Oxford Economic Research Associates

Competition Commission

Consumer Survey Analysis

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Executive Summary

The Competition Commission has requested OXERA to examine evidence from previous studies on bus and train elasticities, and to analyse data collected during the course of the Commission's inquiry into the proposed acquisition by First Group of the ScotRail franchise. The aim of this study is to produce estimates of elasticities relevant to the merger situation. OXERA has worked together with Dr Mark Wardman of the University of Leeds in preparing both the literature review and the current report.

This report presents the results of the second strand of this analysis. A separate literature review has already been provided to the Commission. The concluding section of this paper does, however, draw the two strands of research together, highlighting how the results of OXERA's analysis compare with the results of the literature review.

The Commission contracted the market research company, NOP, to undertake a survey of consumers in those areas in Scotland that are likely to be affected by the merger. OXERA, together with Dr Wardman, advised the Commission in designing the questionnaire subsequently used by NOP to collect the information. The aim was to gather information that, among other things, would enable an analysis of respondents' choices to travel on either the bus or the train. Technically, OXERA set out to estimate a discrete choice model, based on the main journey characteristics and on the respondents' socio-economic characteristics. A further aim was to identify whether there was evidence to suggest that peak-time travellers have significantly different elasticities to off-peak travellers.

The survey identified respondents who had taken a recent bus or train journey in the areas likely to be affected by the merger, and who could have taken the train if their actual journey had been by bus, or by bus if their actual journey had been by train. To obtain a minimum number of peak-time travellers, it was necessary for NOP to boost the sample of peak-time travellers (in particular, train travellers). The NOP survey obtained 433 observations on which to base the estimations. However, examination of the data revealed significant levels of incomplete answers, and more than half of the 433 observations could not be used in the modelling exercise, which was ultimately based on the 196 respondents who had provided a complete set of answers for the key journey characteristics.

This is a relatively small sample on which to base a choice model, and meant that statistically robust results could not be obtained for sub-sets of the sample (in particular, for peak and off-peak travellers).

However, the modelling exercise did produce own- and cross-elasticities of a number of time-related features of the journeys (in-vehicle journey time, headway (ie, frequency), and access and egress time). These are all reported in the following table, along with elasticity estimates for total journey time derived from a separate model.

Mean elasticities for time-related factors

	In-vehicle journey time	Headway	Access and egress time	Door-to-door journey time
Own-elasticities				
All	–0.54	–0.33	–1.01	–1.15
Train	–0.41	–0.41	–1.25	–1.04
Bus	–0.66	–0.25	–0.77	–1.26
Cross-elasticities				
Demand for train with respect to bus characteristics	0.56	0.24	0.53	0.89
Demand for bus with respect to train characteristics	0.41	0.41	1.25	1.04
No. of observations (henceforth, N)	196			

These results are generally in line with previous estimates, for example relating to own-elasticities for the headway of bus and train services. Of these factors, it is only headway and, to a certain extent, in-vehicle time that would be under the direct control of the merged company.

The data did not, however, reveal any significant price effect. A range of techniques to explore this finding was employed, although examination of the data revealed that a significant proportion of the respondents did not face any price incentives: respondents believed they would have paid the same price for the journey regardless of whether they used the bus or the train. This therefore precluded robust results on price.

Previous estimates indicate that short-run bus fare elasticities are in the range –0.35 to –0.5, increasing to around –1 in the long run. The limited evidence on Scotland suggests that elasticities for trips taken within Scotland are slightly higher than the British average. Short-run rail elasticities seem to be in the range –0.5 to –0.7, increasing to –0.75 to –1.0 in the long run. Scottish market studies are broadly consistent with these conclusions, although, again, there is some evidence to suggest that long-run own-price elasticities are slightly higher than the British average. In relation to cross-elasticities, estimates of the cross-price elasticity of rail demand to bus costs (0.45 or below) are higher than estimates of the elasticity of bus demand to train costs (0.15–0.35).

Contents

1. Introduction

OXERA, together with Dr Mark Wardman, and in collaboration with the Competition Commission, designed a questionnaire for market research company, NOP, to collect data on public transport choices in the context of the proposed acquisition of the ScotRail franchise by First Group plc.

One of the aims of the research was to use the data collected by NOP to estimate a discrete choice model, the results of which would enable own- and cross-elasticities of demand for bus and train transport in the areas affected by the acquisition to be established.

This report presents the results of the research, and provides, in particular:

- key statistics relating to the variables used in the modelling exercise, highlighting differences between the total NOP sample and the sample that could be used in the model (section 2);
- information of respondents' ability to switch between modes of transport, and on the modes to which they would switch (section 3);
- the choice modelling techniques and the results obtained (section 4 and Technical Appendix);
- elasticities derived from the choice models (section 5 and Technical Appendix);
- results of additional modelling exercises undertaken to exploit the dataset in full (section 6).

