REVIEW OF FARES ELASTICITIES IN GREAT BRITAIN

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Abstract

A considerable amount of empirical evidence exists in Great Britain relating to the price elasticity of demand for public transport modes. Assembling this evidence and attempting to explain variations in fare elasticities across studies has a considerable number of attractions.

This study reports on meta-analysis of British evidence on fare elasticities. Although there have been many notable studies of fare elasticities, this study is unique in the amount of evidence that is reviewed, the range of issues that are considered, and in its estimation of a quantitative relationship between fare elasticity and a range of variables.

The research reported here is based on 902 public transport fare elasticities. These were collected from 105 studies conducted in Britain between 1951 and 2002. The study covers fare elasticities for inter-urban rail travel, suburban rail travel, urban bus travel and underground. A wide range of data has been collected to explain variations in fare elasticities across studies.

Keywords: Fare elasticities; Meta analysis; Review of British evidence
Topic Area: D6 Travel and Shipper Behaviour Research

1. Introduction

Empirical analysis of the behavioural impact of a wide range of travel variables has been conducted extensively in Britain over the past forty years or so. With the likely exception of the value of travel time (Wardman, 2001), the most widely estimated parameters have been price elasticities of demand and in particular public transport fare elasticities. The wealth of available evidence provides an excellent opportunity to obtain greater insights into fare elasticities and their determinants.

There have been numerous notable reviews of price elasticities (Bly, 1976; TRRL, 1980; Goodwin and Williams, 1985; Goodwin, 1992; Oum et al, 1992; Halcrow Fox et al., 1993; Wardman, 1997; Nijkamp et al., 1998; Pratt, 2000; De Jong and Gunn, 2001; Graham and Glaister, 2002; VTPI, 2003). The unique features of this study are that it covers a much larger amount of public transport evidence and a broader range of issues than previous reviews and, more significantly, it has developed a model to explain variations in fare elasticities across studies.

This review covers 902 public transport fare elasticities obtained from 104 studies conducted in Britain between 1951 and 2002. The markets covered are inter-urban rail travel, suburban rail travel, urban bus travel and London underground.

2. Purpose

Whilst assembling the wealth of empirical evidence and attempting to explain variations in fare elasticities across studies has its limitations, such as an inability to examine detailed issues such as how fare elasticities vary with the level of fare charged or

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socio-economic characteristics, and reliance on the use of proxy variables, it does have a number of significant attractions:

- As a result of drawing together a wealth of evidence on fare elasticities, conclusions can be drawn about the preferred elasticity values to be used in a range of different circumstances. This is particularly useful where it is not otherwise possible to obtain independent fare elasticity estimates. It is also generally preferable to base recommended values on the results of a number of studies rather than a few or a single one.
- Insights can be obtained into methodological issues, such as fare elasticity estimates varying according to the type of data upon which they are estimated.
- It is possible to draw conclusions that are often beyond the scope of a single study. For example, collecting together evidence from numerous studies is particularly useful in indicating how elasticities vary over time. Similarly, few studies estimate elasticities across a wide range of circumstances whereas pooling elasticities estimates allows more detailed analysis of cross-sectional variations according to, for example, area or distance and insights to be obtained into the relationship between ordinary and mode choice elasticities and between conditional and non-conditional elasticities.
- Results which would not otherwise be in the public domain, primarily due to commercial confidentiality, can be exploited because the means of analysis maintains their anonymity.
- The development of models to explain variations in elasticities is useful where there is conflicting evidence across studies and provides a means of appraising current recommendations and conventions and of interpreting the results of a single empirical study in the light of a large amount of previous evidence.
- Traditional reviews tend to focus on mean values rather than the variation. As such, there is always the risk that a comparison of means is distorted by confounding effects. For example, cross-sectional data is more common in older evidence and stated preference data is more common in recent years and this may give a misleading impression of elasticity variation over time.

3. Data assembly

The elasticities in the studies reviewed cover the period 1951 to 2002, although the publication dates of the studies range between 1968 and 2002. A full list of the studies covered is provided in the Wardman and Shires (2003).

The number of studies and fare elasticities broken down by time period are given in Table 1. As can be seen, there is a good temporal spread of data. We have only made use of elasticity figures which have been reported in studies; there has been no attempt to deduce elasticities from estimated parameters.

The number of elasticities and studies covering each mode are given in Table 2. Bus and inter-urban rail are particularly well represented, but even the smallest category of 42 for underground is significant by comparison with many review studies.

This study differs from previous reviews in its sourcing of elasticity values. Oum et al. (1992) concentrated on material published in academic journals. Goodwin (1992) widened the net to include reports produced by government agencies, transport operators or the research organisation responsible but which were “unambiguously in the public domain”. We have here made extensive use of consultancy reports and working papers which are not in the public domain but nonetheless conducted serious research and produced credible results. As is clear from Table 3, this allowed us to amass a much larger data set than would otherwise be possible.

