level of precision.

Table 1: Non Season Ticket Flows Non London Flows Over 30 Miles (42184 Observations)

	I	II	III	IV	V
Fare	-0.704 (74.0)	-1.015 (3.7)	-1.009 (3.7)	-0.772 (23.6)	-0.857 (22.8)
Fare Increase				-0.024 (0.5)	-0.037 (0.7)
Fare Increase				0.061 (1.0)	0.197 (1.3)
2%-5%		-0.063 (0.2)	0.003 (0.0)		
5%-7.5%		0.175 (0.6)	0.228 (0.8)		
7.5%-10%		0.035 (0.1)	0.089 (0.3)		
10%-15%		0.127 (0.5)	0.184 (0.7)		
15%+		0.186 (0.7)	0.284 (1.0)		
Fare Reduction				0.053 (0.8)	0.099 (1.6)
2%-5%		-0.029 (0.1)	-0.078 (0.3)		
5%-7.5%		-0.146 (0.5)	-0.169 (0.6)		
7.5%-10%		-0.010 (0.1)	-0.019 (0.1)		
10%-15%		0.052 (0.2)	0.047 (0.2)		
15%+		0.159 (0.6)	0.156 (0.6)		
Distance				0.00049(4.6)	
51-100 miles		0.110 (2.9)			
101-150 miles		0.184 (4.6)			
151-200 miles		0.233 (5.8)			
200+ miles		0.192 (5.0)			
Fare per Mile					0.013 (6.4)
8-10 p/mile			0.0462 (1.5)		
10-12 p/mile			0.0645 (2.0)		
12-15 p/mile			0.1974 (6.0)		
15+ p/mile			0.2357 (6.7)		
RSS	3019.15	3011.94	3009.95	3017.23	3015.82
$AdjR^2$	0.224	0.226	0.226	0.224	0.225

Models II and III contain incremental effects for increases and reductions of 2%-5%, 5%-7.5%, 7.5%-10%, 10%-15% and over 15%. Models IV and V report a coefficient for a dummy variable denoting whether the fare change was a fare increase in the second row. The remaining two terms relate to the square of the logarithm of the fare ratio, for increases and reductions, as denoted in equation 5.

Models II and III provide no support whatsoever for sign or size effects. There is, however, support for the fare elasticity falling with distance and, surprisingly, the elasticity increasing as fare per mile increases, with the latter providing a better fit of the two. There may be a causality issue present here; rail operators may price up where the market is deemed to be more inelastic.

Model IV and V similarly do not support any sign or size effect. The distance effect in Model IV is significant, although a 200 mile difference only reduces the fare elasticity by 0.1. Similarly, Model V would only imply a 0.13 variation in the fare elasticity for a 10 pence difference in the fare per mile.

Table 2 focuses on London flows, with a much smaller but still substantial data set. The goodness of fit is somewhat better and the fare elasticity in Model I is again very reasonable and precisely estimated.

Table 2: Non Season Ticket Flows London Flows Over 30 Miles (8909 Observations)

	I	II	III	IV	V
Fare	-0.687 (36.9)	-0.324 (1.7)	-0.547 (3.3)	-0.677 (9.8)	-0.982 (12.3)
Fare Increase				-0.077 (0.9)	-0.063 (0.7)
Fare Increase				0.196 (1.0)	0.370 (1.9)
2%-5%		-0.142 (0.8)	-0.141 (0.8)		
5%-7.5%		-0.189 (1.1)	-0.178 (1.0)		
7.5%-10%		-0.409 (2.3)	-0.369 (2.1)		
10%-15%		-0.426 (2.5)	-0.373 (2.2)		
15%+		-0.239 (1.5)	-0.151 (0.9)		
Fare Reduction				-0.056 (0.3)	-0.012 (0.1)
2%-5%		-0.231 (1.3)	-0.250 (1.4)		
5%-7.5%		-0.233 (1.3)	-0.239 (1.4)		
7.5%-10%		-0.202 (1.1)	-0.193 (1.1)		
10%-15%		-0.227 (1.3)	-0.211 (1.3)		
15%+		-0.272 (1.6)	-0.279 (1.7)		
Distance				0.00002(0.0)	
51-100 miles		-0.146 (1.1)			
101-150 miles		-0.069 (0.5)			
151-200 miles		-0.084 (0.6)			
200+ miles		-0.122 (0.8)			
Fare per Mile					0.021 (5.2)
10-12.5 p/mile			0.005 (0.0)		
12.5-15 p/mile			0.039 (0.7)		
15-20 p/mile			0.251 (4.3)		
20+ p/mile			0.266 (3.3)		
RSS	94.88	94.63	94.24	94.85	94.57
$AdjR^2$	0.511	0.512	0.514	0.512	0.513