The report concludes in section 7 with a comparison between the elasticities obtained in this research and those identified during the literature review. The full results of the literature review have been reported in a separate submission to the Commission.

2. Data

The Commission undertook a consumer survey to gather information relating to choices between public transport modes in the localities affected by the merger. Various methods could have been used to select the sample of respondents. The methodology chosen was to select postcode areas where train stations are located, and randomly to dial within those postcode areas, using a few selection questions to identify appropriate respondents. The most important filtering question was:

> Have you made a recent journey from home on local public transport where you had the choice of using either a bus or a train for the main part of the journey?

Other filtering questions specifically asked about the mode of transport taken, and the time of day of the journey. This enabled NOP to use the questionnaire to obtain at least 100 respondents in each of four categories: bus peak; bus off-peak; train peak; and train off-peak. Using this approach, the data supplied by NOP consisted of a representative sample of 1,404 observations, of which 653 had recently taken a relevant journey. It was necessary for NOP to focus its efforts on obtaining respondents in the peak-time categories in order to fulfil the quotas. As a result, a number of respondents who had taken a relevant journey, but during the off-peak period, were not asked the more detailed questions about the choice characteristics of their journeys. Consequently, of the 653 respondents who had taken a relevant journey, only 433 were asked the detailed questions that were needed for the modelling exercise—ie, relating to price; in-vehicle, access, and egress time; and headway of their actual journey and their alternative journey.[1]

This section explores the sample to highlight how the main features of the journeys differ between bus and train users, peak and off-peak journeys, and between actual and alternative journeys. The characteristics of the various samples are also detailed to highlight where any significant differences arise as a result of the boost for the peak-time sample.[2]

2.1 Comparison of the samples

Table 2.1 shows how the 653 and 433 respondents are distributed between the two modes and time periods. As this shows, the peak samples—in particular, that for train users—were boosted as a result of the quotas.

[1] Headway of services is inversely proportional to the frequency of services, measured in minutes—the less frequent the service, the higher the measure of headway.

[2] If the modelling had produced significant results separately for peak and off-peak users, and there was clear evidence that different groups have different elasticities, this information could have been used to weight the results so that they were representative of the complete NOP sample of 633 respondents. However, significance was only obtained when modelling the sample as a whole, and therefore no such weighting was possible.

Table 2.1: Distribution of bus and train users by peak/off-peak, entire sample

	Frequency	%	Frequency	%
Bus peak	131	20.1	97	22.4
Bus off-peak	268	41.0	139	32.1
Train peak	94	14.4	94	21.7
Train off-peak	160	24.5	103	23.8
Total	**653**	**100**	**433**	**100**

In order for the respondents' answers to be used during the modelling process, it was necessary to have answers for all of the main journey characteristics (price, in-vehicle time, headway and access and egress time) for both the mode of transport that they actually took, and for the alternative mode that they could have taken. It was expected that some of the observations would be lost due to an incomplete set of answers; however, a surprisingly large proportion of the sample did not answer one or more questions from the key variables identified. This meant that, of the 433 respondents that were asked the full set of questions, answers from only 196 of them were available to be used in the modelling (205 answered all the relevant questions, but nine of these were excluded due to data errors or anomalies).[3] Table 2.2 shows the distribution of bus and train users by peak and off-peak for those observations that were eligible for the modelling, highlighting by how much these proportions differed from those in the main sample of 653 respondents.

Table 2.2: Distribution of bus and train users by peak/off-peak, modelled sample

	Frequency	%	Difference from total sample
Bus peak	46	23.5	+3.4
Bus off-peak	60	30.6	–10.4
Train peak	48	24.5	+10.5
Train off-peak	42	21.4	–4.1
Total	**196**	**100**	**n/a**

Tables 2.3 to 2.7 describe some of the demographics of the sample, comparing the characteristics of those in the total sample against those who were included in the detailed questioning and in the modelling. As the data in these tables shows, the proportion of 15–24-year olds was boosted in the sample used for modelling, as was that of full-time employees and those earning between £10,000 and £30,000 per year. The boost for full-time employees is also reflected in the higher proportion of people travelling work included in the sample used for modelling purposes.

[3] The data was examined closely to see whether it might be possible to increase the number of observations that could be used in the modelling by imputing the missing responses. Had the number of missing observations been limited to a relatively small proportion of the sample, this approach could have been applied. However, as such a high proportion of the respondents would have needed missing data imputed, this would have called into question any results obtained based on a larger, but imputed data sample. No data has therefore been imputed in an attempt to boost the samples available for modelling.