Table 1: Studies and Elasticities by Time Period

Elasticity Time Period			**Publication Date**		
Years	**Studies**	**Elasticities**	**Years**	**Studies**	**Elasticities**
1951-1955	1	2	1968-1972	5	10
1956-1960	0	3	1973-1977	8	65
1961-1965	3	24	1978-1982	11	90
1966-1970	7	31	1983-1987	16	235
1971-1975	9	99	1988-1992	28	166
1976-1980	18	235	1993-1997	22	74
1981-1985	14	49	1998-2002	14	262
1986-1990	32	224			
1991-1995	15	194			
1996-2002	5	41			

Note: The time period relates to that for which the elasticity was estimated. In the case of time series data, the midpoint is used.

Table 2: Modal Coverage

Mode	**Studies**	**Values**
Bus	41	305
Underground	12	42
Suburban Rail	28	99
Inter Urban Rail	57	456

Table 3: Sources of Elasticity Evidence

Source	Studies	Elasticities
Journal/Book	12 (12%)	137 (15%)
Conference Paper	2 (2%)	54 (6%)
Review Study	4 (4%)	39 (4%)
Published Report	16 (15%)	200 (22%)
Unpublished Operator Commissioned Report	34 (33%)	309 (34%)
Unpublished Government Commissioned Report	4 (4%)	22 (2%)
Unpublished Academic Report	12 (12%)	57 (6%)
Unpublished 'In House' Report	20 (19%)	84 (10%)

Notes: A review study might be published as, say, a journal article, but material that is not the author's own and therefore where we have not accessed the primary material is here separately identified. Published reports include TRRL and LGORU reports and other publicly available documents such as University Working Papers and final reports published by operators or government agencies. Unpublished academic reports include PhD and Masters dissertations.

Separate elasticities were collected from a single study if they represented different modes, journey purposes, types of data, routes or areas, ticket types, distances, or market segments, or if they distinguished between short run and long run effects, mode choice and ordinary elasticity, and conditional and non-conditional elasticity.

Table 4 indicates the distribution of elasticities per study. The average number of elasticities per study is 8.6, with around a half of the studies providing 5 or fewer elasticities and 90% providing 15 or less. The principal reasons for a study containing a large number of elasticities are that separate models are estimated by area of flow type or a distinction is made between short run and long run elasticities (Owen and Phillips, 1987; Phillips, 1987; Dargay and Hanly, 1999).

Table 4: Number of Elasticities per Study

η	Studies	η	Studies	η	Studies
1	26	6	10	11-15	12
2	15	7	4	16-20	3
3	5	8	3	21-30	3
4	7	9	1	31-50	2
5	4	10	6	51+	3

A wide range of information was collected to explain variations in fare elasticities across studies. These included: the type of data to which the elasticity was estimated; whether the elasticity represented a short or long run effect; the level of aggregation; the year to which the elasticity relates; whether the elasticity was conditional or not; mode; journey purpose; ticket type; market segment; journey distance; concessionary travel or not; and whether the elasticity was ordinary or mode choice. The characteristics of the data set are described in detail in Wardman and Shires (2003).

4. Results

The main aim of this study is to explain variations in fare elasticities across a large number of British studies and regression analysis provides a means of achieving this. The regression model explaining fare elasticity variation as a function of variations in a range of explanatory variables could take several forms. The main two contenders are a multiplicative form or an additive form. The multiplicative model takes the form:

$$\eta = \tau \prod_{i=1}^{n} X_i^{\alpha_i} e^{\sum_{j=1}^{p} \sum_{k=1}^{q-1} \beta_{jk} Z_{jk}} \tag{1}$$

There are n continuous variables (X_i) and the α_i denote elasticities of the fare elasticity with respect these variables. Thus if X were distance, its coefficient would indicate the proportionate change in the fare elasticity resulting from a proportionate change in distance. The Z_{jk} are dummy variables representing the p categorical variables. We can specify q-1 dummy variables for a categorical variable of q levels and their coefficient estimates (β_{jk}) are interpreted relative to the arbitrarily omitted level. The exponential of β_{jk} denotes the proportionate effect on the fare elasticity of level k of the j'th categorical variable relative to its omitted category. Thus if a dummy variable is specified for inter-urban travel, the exponential of its coefficient indicates the proportionate impact on the fare elasticity of a journey being inter-urban rather than urban.

A logarithmic transformation of the multiplicative model allows the estimation of its parameters by ordinary least squares[2]. The additive form of the model is represented as:

$$\eta = \mu + \sum_{i=1}^{n} \alpha_i X_i + \sum_{j=1}^{p} \sum_{k=1}^{q-1} \beta_{jk} Z_{jk} \tag{2}$$

Here the α_i represent the marginal effect of a change in X_i on the fare elasticity whilst the β_{jk} denote the additive effect on the fare elasticity of a particular level of a categorical variable relative to its base level.

[2] The elasticities are therefore specified in absolute form prior to taking logarithms

After making appropriate adjustments for the different dependent variables, the multiplicative model was found to achieve a somewhat better fit and is that reported.

The estimated model is reported in Table 5. It contains all but six of the 902 elasticity values collected. The six elasticities identified as outliers all related to inter-urban rail trips and were less than -0.15. The goodness of fit at 0.52 seems quite respectable given the disparate nature of the studies, the inherent inability of this type of approach to examine detailed variations in elasticities, and the sampling distribution surrounding any individual fare elasticity estimate.