Models II and III indicate that the fare elasticity is higher for any fare variation other than the base which reflects variations within +/-2%. However, the coefficients for reductions above 2% are remarkably similar whilst the increases could indicate a size effect. Model II does not indicate any distance effect but the better fitting Model III again suggests that the fare elasticity is lower where the fare per mile is higher.

Model IV does not detect any significant sign, size or distance effect. Model V does point to a sign effect, for increases in fare, but it is the not the effect that we would expect from Models II and III. The fare per mile effect is significant but not particularly strong.

The models for shorter distance flows up to 30 miles are presented in Table 3. Here no distance or fare per mile effect is reported since there is little variation. The fare elasticity in Model I is precisely estimated, if a little larger than expected for such flows. Model II does not discern any significant effects and there is no clear pattern in the incremental effects. Despite this, Model IV does have a significant effect on the size effect for reductions. It implies that the fare elasticity is 0.1 smaller for a 5% fare reduction and 0.21 for a 10% fare reduction.

Table 3: Non Season Ticket Flows Up to 30 Miles (6125 Observations)

	I	II	IV
Fare	-1.165 (33.7)	-1.125 (3.6)	-1.291 (12.8)
Fare Increase			0.088 (0.5)
Fare Increase			-0.050 (0.1)
2%-5%		0.253 (0.7)	
5%-7.5%		0.067 (0.2)	
7.5%-10%		-0.099 (0.3)	
10%-15%		-0.167 (0.5)	
15%+		-0.065 (0.2)	
Fare Reduction			-0.978 (2.5)
2%-5%		-0.312 (0.9)	
5%-7.5%		-0.163 (0.5)	
7.5%-10%		-0.121 (0.4)	
10%-15%		-0.068 (0.2)	
15%+		0.129 (0.4)	
RSS	167.70	167.32	167.45
$AdjR^2$	0.262	0.263	0.263

Finally for this data set, Table 4 reports the season ticket models for flows to London. The fare elasticity in Model I is higher than might be expected for commuting travel, but there is competition here with other tickets. Model II does not indicate any clear or statistically significant pattern in the increase and reduction coefficients.

Model IV does recover significant effects for the size terms. However, the effect would be relatively minor. For a 10% fare variation, the fare elasticity would be 0.1 smaller in the case of an increase and 0.06 smaller in the case of a reduction. It is also surprising that the fare elasticity becomes smaller for larger fare increases.

Table 4: Season Ticket Flows to London (6107 Observations)

	I	II	IV
Fare	-1.363 (35.6)	-3.658 (3.0)	-1.765 (19.2)
Fare Increase			-0.124 (0.8)
Fare Increase			0.504 (5.9)
2%-5%		-0.686 (0.5)	
5%-7.5%		0.467 (0.3)	
7.5%-10%		-0.203 (0.2)	
10%-15%		0.397 (0.3)	
15%+		2.427 (2.0)	
Fare Reduction			-0.298 (6.0)
2%-5%		-0.942 (0.7)	
5%-7.5%		-0.027 (0.0)	
7.5%-10%		0.185 (0.2)	
10%-15%		0.826 (0.7)	
15%+		2.420 (2.0)	
RSS	2133.76	2065.12	2106.36
$AdjR^2$	0.307	0.328	0.315

Scottish Flows

The results for non season Scottish flows over 30 miles are contained in Table 5. Model I recovers a fare elasticity which is very close to that recommended by PDFH for these types of flow.