Table 2.3: Age of respondents (%)

Age	Total sample	Detailed questions	OXERA model	Difference between OXERA model and total sample
15–24	16.1	17.8	24.0	7.9
25–34	20.0	21.2	21.9	2.0
35–44	20.0	19.4	20.9	0.9
45–54	16.1	16.9	15.3	–0.8
55–64	11.8	10.6	8.7	–3.2
65 and over	15.8	13.9	9.2	–6.6
	100.0	100.0	100.0	
Total (N)	**651**	**433**	**196**	

Table 2.4: Personal situation of respondents (%)

Personal situation	Total sample	Detailed questions	OXERA model	Difference between OXERA model and total sample
Employed full-time	42.9	48.0	51.0	8.2
Employed part-time	9.8	9.9	10.7	0.9
Looking after home/family	8.0	7.2	6.1	–1.9
Permanently retired from work	20.7	18.5	12.2	–8.5
Unemployed and seeking work	5.4	3.7	4.1	–1.3
Full-time higher education	6.9	7.6	10.2	3.3
Full-time education	2.8	2.1	2.6	–0.2
Permanently sick or disabled	3.4	2.8	3.1	–0.3
	100.0	100.0	100.0	
Total (N)	**651**	**433**	**196**	

Table 2.5: Annual gross income of respondents (%)

Income (£)	Total sample	Detailed questions	OXERA model	Difference between OXERA model and total sample
Under 10,000	23.7	19.2	17.3	–6.3
10,000–19,999	22.7	24.0	28.1	5.3
20,000–29,999	17.7	20.3	25.0	7.3
30,000–39,999	9.2	9.2	8.2	–1.1
40,000–49,999	3.7	4.4	4.6	0.9
50,000–59,999	3.4	3.5	3.1	–0.3
60,000–99,999	3.2	3.5	2.0	–1.2
100,000+	0.6	0.7	0.5	–0.1
Refused to answer	15.8	15.2	11.2	–4.6
	100.0	100.0	100.0	
Total (N)	**651**	**433**	**196**	

Table 2.6: Gender of respondents (%)

Gender	Total sample	Detailed questions	OXERA model	Difference between OXERA model and total sample
Male	39.2	39.5	40.8	1.6
Female	60.8	60.5	59.2	–1.6
%	100.0	100.0	100.0	
Total (N)	**651**	**433**	**196**	

Table 2.7: Journey purpose of respondents (%)

Journey purpose	Detailed questions	OXERA model	Difference between OXERA model and those asked detailed questions (percentage points)
Going to work	30.6	37.2	6.7
Taking children to/from school	0.2	0.5	0.3
Going to school/college	5.6	7.1	1.6
Shopping for food	7.6	6.1	–1.5
Shopping for non-food items	20.8	19.9	–0.9
Personal business	8.3	5.1	–3.2
Leisure trips	21.3	18.4	–2.9
Going out in the evening	5.6	5.6	0.1
	100.0	100.0	
Total (N)	**432**	**196**	

The modelled sample includes a higher proportion of peak train users and a lower proportion of off-peak bus users, reflecting the desire to have a minimum number of respondents from each category. The modelled sample included more respondents in the younger categories, and fewer in the older categories, than suggested by the wider sample. Similarly, a higher proportion of people in work (and people whose journey purpose was to get to work) is included in the modelled sample than in the wider survey. As a result, the tabulations and the results of the modelling, which is based on the sample of 196, may not be representative of the larger NOP sample.

2.2 Data relating to choices

Each respondent was asked about their actual journey and then about the alternative journey they could have taken by a different mode. Each individual has supplied information on their actual and alternative choices. If their actual journey was by bus, their alternative was by train, and vice versa.

During the course of analysis, it was noted that the data contains a number of outliers. For example, one respondent claimed to take 480 minutes (ie, eight hours) for a single journey on local public transport. This observation and other outliers in the data were examined for consistency, taking into account the length of journey time, the price paid, and the postcode of where the journey started and that of the stated destination. Where this data appeared internally inconsistent, the observations were dropped from the subsequent modelling exercise. These modifications were agreed with the Commission.

The following sections present information on the main explanatory factors about which respondents were asked, starting with journey price.

2.3 Price data

The data on price of the actual journey represents the price of a single journey. The questions were designed to enable this figure to be calculated from the total cost of the ticket and the number of journeys for which the ticket was used, taking into account the range of ticket types that consumers can buy:

- for those buying single tickets, the answer to the cost question was the relevant price;
- for return tickets, the journey price was half of the ticket cost;
- for tickets allowing a fixed number of journeys, respondents were asked how many times the ticket was used, in order to calculate the single journey price;
- for season tickets valid for a week or more, respondents were asked how many journeys they would make in a typical week using that ticket. This was then used to estimate the single journey price.

The price variable was constructed from the total ticket cost (in pence). Data on the price of the alternative journey was calculated in the same way using the equivalent questions in the section regarding the alternative choice.

Table 2.8 summarises the average (mean) price data for bus travel and for train travel, broken down into peak and off-peak journeys. Train fares were on average more expensive than bus fares in both peak and off-peak times. This also holds when comparing the perceived price of the actual and alternative modes of transport used. In the case of bus users, their expectation was that the alternative trip by train would have been substantially more expensive; the opposite holds for train users (ie, they would expect to pay less if they were to travel by bus). Nevertheless, a proportion of the respondents believed that they would pay the same price for the journey regardless of whether they used the bus or train (see section 4.6 below).