The model contains only one continuous variable relating to distance in miles for inter-urban rail trips and its coefficient is therefore an elasticity. All the other variables are categorical and are represented by dummy variables. In each case, the base category is specified, which can take the form of a number of categories combined, and the proportionate effect on a fare elasticity of each other category is reported.

Collinearity is not a problem to any great extent. Coefficient estimates with correlations in excess of 0.5 were non commuting and all purposes (0.61), commuting outside the South East and all purposes (0.59), conditional first class and non commuting (0.58), and commuting within the South East and all purposes (0.54).

Excluded Variables

In general, interaction terms were specified to explore whether the incremental effects varied across modes in particular but according to other factors, such as area or journey purpose where there was reasonable reason to expect elasticity variation. The reported model contains only those distinctions that were statistically significantly or which were of sufficient important to merit retention.

A number of variables did not have a statistically significant influence on the fare elasticity. Of particular interest was the testing of whether the fare elasticity increased over time. This was specified in relation to both a time trend term and GDP per capita and separate effects were allowed for each mode as well as pooled terms across modes. Despite the view that at least in the bus market the fare elasticity has increased over time, we found not the slightest evidence to support inter-temporal variations in fare elasticities for any mode. The coefficients on both GDP and the time trend and their associated t statistics were to all intents and purposes zero. We return to this issue below. Nor were there any significant effects attributable to the type of elasticity function estimated, the spatial aggregation of the estimated model, the source of the data for model estimation or ticket type for urban journeys.

Distance

We cannot take distance as a proxy for fare level because of distance tapers whilst in any event the fare elasticity might depend not only on the absolute fare but also, as a measure of value for money, on the fare per mile. However, we might expect the fare elasticity to vary with distance since a given proportionate change implies a larger absolute change at longer distances but offsetting this is that public transport tends to achieve higher shares as distance increases. Any distance effect must be included to allow transferability of the results, and casual inspection of only a few rail studies soon reveals that fare elasticities are clearly larger for longer distance journeys.

Separate distance terms were specified for each mode. However, we did not anticipate an effect for urban journeys both because the range of distances is small and because of the approximations introduced in estimating a representative distance for urban journeys where none was reported. The results confirmed our expectations and no distance effects were apparent for bus, suburban rail, or underground.

Table 5: Regression Model Results

	Coeff (t)	Effect
Intercept	-0.335 (4.0)	*0.715
Distance - Inter Urban Rail	0.086 (4.4)	
Rail	Base	
Bus	-0.375 (6.3)	-31%
UG	-0.345 (3.1)	-29%
Short Term/Neither/Before and After	Base	
Long Run Rail	0.386 (7.1)	+47%
Long Run Bus	0.670 (9.8)	+95%
Cross Sectional - Urban	0.169 (1.9)	+18%
Cross Sectional - Inter Urban Rail	0.671 (2.0)	+96%
SP-Rail	0.193 (2.3)	+21%
Stated Intention	0.464 (6.0)	+59%
Ordinary Elasticity	Base	
Mode Choice Leisure	-0.451 (3.9)	-36%
Urban and Inter Urban London	Base	
Inter Urban Non London	-0.118 (2.3)	-11%
Leisure	Base	
Business Rail	-0.620 (4.7)	-46%
Business UG	-1.845 (3.9)	-84%
Business Bus	-0.199 (1.9)	-18%
Commute South East	-0.530 (5.5)	-41%
Commute Not South East	-0.413 (4.6)	-34%
All Purposes	-0.278 (3.9)	-24%
Not Commute	-0.293 (4.2)	-25%
No Concessions	Base	
Elderly Full	0.226 (2.1)	+25%
Elderly Concession	-0.718 (5.6)	-51%
Child	0.125 (1.7)	+13%
Non PTE and Non Rural	Base	
PTE	-0.142 (2.6)	-13%
Rural Bus	0.473 (4.7)	+60%
Rural Rail	-0.348 (2.2)	-29%
Std and 1^{st} Rail/Non Conditional Full	Base	
Conditional 1^{st}	-0.484 (5.2)	-38%
Conditional Full	-0.216 (1.9)	-19%
Conditional Reduced	0.130 (2.2)	+14%
Non Conditional 1^{st}	-0.407 (2.5)	-33%
Non Conditional Reduced	0.402 (3.3)	+50%
Non Conditional Bus	Base	
Conditional Bus	-0.214 (2.1)	-19%
Non Conditional UG	Base	
Conditional UG1	-0.815 (4.5)	-56%
Conditional UG2	-1.007 (5.6)	-64%
Non Conditional Rail	Base	
Conditional Rail	-0.072 (1.1)	-7%
Adjusted R^2	0.52	
Observations	896	

Within inter-urban rail journeys, a statistically significant effect from distance on the fare elasticity was discerned. However, the distance elasticity of 0.086 is not particularly strong. For inter-urban rail, the majority of evidence relates to analysis of ticket sales and only limited allowance for journey purpose effects can be made by segmenting by ticket type. The distance effect may therefore also reflect a larger proportion of more elastic leisure travel at longer distances as well as any absolute fare variation effects.

Mode

The base category is rail, with no distinction necessary between suburban and inter-urban rail. The results show that, other things equal, the bus and underground fare elasticities are respectively 31% and 29% lower than rail fare elasticities.