Table 5: Non Season Ticket Flows Over 30 Miles (10570 observations)

	I	II	III	IV	V
Fare	-0.893 (43.2)	-0.834 (3.2)	-0.859 (3.3)	-1.009 (12.6)	-1.170 (9.7)
Fare Increase				-0.095 (0.9)	-0.094 (0.9)
Fare Increase				0.305 (1.6)	0.454 (2.3)
2%-5%		-0.128 (0.4)	-0.100 (0.3)		
5%-7.5%		-0.170 (0.6)	-0.145 (0.5)		
7.5%-10%		-0.302 (1.1)	-0.257 (0.9)		
10%-15%		-0.264 (1.0)	-0.227 (0.9)		
15%+		-0.051 (0.2)	-0.038 (0.2)		
Fare Reduction				-0.325 (1.4)	-0.238 (1.1)
2%-5%		-0.216 (0.8)	-0.205 (0.7)		
5%-7.5%		-0.234 (0.9)	-0.222 (0.8)		
7.5%-10%		-0.021 (0.1)	-0.032 (0.1)		
10%-15%		-0.089 (0.3)	-0.106 (0.4)		
15%+		0.006 (0.0)	-0.043 (0.2)		
Distance				0.00097(2.3)	
41-70 miles		-0.157 (2.3)			
71-100 miles		0.001 (0.1)			
101-150 miles		0.281 (3.8)			
151+ miles		0.041 (0.6)			
Fare per Mile					0.029 (2.6)
7-8.5 p/mile			0.0667 (1.2)		
8.5-10 p/mile			-0.0379 (0.6)		
10-12 p/mile			0.107 (1.6)		
12+ p/mile			0.464 (4.3)		
RSS	286.15	284.45	284.97	285.76	285.72
$AdjR^2$	0.333	0.336	0.335	0.334	0.334

Models II and III provide some indication that the fare elasticity is less for the base case of small variations but other than that there is no clear pattern. No clear distance effect is apparent in Model II although Model III indicates a fare per mile effect may be apparent.

Model IV does not detect significant sign and size effects but there is a significant distance effect. However, even a 100 mile difference in trip length would only reduce the fare elasticity by 0.1. Model IV does have a significant size effect for increases, but paradoxically leads to a lower fare elasticity for larger fare increases. The fare per mile variations on these flows is quite limited and the significant fare per mile effect would only imply a 0.15 variation in fare elasticity across almost all flows. Again there would seem to be a confounding effect from causality with pricing up on more inelastic routes.

Table 6 reports the results for the short distance non season Scottish flows. The fare elasticity is plausible and very precisely estimated in Model I. Model II seems to imply larger fare elasticities for variations other than the smallest, but there is no clear pattern. Model IV does contain significant size effects. That for increases again yields the counter-intuitive result that the fare elasticity falls as the fare increase becomes larger. The effect for reductions is just significant, and implies a relatively large effect. For example, the fare elasticity is 0.35 lower for a 10% fare reduction. This is a large effect, although the relative imprecision of the coefficient may well be a contributory factor here.

Table 6: Non Season Ticket Flows Up to 30 Miles (5549 observations)

	I	II	IV
Fare	-1.030 (30.3)	-0.751 (5.3)	-1.175 (10.7)
Fare Increase			-0.172 (1.0)
Fare Increase			2.661 (4.6)
2%-5%		-0.434 (2.6)	
5%-7.5%		-0.465 (2.8)	
7.5%-10%		-0.411 (2.3)	
10%-15%		-0.335 (1.9)	
15%+		0.075 (0.5)	
Fare Reduction			-1.651 (2.0)
2%-5%		-0.604 (3.7)	
5%-7.5%		-0.477 (2.8)	
7.5%-10%		-0.194 (1.0)	
10%-15%		0.097 (0.5)	
15%+		-0.126 (0.7)	
RSS	34.33	33.96	34.15
$AdjR^2$	0.535	0.539	0.537

Finally Table 7 reports the models for the Scottish season ticket flows. The fare elasticity is large, and this might reflect competition from period Travelcards in the Strathclyde region as well as some very strong competition from bus. Model II seems to indicate that the fare elasticity estimated to the base level of small fare variations is unreliable, but there is no indication of a sign or size effect. This is confirmed by the results in Model IV.

Table 7: Season Ticket Flows Up to 30 Miles (5549 observations)

	I	II	IV
Fare	-1.619 (23.2)	-2.465 (2.7)	-1.645 (7.7)
Fare Increase			-0.083 (0.2)
Fare Increase			0.119 (0.1)
2%-5%		-0.194 (0.2)	
5%-7.5%		0.731 (0.7)	
7.5%-10%		1.026 (1.0)	
10%-15%		0.897 (0.9)	
15%+		0.675 (0.7)	
Fare Reduction			-0.338 (0.6)
2%-5%		1.206 (1.1)	
5%-7.5%		1.442 (1.5)	
7.5%-10%		1.672 (1.7)	
10%-15%		1.166 (1.2)	
15%+		0.845 (0.9)	
RSS	200.00	198.95	199.89
$AdjR^2$	0.467	0.467	0.466

CONCLUDING REMARKS

As far as we are aware, this is the most extensive investigation of sign, size and duration effects using aggregate RP data. The data sets that have been analysed are large, yielding sensible and very precisely estimated fare elasticities in conventional model forms.