Table 2.8: Price (pence)

Price	Observations	Mean	Standard deviation	Min.	Max.
Actual journeys					
Bus	*106*	*101.3*	*160.4*	*0*	*1,500*
Price (off-peak)	60	77.3	73.3	0	412.5
Price (peak)	46	132.6	226.3	0	1,500
Train	*90*	*242.5*	*381.5*	*0*	*2,500*
Price (off-peak)	42	213.5	236.3	35	1,250
Price (peak)	48	267.9	474.8	0	2,500
Alternative journeys					
Bus	*90*	*173.6*	*272.6*	*0*	*2,000*
Price (off-peak)	42	157.3	145.6	14.29	900
Price (peak)	48	187.8	349.0	0	2,000
Train	*106*	*156.1*	*199.0*	*0*	*1,500*
Price (off-peak)	60	133.4	114.7	0	500
Price (peak)	46	185.8	271.2	0	1,500

Note: This covers only those 196 respondents included in the modelling.

A proportion of respondents reported that they do not pay for their journey (11.2% of the respondents used in the modelling; 10.7% of the 433 asked detailed questions about their actual and alternative journeys). Almost all of these are respondents who receive a concessionary bus pass.

Table 2.9 shows average bus and train prices for a single journey by type of ticket bought.

Table 2.9: Average price of actual tickets by ticket type and mode (pence)

	Average train price	Average bus price
A fixed number of journeys (incl. single and return)	261.9	103.8
A ticket allowing many journeys	225.3	185.2
Concessions	177.9	4.7
Total	**242.5**	**101.3**

Note: This covers only those 196 respondents included in the modelling.

Figures 2.1 and 2.2 show the distribution of bus and train prices. These graphs were prepared using data from those respondents whose tickets cost £7.50 or less. In all of the graphs in this report, the vertical axis (density) represents the proportion of the sample in each column, for example, the first column in Figure 2.1 shows that 0.0125 (or 12.5%) of the sample paid between zero and 10 pence for their bus journey.

Figure 2.1: Bus prices (pence)

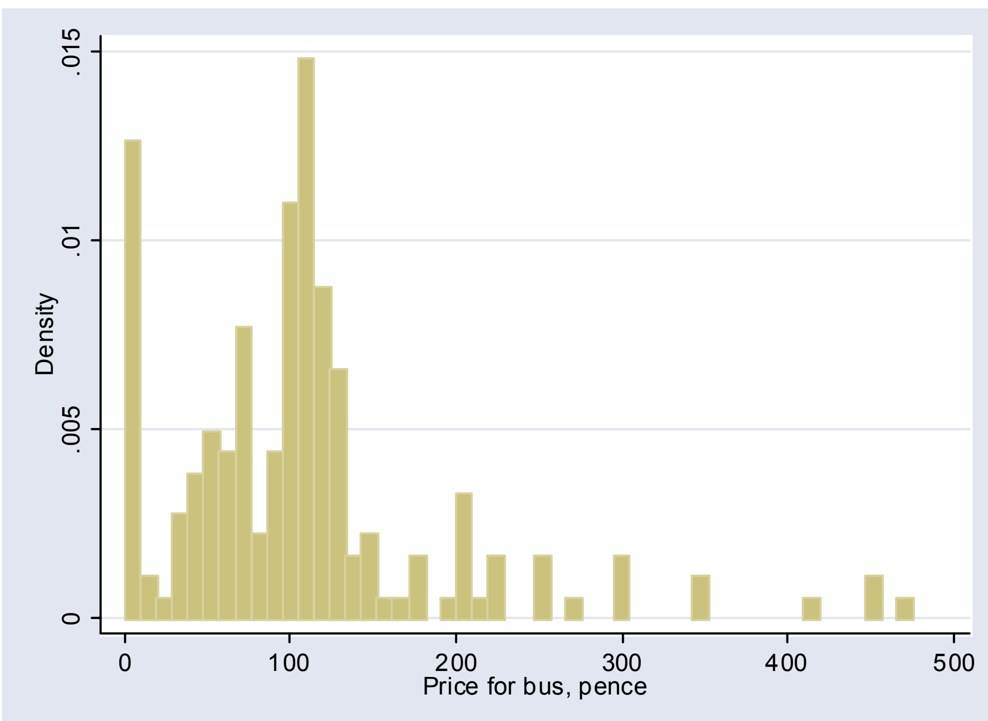
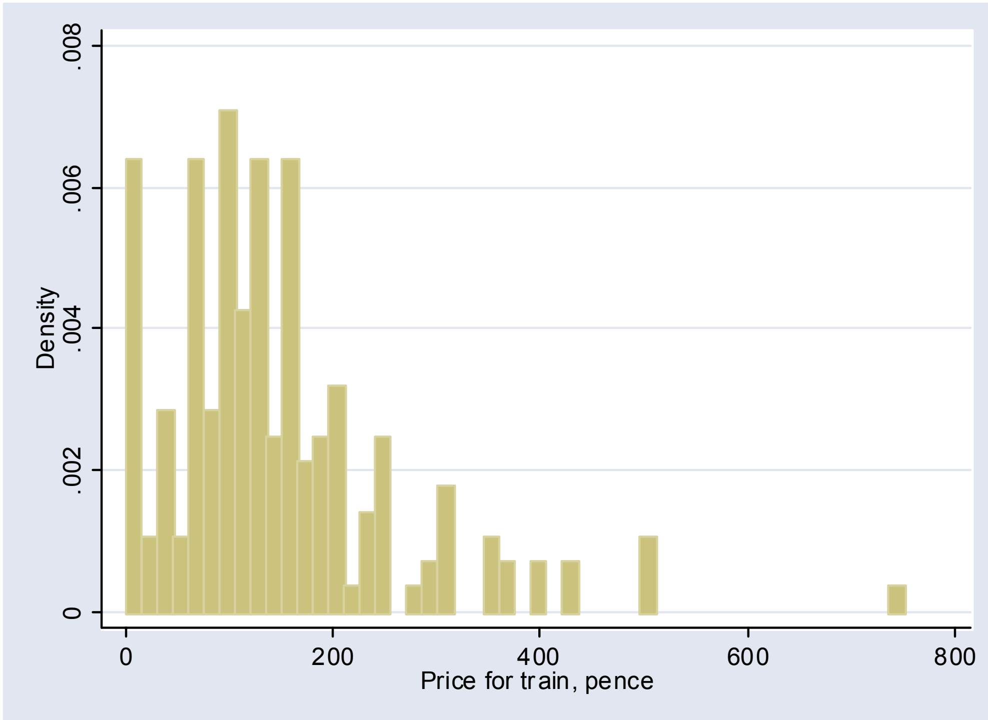