Data Type and Time Period

This is an area where meta-analysis can provide valuable insights of a methodological nature as well as drawing together evidence from a range of sources to obtain a collective value for dynamic effects.

The base category was specified as elasticities estimated to time series data which were explicitly short term in nature. In addition, as a result of their effects being far from statistically significant, the base also include those fare elasticities obtained from time series models where no distinction was made between short and long run and also those estimated in before and after studies.

There was no evidence to allow a distinction between long run and short run underground fare elasticities. For rail travel, the incremental effect of the long run was similar for inter-urban and suburban rail (0.42 and 0.38) and hence a single term was specified. For bus, the variation between long run and short run elasticities is somewhat larger.

The long run rail elasticities are 47% larger than the short run elasticities whilst for bus the figure is 95%. Presumably, in the long run the number of alternative courses of action are greater for bus than for rail. The bus evidence will relate to commuting trips, where lagged home and employment location decisions are relevant, much more than for rail. The figure estimated for bus is very consistent with the conclusions of Dargay and Hanly (2002) who state that, “The evidence suggests that the long-run elasticities are about twice the short-run elasticities”.

Given that there was not a great deal of cross-sectional evidence for urban travel, a single figure was estimated for bus and rail. This indicates that cross-sectional urban values are 18% higher than short run time series values. In contrast, the figure for cross-sectional inter-urban rail indicates the fare elasticity to be 96% larger than the short run time series value.

Those fare elasticities here denoted as cross-sectional were estimated to spatial variations in aggregate data. Although they are often regarded to represent longer term effects, and the results here would to some extent support this, they can suffer from specification errors associated with cross-sectional models, such as adequate specification of catchment areas and ‘size’ effects and a failure to distinguish between cause and effect. This may have contributed to the lack of consistency between the long run time series and cross sectional effects.

Terms were specified to denote whether the fare elasticity was obtained from disaggregate RP choice data or from SP data. No significant effect was detected in the case of the former but some interesting findings emerged with respect to SP data.

Our data set contains only a small amount of SP based evidence for underground and bus and the SP coefficient was far from significant for these modes separately or together. In contrast, most evidence comes from rail studies and the coefficient estimate indicates that SP based elasticities are on average 21% higher than the base.

The fare elasticity for a public transport mode X (η_x) implied by a logit model, which is that by far most commonly estimated, and for the almost universally estimated linear-additive utility function, would be :

$$\eta_X = \beta_X F_X (1 - P_X) \qquad (3)$$

where β_X is the marginal utility of variations in the cost of X, F_x is the fare of X and P_x is the probability of choosing X.

The coefficients and hence forecast choice probabilities of discrete choice models are estimated in units of residual variation. If, as we might reasonably expect, the amount of random error in an SP model is greater than is consistent with actual decision making, then β_X will be too low. Given that the public transport mode will be the minor mode in most of the instances covered, since it was compared with car, P_X will then be too large and will also operate to reduce the fare elasticity.

It is therefore of some concern that the SP effect denotes a higher elasticity when we would expect it to be lower and given that allowance has been made in the leisure market for SP models covering only part of the behavioural response. In any event, a failure of SP choice models to cover all aspects of choice relevant to the overall elasticity would again lead to lower elasticities than otherwise.

A possible, and we believe very likely, explanation of the high elasticities obtained from SP data is that the stated sensitivity to cost is much higher than it should be as a result of protest response. Public transport fares are a sensitive issue and are often perceived to be very much in the control of the operators such that there is an incentive to send a signal that increases would not be tolerated but reductions would very much be appreciated.

It is not clear whether SP models can be regarded as providing short run or long run effects. To the extent that individuals evaluate hypothetical scenarios in the context of a specific journey, the responses will not include long run effects associated with moving house or job. However, they cannot be regarded as short term effects to the extent that the presentation of information and the requirement to make decisions overcome issues of misperception and habit which are barriers to behavioural change. Nonetheless, even in the long-run the demand forecast by SP based parameters may not materialise because of remaining issues of misperception.

Whilst it has often been claimed that stated intention data will produce demand forecasts which over-predict behavioural response to changes in fare and other attributes, quantitative evidence on the degree of inaccuracy is both sparse and potentially valuable as a correction factor for what is otherwise a very straightforward technique.

The stated intention evidence was almost entirely obtained from studies of inter-urban rail travel. The results indicate that such elasticities are 59% larger than the short run rail elasticity. Thus regardless of whether stated intention data reflects short or long run effects, it would produce higher elasticities. However, the uncertainty of the extent to which it is short or long run means that unfortunately correction factors cannot be derived with any great degree of confidence.

Mode Choice Elasticity

In their review of price elasticities, Oum et al. (1992) recognised the key area of disaggregate choice modelling and its potential to provide evidence. However, given the absence of trip generation effects from the implied elasticities, they concluded, “Consequently, it is virtually impossible to draw on the extensive mode-choice literature to help establish values of ordinary demand elasticities”.

We would expect the mode choice elasticity to provide a reasonably accurate account of the ordinary elasticity for commuting and business trips where mode choice will provide the vast majority of the change in demand for any public transport mode. For leisure travel, there will be a trip generation effect and thus the mode choice elasticity will underestimate the ordinary elasticity.