We find little compelling evidence to support size and sign effects across the numerous models developed. In the few instances where there are significant coefficient estimates, the implied elasticity variation is small or, in some cases, inconsistent with what we might expect. This is in contrast to the large body of disaggregate literature, based upon SP evidence, where sign and size effects are prominent.

As for a duration effect, this exists in two of the three cases where tested, implying the fare elasticity falls as distance increases. This has an element of consistency with the sensitivity to cost falling with distance in the disaggregate modelling evidence, although of course the latter is only one part of the elasticity relationship and the absolute cost level can influence the pattern in the cost elasticity. Nonetheless, the elasticity variation with distance is not particularly strong. We note, however, that this contrasts with the findings of an extensive meta-analysis of rail fare elasticity evidence (Wardman and Shires, 2003) where there was strong support for a modest increase in the fare elasticity with journey distance.

Surprisingly, the fare elasticity is seen to fall as the fare per mile increases. We have attributed this to rail operators charging higher fares in more inelastic markets. Further analysis of this issue is required.

We do not claim that these results provide conclusive evidence that there are no sign or size effects or that the distance effect is minor. This research has been largely exploratory and is, as we have stated, novel, but further work is warranted.

Firstly, the models are static and we might expect the full effect of a fare variation to take longer than four weeks to work through. In particular, we might expect reductions in fares to take longer to have their full effect than increases, and hence the absence of a dynamic effect could have affected the relationship between the fare increase and fare reduction effects here reported.

Secondly, more flexible functional forms could be examined. For example, an estimation technique such as non-linear least squares could be used to estimate functions that allow, for example, for a non-linear distance effect or a size effect that is dependent upon something other than the logarithm of the proportionate fare change. We might also examine the effects of fare changes expressed as differences rather than ratios.

Thirdly, except for season tickets, the demand measure covers more than one ticket and hence there can be switching between ticket types in response to fare changes. This will impact on the fare measure, specified as revenue per trip, such that fares can increase but revenue per trip can fall as travellers switch into cheaper tickets. Experimentation with price indices and the estimation of ticket specific models is warranted.

In addition to further analysis relating to fares elasticities, it would also be illuminating to test whether sign, size and distance effects were apparent for journey time and other aspects of service quality.

Finally, it could be argued that if sign, size and duration effects are apparent in models based on individuals' responses to SP based stimuli, then they must exist. And that if they cannot be detected in analysis of ticket sales data then that is a limitation of ticket sales data and aggregate analysis. We note, however, that with the exception of travel on season tickets, a rail journey between two specific places is generally a rare event. There is a considerable amount of 'churn' in the market. Hence the concept of a reference point might not be particularly meaningful. It then remains that individuals may indeed exhibit sign and size effects when confronted by a specific SP exercise but that this cannot translate into any real world equivalent effect.

REFERENCES

Adamowicz, W., Boxall, P., Williams, M. and Louviere, J. (1998) Stated Preference Approaches to Measuring Passive Use Values: Choice Experiments and Contingent Valuation. American Journal of Agricultural Economics 80 (1), pp.64-75.

AEAT (1999) Inter-Urban Fare Elasticities. Prepared for Association of Train Operating Companies, London.

Ampt, E.S., Swanson, J. and Pearmain, D. (1995) Stated Preference: Too much Deference? Perspectives 4.

Arsenio, E. (2002) The Valuation of Environmental Externalities: A Stated Preference Case Study on Traffic Noise in Lisbon. Phd Thesis, University of Leeds.

ATOC (2005) Passenger Demand Forecasting Handbook.

Axhausen, K.W., Hess, S., König, A., Abay, G., Bates, J.J. and Bierlaire, M. (2008) Income and Distance Elasticities of Values of Travel Time Savings: New Swiss Results. Transport Policy 15, pp.173-185.