Figure 2.2: Train prices (pence)



2.4 In-vehicle journey time data

Data for several time-related factors was collected. This section reports the data collected in relation to in-vehicle journey time for the mode of transport chosen, as well as for the alternative. The data in these questions was combined into single measures of in-vehicle journey time, measured in minutes.

Table 2.10 summarises the length of journey by mode in minutes.

Table 2.10: In-vehicle journey time (minutes)

Time	Observations	Mean	Standard deviation	Min.	Max.
Actual journeys					
Bus	*106*	*28.9*	*16.82*	*5*	*120*
Time (off-peak)	60	27.3	13.1	5	60
Time (peak)	46	31.0	20.67	10	120
Train	*90*	*23.5*	*20.42*	*4*	*150*
Time (off-peak)	42	24.7	24.68	4	150
Time (peak)	48	22.4	15.98	5	90
Alternative journeys					
Bus	*90*	*46.4*	*24.40*	*10*	*120*
Time (off-peak)	42	46.2	23.91	15	120
Time (peak)	48	46.6	25.07	10	120
Train	*106*	*20.7*	*15.96*	*3*	*105*
Time (off-peak)	60	22.1	18.16	3	105
Time (peak)	46	18.8	12.48	5	70

Note: This data covers only those 196 respondents included in the modelling.

Table 2.10 demonstrates that, overall, respondents perceive train journeys to be shorter than bus journeys, although there is an interesting comparison to be made between the actual and the alternative data. The information from bus users shows that, on average, bus users perceive trains to take eight minutes less than the bus for their actual journey, while train users perceive the bus to take twice as long as the train—23 minutes longer.

Looking at the differences between peak and off-peak in-vehicle journey times, the difference between actual bus journeys and the alternative train options is greater during peak hours, and is smaller during off-peak times.

Figures 2.3 and 2.4 show the distribution of bus and train journey times, truncated for the purposes of these graphs to show those journeys that took 60 minutes or less.

Figure 2.3: Distribution of bus journey time (minutes)