We therefore specified a term to denote those elasticities which were based on the output of disaggregate choice models, estimated to either RP or SP data, and which related to leisure travel. A statistically significant effect was detected, indicating quite plausibly that the mode choice elasticity for leisure travel is 36% less than the ordinary elasticity.

Not only is this a useful parameter in allowing us to make use of the other information context of the mode choice elasticities alongside the ordinary elasticities, but it provides a measure which is potentially useful to those using disaggregate models to convert from mode choice to ordinary elasticities.

Analysis was conducted to determine variation in the effect across modes but none was apparent. The very small number of observations when split by mode may well have contributed to this finding.

Inter Urban Non London Rail Travel

One of the most consistent findings across studies of which we are aware is an estimated fare elasticity of around –0.9 on Non London inter-urban rail flows. This elasticity is lower than is typically obtained on London based flows at least for tickets where, as on Non London flows, leisure travel dominates. The result indicates that the fare elasticity is 11% lower on Non London than London inter-urban flows. This is presumably the result of the lower fares charged on the former.

Journey Purpose

A wide variety of distinctions by journey purpose are made across studies. Within the urban travel market, a distinction often made is between peak and off-peak travel. For the purposes of this study, values estimated for peak travel have been subsumed within commuting whilst off-peak values are included within leisure travel.

For the rail market, a large proportion of the fare elasticity evidence is obtained from analysis of ticket sales where segmentation by journey purpose is not always straightforward. In such cases, season tickets are also indicated as commuting trips whilst Non London inter-urban flows are assigned to the leisure category. First class rail trips are assigned to a journey purpose of first class business alongside such evidence obtained from other forms of data.

Elasticities estimated to non-season ticket sales data on suburban services are assigned to a category which indicates all journey purposes whilst full, reduced and combined standard class ticket types on London inter-urban flows are denoted as non commuting trips as far as journey purpose is concerned.

Business travellers generally have, as expected, the least sensitivity to cost. The differential is small for bus but there will be few in this category. No additional effect was apparent for the first class business travellers.

Commuters are also somewhat less sensitive to fare than are leisure travellers. This is to be expected given that public transport has higher shares in the commuting than leisure market, although the generally higher fares in the peak can be expected to have had a dampening effect. The higher impact in the South East may stem from public transport’s particularly strong position in that area whilst the generally higher incomes in the South East may also have contributed. No significant differences in the commuting elasticity according to mode were apparent.

The remaining two significant categories relate to all purposes and to non commuting purposes. Given that all purposes contains leisure travel, the effect is consistent with the relative fare elasticities for business travel, commuting and leisure, lying as it does broadly between the leisure and commuting effect. Given that business trips will form a larger proportion of the non commuting trips than the all purposes trips, the non commuting effect is, as expected, larger than the all purposes effect.

Concessionary Travel

Elderly travellers paying full fares have higher elasticities than other adults. This is presumably because they have lower incomes and because the journeys largely relate to discretionary travel. However, where concessionary fares apply, the fare elasticity for the elderly is somewhat lower. There was insufficient data to examine variations by mode.

For child fare elasticities, there were too few observations to split by concession or not, but most relate to concessionary travel. Even at the lower fares, the elasticity is a little higher than for adults, again presumably reflecting income effects.

Area

Few significant variations by area were apparent. In addition to different commuting elasticities between the South East and elsewhere, Passenger Transport Executive (PTE) areas exhibit lower elasticities. This is presumably because in these areas public transport has a relatively high share and fares tend to be lower. For quite the reverse reasons, the bus fare elasticities are 60% higher in rural areas.

The rail fare elasticity is somewhat lower for rural travel. This may be because those who do use such rail services are highly dependent upon it, although it should be pointed out that there are few observations.

Conditional and Non-Conditional Ticket Type Elasticities

A conditional price elasticity denotes the proportionate change in the demand for an alternative after a proportionate change in its price conditional upon the same proportionate change in the price of a competing alternative. This is not uncommon in transport markets. For example, bus and rail fares can be closely linked where fare setting is the responsibility of a local authority whilst an operator may apply across-the-board fare increases to some or all of a range of tickets offered. In such cases, a price variation leads to a 'first order' effect of a direct change in the demand for the alternative but there is also a 'second order' effect due to switching between alternatives as a result of the variation in the price of the competing alternative. More formally, we have:

$$C_i = \eta_{ii} + \eta_{ij} \qquad (4)$$

The conditional elasticity for i (C_i) equals the non-conditional elasticity for alternative i as the price of i changes (η_{ii}) plus the cross-elasticity of demand for alternative i as the price of j changes.

The ticket type conditional elasticities relate to the inter-urban travel market. The ticket type distinctions were: first class; standard class tickets where there are no restrictions on travel, which are termed full fare tickets; standard class tickets where there are restrictions on times of travel, which are termed reduced tickets; standard class tickets, where the elasticity makes no distinction between different standard class tickets; and cases where no distinction was made between first and standard class tickets.