Daly, A.J. (2008) The Relationship of Cost Sensitivity and Trip Length. Paper presented at AET European Transport Conference.

Dargay, J.M. (2001) The Effect of Income on Car Ownership: Evidence of Asymmetry. Transportation Research Part 35A, pp.807–21.

Dargay, J.M. and Gately, D. (1997) The Demand for Transportation Fuels: Imperfect Price-Reversibility?, Transportation Research B 31 (1), pp. 71-82.

Dillen, J.L and Algers, S. (1999) Further Research on the National Swedish Value of Time Study. 8th World Conference on Transport Research.

Fowkes, A.S., Nash C.A. and Whiteing, A.E. (1985) Understanding Trends in Inter-City Rail Traffic in Great Britain. Transportation Planning and Technology, pp. 65-80

Gunn, H.F. (2001) Spatial and Temporal Transferability of Relationships between Travel Demand, Trip Cost and Travel Time. Transportation Research 37E, 2-3, pp.163-189.

Hague Consulting Group and Accent (1999) The Value of Travel Time on UK Roads. The Hague.

Hess, S., Rose, J. and Hensher, D.A. (2008) Asymmetric Preference Formation in Willingness to Pay Estimates in Discrete Choice Models. Transportation Research E, 44, pp.847-863.

Hess, S., Erath, A. and Axhausen, K.W. (2009) Estimates of the Valuation of Travel Time Savings in Switzerland obtained from Pooled Data. Transportation Research Record, 2082, pp.43-55.

Horowitz, J. and McConnell, K. (2002) A review of WTA/WTP studies. Journal of Environmental Economics and Management, 44, pp. 426-447.

Hultkrantz, L. and Mortazavi, R. (2001) Anomalies in the value of travel-time changes. *Journal of Transport Economics and Policy*, 35(2), pp.285-300.

Jevons, D., Meaney, A., Robins, N., Dargay, J., Preston, J., Goodwin, P. and Wardman, M. (2005) How Do Rail Passengers Respond to Change? Paper presented at AET European Transport Conference

Mackie, P.J., Wardman, M., Fowkes, A.S., Whelan, G. and Bates, J. (2003) Values of Travel Time Savings in the UK. Prepared for the Department for Transport.

Ramjerdi, F., Rand, L. and Sælensminde, K. (1997) The Norwegian Value of Time Study: Some Preliminary Results. Institute of Transport Economics, Oslo, Norway.

Steer Davies Gleave (1982) Research into Elasticity of Demand in Respect of Service Frequency and Through Trains. Prepared for British Railways Board.

Tapley, N. (2008) Nonlinearities in Discrete Choice Attributes: A Study of Transport-Related Choices. PhD Thesis, Institute for Transport Studies, University of Leeds.

Tapley, N., Wardman, M. and Whelan, G. (2006) Nonlinearities in discrete choice attribute valuations. Paper presented to European Transport Conference.

Tversky, A. (1972) Choice by Elimination. Journal of Mathematical Psychology, 9, pp341-367.

Tversky A. and Kahneman D. (1991) Loss Aversion in Riskless Choice: A Reference Dependent Model. Quarterly Journal of Economics. 106(4), pp1039-1061

Wardman, M. (1994). Forecasting the Impact of Service Quality Changes on the Demand for Inter Urban Rail Travel. Journal of Transport Economics and Policy, 28(3), 287-306.

Wardman, M. (1997). Inter Urban Rail Demand, Elasticities and Competition in Great Britain: Evidence from Direct Demand Models. Transportation Research E, 33(1), pp.15-28.

Wardman, M. (2004) Public Transport Values of Time. Transport Policy 11, pp.363-377.

Wardman, M., Toner, J.P and Whelan, G.A. (1997) Interactions between Rail and Car in the Inter Urban Leisure Travel Market in Great Britain. Journal of Transport Economics and Policy, 31(2), 163-181.

Wardman, M. and Bristow, A.L. (2004) Traffic Related Noise and Air Quality Valuations: Evidence from SP Residential Choice Models. Transportation Research 9D (1) pp1-27

Wardman, M. and Whelan, G. (2004) Estimating the Effects of Service Quality Changes on the Demand for Rail Travel. Paper presented at European Transport Conference.

Wardman, M., Dargay, J.M., Toner, J.P. and Whelan, G.A. (2006) Fare Elasticity Evidence in Scotland: A Review. Prepared for Transport Scotland.