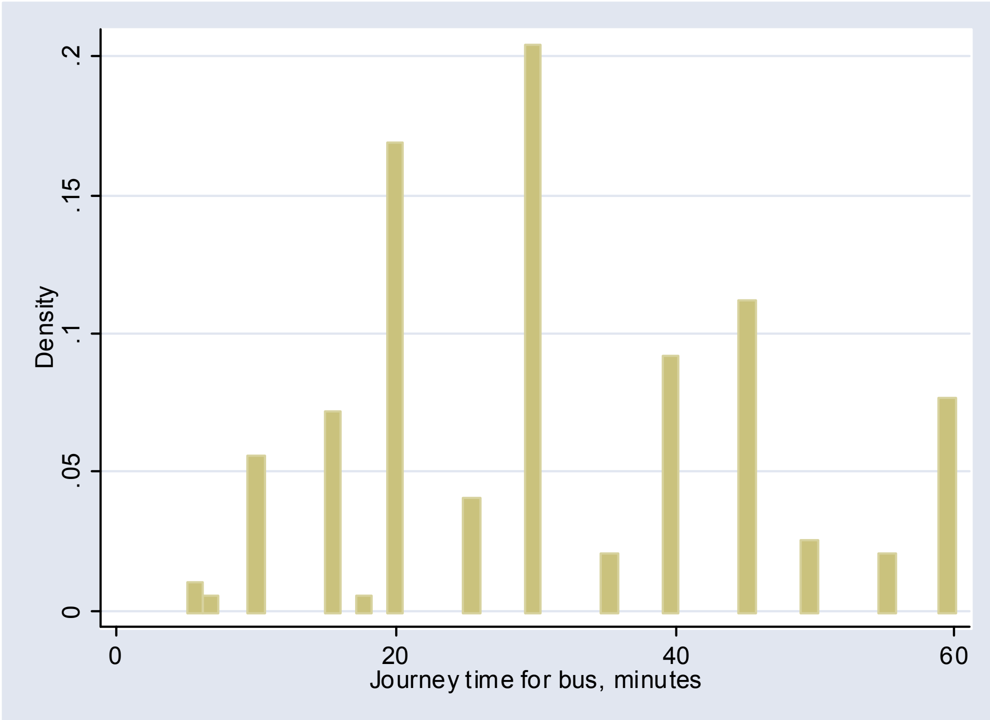
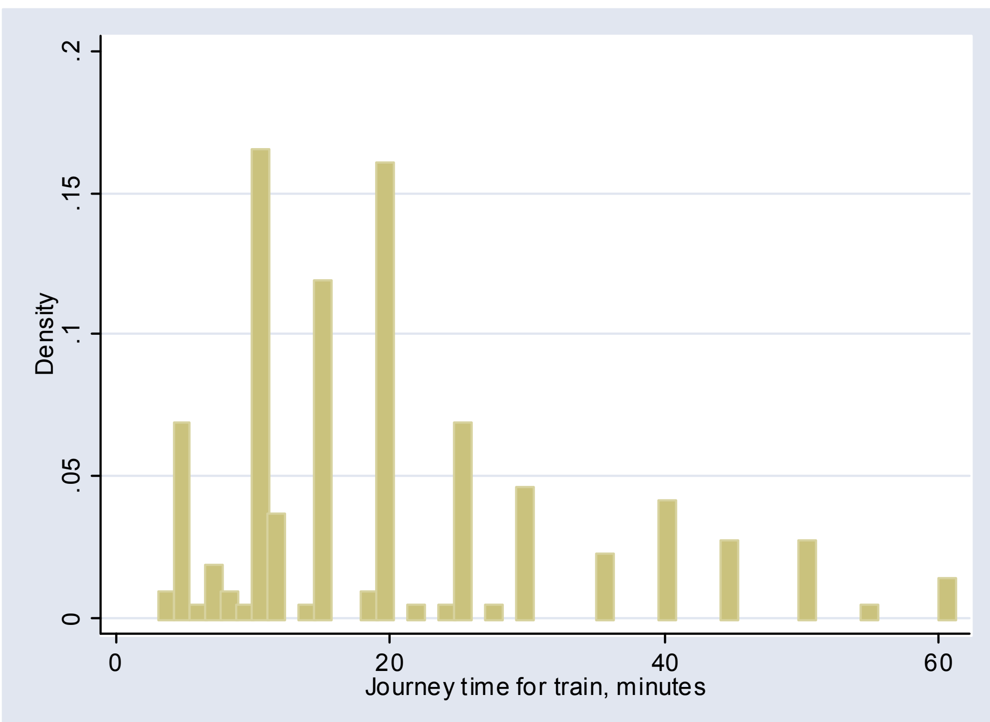


Figure 2.4: Distribution of train journey time (minutes)



2.5 Access and egress time data

An important determinant in any transport mode choice is the convenience of the start and end points of the transport link, and the time it takes to reach both the starting point of the journey (access time) and the final destination (egress time). Data was therefore collected on these attributes, and combined to form a variable showing the total access and egress time.[4] Table 2.11 summarises the access and egress times by mode.

Table 2.11: Access and egress time (minutes)

Time	Observations	Mean	Standard deviation	Min.	Max.
Actual journeys					
Bus	*106*	*13.7*	*12.14*	*2*	*75*
Time (off-peak)	60	13.5	10.48	2	60
Time (peak)	46	14.1	14.25	2	75
Train	*90*	*20.3*	*16.93*	*5*	*120*
Time (off-peak)	42	21.2	20.26	5	120
Time (peak)	48	19.6	13.5	5	70
Alternative journeys					
Bus	*90*	*24.6*	*19.13*	*3*	*100*
Time (off-peak)	42	27.3	22.38	3	100
Time (peak)	48	22.3	15.63	7	92
Train	*106*	*32.8*	*21.72*	*4*	*110*
Time (off-peak)	60	35.0	23.85	4	90
Time (peak)	46	30.0	18.4	6	110

Note: This data covers only those 196 respondents included in the modelling.