The conditional ticket type elasticity is obtained if the fares of competing tickets are changed in the same proportion as the ticket of interest. This will be lower than the non-conditional elasticity since the fare increase on competing tickets means that there will be some switching from those tickets to the ticket of interest. The conditional elasticity for a particular ticket is simply the sum of its non-conditional elasticity and the cross elasticities with respect to the prices of competing tickets.

The base was initially chosen as the full fare non-conditional elasticity. However, the base also subsequently contained the fare elasticities for standard class and for first and standard class combined which were not significantly different from the full fare non-conditional elasticity. There were too few inter-urban season tickets to distinguish this from the other commuting evidence.

The results split by ticket type generally appear plausible. The conditional elasticities for first, full and reduced tickets are all less than their non-conditional elasticities whilst, as expected, the first class largely business travel tickets have the lowest elasticities and the reduced tickets which are dominated by leisure travel have the highest elasticities. The difference between the conditional and non-conditional elasticities indicates low cross elasticities between ticket types, suggesting that the railways are effectively segmenting their different markets. The cross elasticities between first and the other tickets are lowest, not unreasonably indicating that first class is a quite distinctly different market. There is insufficient data to reliably distinguish distance effects by ticket type.

Conditional and Non-Conditional Mode Choice Elasticities

These relate entirely to urban trips where there can sometimes be close links between the fare variations for different public transport modes as a result of local authorities having control over the fares charged. However, there is no such link for inter-urban rail journeys.

The conditional elasticity is the sum of the non-conditional elasticity and relevant mode choice cross price elasticities. For all three modes, the conditional elasticity is, as expected, lower than the non-conditional elasticity. The effect is largest for underground. Here two conditional elasticities are specified. UG1 denotes the underground elasticity conditional on competing bus fares vary the same proportion as the underground fares whilst UG2 denotes the conditional elasticity where additionally the rail mainline fares are also varied in the same proportion. Given that bus provides more extensive competition to underground than does rail, it is not surprising that the largest effect comes from UG1.

The difference between the conditional and non-conditional elasticities is greater for bus than rail, presumably because rail provides stronger competition to bus than bus to rail.

5. Implied fare elasticities and other review evidence

Fare elasticities implied by the estimated model for a range of situations are provided for inter-urban travel in Table 6 and urban travel in Table 7. To assist with the interpretation of the results, suppose that a long run non-conditional fare elasticity is required for urban bus leisure journeys within a PTE area by adults receiving no concessions. Given a preference for elasticities estimated to revealed preference data, the elasticity would be:

$$\eta = -e^{-0.335-0.375+0.670-0.142} = -0.83 \qquad (5)$$

The fare elasticity has been scaled to convert from the absolute units in which the equation was estimated to their natural units.

The variations in elasticities discussed in preceding sections are apparent in the elasticities reported in Table 6 and 7 and thus further discussion is not required. However, one issue warrants further attention both because of the implications of the numbers quoted and as an illustration of one of the key shortcomings of meta-analysis.

The figures in Table 7 for the long term elasticity for elderly bus travel, both concessionary and full fare, suggested as results of the meta-analysis are substantially greater than those suggested in the fare chapter in TRL et al. (2004) and by Goodwin (2003). We should point out that this is not because there is any source evidence of such high elasticities. In fact the average value of elasticity for elderly bus travellers, entered as data into the meta-analysis, was –0.5 for full fare payers and –0.29 for concessionary travellers, based on 38 elasticities drawn from six separate studies. The higher figures in Table 7 are an artefact of the meta-analysis, and stem from the use of the relationship between short run and long run estimated for other groups of bus users. For practical use, we would favour the use of figures actually drawn from studies of concessionary travellers, in preference over such extrapolated results based on other groups, until further information is available.

Table 6: Illustrative Elasticities: Inter Urban Rail

		50 miles	100 miles	150 miles	200 miles	250 miles	300 miles
London First	SR-NC	-0.67	-0.71	-0.73	-0.75	-0.77	-0.78
	SR-C	-0.62	-0.65	-0.68	-0.70	-0.71	-0.72
	LR-NC	-0.98	-1.04	-1.08	-1.10	-1.13	-1.14
London Full	SR-NC	-0.75	-0.79	-0.82	-0.84	-0.86	-0.87
	SR-C	-0.60	-0.64	-0.66	-0.68	-0.69	-0.70
	LR-NC	-1.10	-1.17	-1.21	-1.24	-1.26	-1.28
London Reduced	SR-NC	-1.12	-1.18	-1.23	-1.26	-1.28	-1.30
	SR-C	-0.85	-0.90	-0.93	-0.96	-0.98	-0.99
	LR-NC	-1.64	-1.74	-1.80	-1.85	-1.89	-1.92
London Business	SR	-0.54	-0.57	-0.59	-0.61	-0.62	-0.63
	LR	-0.79	-0.84	-0.87	-0.89	-0.91	-0.92
London Leisure	SR	-1.00	-1.06	-1.10	-1.13	-1.15	-1.17
	LR	-1.47	-1.56	-1.62	-1.66	-1.69	-1.72
Non London Business	SR	-0.48	-0.51	-0.53	-0.54	-0.55	-0.56
	LR	-0.70	-0.75	-0.77	-0.79	-0.81	-0.82
Non London Leisure	SR	-0.89	-0.94	-0.98	-1.00	-1.02	-1.04
	LR	-1.31	-1.39	-1.44	-1.47	-1.50	-1.53

Note: SR, LR, C and NC denote short run, long run, conditional and non-conditional.