The notable points to highlight from this data are that, on average, respondents have lower access and egress times for their actual transport mode, when compared with the alternatives. For train users, the difference is four minutes, while, for bus users, the difference is much greater, at 19 minutes. This pattern is unchanged when looking at peak and off-peak journeys.

Figures 2.5 and 2.6 show the distribution of bus and train journey times.

[4] Modelling access and egress times together is standard practice in transport modelling, rather than attempting to model separate effects for each.

Figure 2.5: Distribution of bus access and egress times (minutes)

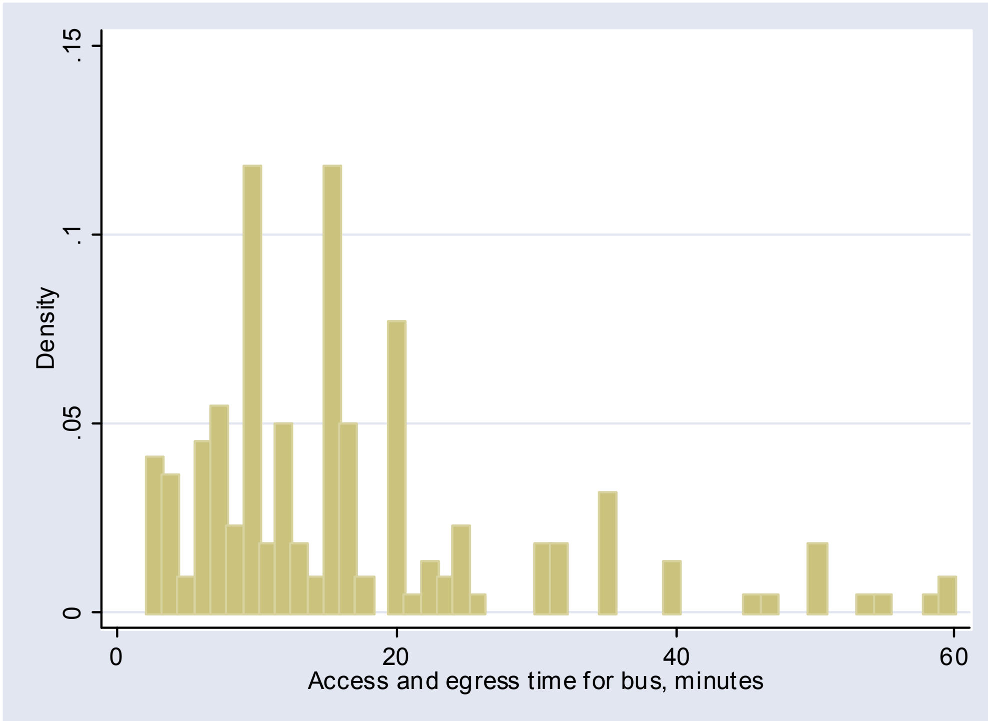
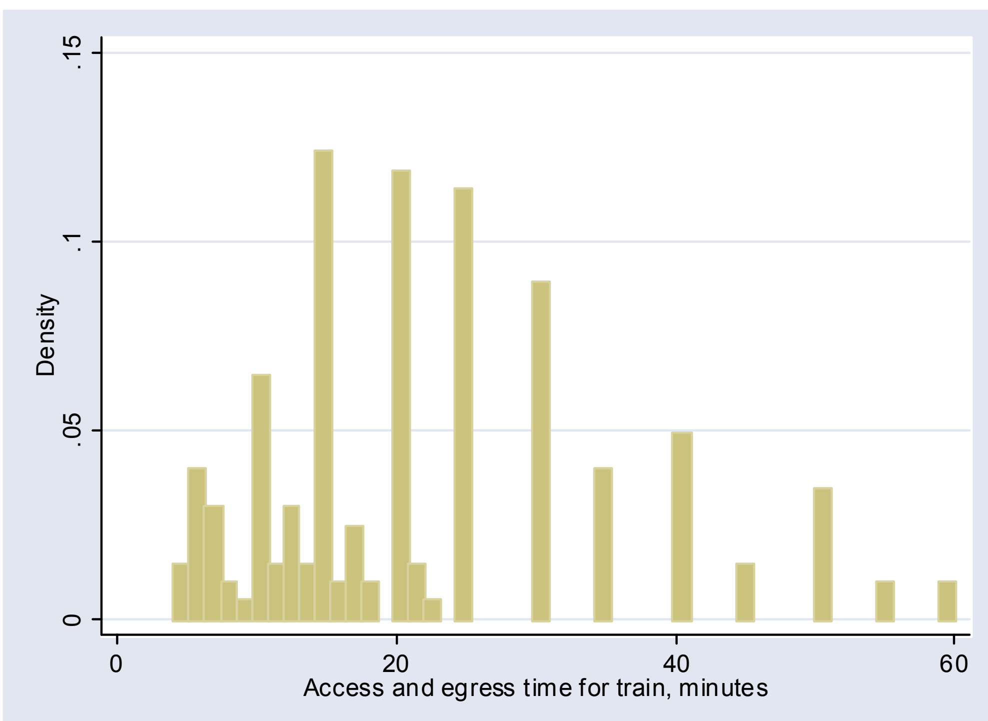