Another issue is the degree of correspondence between the elasticities predicted by the meta-analysis for urban travel in Table 7 with the mean figures of the tabulations in TRL et al. (2004) and the mean figures obtained by the first ‘Demand for Public Transport’ review study (TRRL, 1980). Key values are summarised in Table 8. It can be seen that there is generally a close correspondence between the values obtained in this meta-analysis and the TRL et al. (2004) review. The largest discrepancy is for the long run bus fare elasticity and this is due in large measure to the inclusion in the latter of a very large elasticity. Comparing the 1980 study with the more recent evidence, there is a suggestion that the bus fare elasticity has risen over time.

Table 7: Illustrative Elasticities: Urban Travel

	Bus			Suburban Rail			Undeground			
	SR-NC	SR-C	LR-NC	SR-NC	SR-C	LR-NC	SR-NC	SR-C1	SR-C2	LR-NC
Leisure No Concessions PTE	-0.43	-0.34	-0.83	-0.62	-0.58	-0.91	-	-	-	-
Leisure No Concessions Rural	-0.79	-0.64	-1.54	-0.51	-0.47	-0.74	-	-	-	-
Leisure No Concessions	-0.49	-0.40	-0.96	-0.72	-0.67	-1.05	-0.51	-0.22	-0.18	-0.75
Leisure Elderly Full	-0.62	-0.50	-1.20	-0.90	-0.83	-1.32	-0.64	-0.28	-0.23	-0.95
Leisure Elderly Concession	-0.24	-0.19	-0.47	-0.35	-0.32	-0.51	-0.25	-0.11	-0.09	-0.36
Leisure Child	-0.56	-0.45	-1.09	-0.81	-0.75	-1.19	-0.57	-0.25	-0.21	-0.84
Commute No Concessions S East	-0.29	-0.23	-0.57	-0.42	-0.39	-0.62	-0.30	-0.13	-0.11	-0.44
Commute No Concessions Not S East	-0.33	-0.26	-0.64	-0.47	-0.44	-0.70	-	-	-	-
Commute No Concessions Not S East PTE	-0.28	-0.23	-0.55	-0.41	-0.38	-0.60	-	-	-	-
Commute No Concessions Not S East Rural	-0.52	-0.42	-1.02	-0.33	-0.31	-0.49	-	-	-	-
Commute Elderly Full Not South East	-0.41	-0.33	-0.80	-0.59	-0.55	-0.87	-	-	-	-
Commute Elderly Concession Not S East	-0.16	-0.13	-0.31	-0.23	-0.21	-0.34	-	-	-	-
Commute Child Not S East	-0.37	-0.30	-0.72	-0.54	-0.50	-0.79	-	-	-	-
Business No Concessions PTE	-0.35	-0.28	-0.68	-0.33	-0.31	-0.49	-	-	-	-
Business No Concessions Rural	-0.65	-0.52	-1.26	-0.27	-0.25	-0.40	-	-	-	-
Business No Concessions	-0.40	-0.33	-0.79	-0.38	-0.36	-0.57	-0.08	-0.04	-0.03	-0.12

Note: SR and LR denote short and long run. C and NC denote conditional and non-conditional elasticities. For underground, there are two conditional elasticities depending upon whether there are corresponding variations in just bus (C1) or both bus and rail (C2) fares.

Table 8: Comparison of Fare Elasticities

Context	Individual studies TRL et al. (2004)			Meta Analysis Predicted	TRRL (1980) Study
	Mean	Range			
		from	To		
Public transport – UK and outside UK – short run	-0.41	-0.07	-1.02	n/a	
Public transport – UK – short run	-0.44	-0.07	-1.02	n/a	
Public transport – outside the UK – short run	-0.35	-0.09	-0.86	n/a	
Bus – UK and outside the UK – short run	-0.42	-0.07	-0.86	n/a	
Bus – UK – short run	-0.43	-0.07	-0.86	-0.36	-0.30
Bus – outside the UK – short run	-0.37	-0.23	-0.58	n/a	
Metro – UK and outside the UK – short run	-0.30	-0.13	-0.86	n/a	
Metro – UK – short run	-0.31	-0.15	-0.55	-0.37	-0.15
Metro – outside the UK – short run	-0.29	-0.13	-0.86	n/a	
Suburban rail – UK and outside UK – short run	-0.50	-0.09	-1.02	n/a	
Suburban rail – UK – short run	-0.58	-0.10	-1.02	-0.52	-0.50
Suburban rail – outside the UK – short run	-0.37	-0.09	-0.78	n/a	
Bus – UK – medium run	-0.56	-0.49	-0.63	n/a	
Bus – UK – long run	-1.25	-0.80	-1.92	-0.70	
Metro – UK – long run	-0.57	-0.40	-0.69	-0.54	
Bus – London – short run	-0.41	-0.14	-0.84	-0.37	-0.44
Bus – outside London – short run	-0.45	-0.07	-0.86	-0.36	
Suburban rail – SE England – short run	-0.61	-0.10	-0.95	-0.50	
Suburban rail – outside SE England – short run	-0.59	-0.15	-1.02	-0.60	
Bus – UK – peak – short run	-0.26	0.00	-0.42	-0.30	
Bus – UK – off- peak – short run	-0.48	-0.14	-1.00	-0.40	
Metro – UK – peak – short run	-0.25	-0.15	-0.35	-0.30	-0.38
Metro – UK – off- peak - short run	-0.42	-0.23	-0.63	-0.44	-0.45
Suburban rail – UK – peak - short run	-0.34	-0.27	-0.50	-0.42	
Suburban rail – UK – off- peak - short run	-0.79	-0.58	-1.50	-0.65	

Source: Reproduced from TRL et al. (2004)

6. Variations over time

There is a widely held view that bus fare elasticities have increased over time, and this is confirmed by specific studies (Dargay and Hanley, 2002) and also the evidence summarised in Table 8. Against this backdrop, the development of the meta-analysis model had explicitly examined whether GDP variation or the closely correlated time trend could explain the elasticity variation, but no effect was detected. This could be because the causes of the elasticity changes over time go unaccounted for in the tabulations but are discerned by the meta-analysis model. For example, fare elasticity increases due to different data sources over time or changes in journey purpose mixes would be included in the coefficient estimates for the data source and journey purpose variables.

Table 9 reports both the actual elasticities in the meta-analysis data set and the elasticities that would be predicted by the estimated model for the independent variables relating to the same observations. It can be seen that, at face value, there has been an increase in the bus fare elasticity and the suburban rail fare elasticity over time.

The purpose of the predicted model is to determine whether the elasticity variation can be accounted for by factors within the model. It can be seen that the model does particularly well for inter-urban rail and can predict the fall and subsequent rise in the underground elasticity. For bus and suburban rail, however, the model cannot fully explain the elasticity increase. The failure of the time trend to discern any effect may be because this residual effect is only a small annual change. However, given that there is a widespread view that it is increases in real fares that have caused a drift upwards in the elasticity, it may be that experimentation with fare indices in place of GDP or time trends would prove fruitful. Notably, the lower fare elasticities for the underground correspond with a period of relatively low underground fares.

Table 9: Meta-Analysis Actual and Predicted Elasticities

PERIOD	ACTUAL	PREDICTED	CASES
Bus			
Up to 1980	-0.35 (0.015)	-0.34 (0.006)	71
1981-1990	-0.39 (0.026)	-0.36 (0.013)	56
After 1990	-0.46 (0.027)	-0.40 (0.011)	112
Underground			
Up to 1980	-0.30 (0.034)	-0.29 (0.028)	22
1981-1990	-0.25 (0.070)	-0.20 (0.033)	7
After 1990	-0.29 (0.041)	-0.27 (0.029)	13
Suburban Rail			
Up to 1980	-0.51 (0.050)	-0.50 (0.000)	4
1981-1990	-0.58 (0.044)	-0.51 (0.013)	61
After 1990	-0.62 (0.061)	-0.54 (0.017)	30
Inter Urban Rail			
Up to 1980	-0.65 (0.189)	-0.69 (0.061)	3
1981-1990	-0.90 (0.032)	-0.90 (0.018)	223
After 1990	-0.74 (0.028)	-0.77 (0.014)	133

Note: Given the large difference between short run and long run elasticities, there is potential for these to distort the inter-temporal variations and hence they have been removed from these calculations. Standard errors in brackets.

Noticeably there have been increases in the bus and suburban rail fare elasticities whereas there is no evidence for such an effect in the inter-urban rail market. This may point to the operation of changing socio-economic characteristics within these markets. Public transport users in general, but bus users in particular, have lower incomes and levels of car ownership on average. As incomes grow over time, the more affluent of the public transport users will purchase cars and use public transport less. The public transport market will therefore become increasingly dominated by those of lower incomes and conceivably the average incomes of public transport users could actually fall even though incomes in general are rising. Those with lower incomes can be expected to be more sensitive to fare increases and as they increase in importance so the fare elasticity will increase. Insofar as the underground and inter-urban rail markets have not experienced such changes, because the former has a strong market position and the latter is often regarded a luxury good, they will not have experienced an upward trend in fare elasticity. In drawing a balance between the effects of fare increases and changing socio-economic characteristics, it is worth noting that as with bus fares there have been gradual increases in average rail fares.

7. Conclusions

This work commenced towards the final stages of the project to update the TRRL (1980) Demand for Public Transport. It provides, as far as we are aware, the most comprehensive review of fare elasticity evidence and a number of important insights into methodological issues and fare elasticity variations have been provided. Nonetheless, we regard this to be very much work in progress, and it cannot be taken as our final word on this matter. It has stimulated debate and raised a number of interesting and challenging questions which need to be addressed. In particular, more information is required on the dynamic nature of time series models, and especially the length of the time period used in model estimation. Such data will be collected to be able to conduct more detailed analysis whilst variations in the dynamic effects by journey purpose will also be explored. Other issues include the further analysis of changes over time, including the use of fare indices and car ownership data at a suitable local level, whilst there would seem to be considerable merit in extending the data set to cover car cost elasticities. No doubt by the time this additional work is embarked upon, the results of further empirical studies will be available.

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