Figure 2.6: Distribution of train access and egress times (minutes)



2.6 Headway data

The final, separate component of journey time on which data was collected related to headway (a measure of the frequency of the public transport service). Respondents were asked how frequently the service arrived at the time of day that they took their journey. Respondents were asked to indicate, within a range, how often the service arrives (in minutes). The midpoint of the range was used to define the variable. This data is summarised by mode in Table 2.12.

Table 2.12: Headway (minutes)

Time	Observations	Mean	Standard deviation	Min.	Max.
Actual journeys					
Bus	*106*	*13.3*	*10.12*	*3*	*75*
Time (off-peak)	60	14.5	8.52	3	53
Time (peak)	46	11.7	11.80	3	75
Train	*90*	*22.3*	*14.91*	*3*	*75*
Time (off-peak)	42	22.5	16.19	3	75
Time (peak)	48	22.1	13.85	8	75
Alternative journeys					
Bus	*89*	*19.7*	*13.24*	*3*	*75*
Time (off-peak)	42	18.7	11.71	3	53
Time (peak)	48	20.6	14.50	3	75
Train	*106*	*23.9*	*12.12*	*3*	*75*
Time (off-peak)	60	22.8	8.98	3	53
Time (peak)	46	25.4	15.26	8	75

Note: This data covers only those 196 respondents included in the modelling.

As might be expected, users reported lower headways for bus (around 13 minutes) than for rail (around 22 minutes). While users of peak bus services reported lower headways than others, the same pattern did not hold for rail users. Average headways quoted by respondents for their alternative mode journeys tended to be higher than for people who actually travelled on that mode; this may reflect discrepancies in the level of service across different areas, or the typical location of bus and rail users. At peak times, the perceived headway for bus users (11.7 minutes) is less than half that of the train as an alternative (25.4 minutes). The differences perceived by train users still show buses to have a lower headway on average, but the magnitude of the differences is less.

Table 2.13 presents the frequency distribution of respondents' answers (headway) and shows that it is uneven. There are peaks at 6–10 minutes for bus and 11–15 minutes for train, and further peaks for both forms of transport at 21–30 minutes.

Table 2.13: Headway (number of respondents in each category)

Range (minutes)	Midpoint (minutes)	Bus (frequency)	Train (frequency)
1–5	3	21	3
6–10	8	56	25
11–15	13	37	33
16–20	18	29	23
21–30	25.5	41	87
31–45	38	4	11
45–60	53	6	9
60+	75	2	5
Total		**196**	**196**

Note: This includes actual and hypothetical journeys.

2.7 Total journey time (door to door)

As an alternative to the separate time-related components of a journey, respondents were also asked about their total journey time. For journeys in which the respondents took only a single bus or train, total journey time was expected to be less than the sum of the access and egress times, in-vehicle times and headway. This is because transport users will normally try to reach the station or bus stop just in advance of the departure time, so that, for example, even if the train leaves only every half-hour, that would represent the maximum possible waiting time.

If respondents' journeys involved multiple stages, the total journey time would also incorporate the waiting time for each stage, as well as the additional travel time for the other modes. Of the sample of respondents used in the modelling exercise, the majority of journeys (75%) involved only a single stage; almost all of the others consisted of two stages.

Table 2.14 shows door-to-door journey time by actual and alternative choice, and for bus and train. Average door-to-door journey times reported by bus and rail users were quite similar (51 versus 47 minutes). It is interesting to note that the rail users felt that the total journey time for alternative bus journeys would have been substantially greater than their actual journey time, whereas bus users on average would have faced a small increase in journey time had they travelled by rail. Nevertheless, the latter finding is relevant, in that it suggests that the typical bus user faces a rail alternative that is on average both more expensive and would take longer. This suggests that, even if train services offered a feasible alternative to bus, switching from bus to rail by this group would be unlikely in the absence of substantial changes in journey price and duration.

Table 2.14: Door-to-door journey time (minutes)

Time	Observations	Mean	Standard deviation	Min.	Max.
Actual journeys					
Bus	*106*	*51.3*	*39.94*	*5*	*300*
Time (off-peak)	60	53.4	44.87	5	300
Time (peak)	46	48.5	32.70	15	180
Train	*90*	*47.0*	*38.22*	*5*	*300*
Time (off-peak)	42	49.9	50.56	5	300
Time (peak)	48	44.5	22.8	10	120
Alternative journeys					
Bus	*89*	*80.1*	*70.81*	*18*	*600*
Time (off-peak)	41	88.4	91.03	20	600
Time (peak)	48	73.0	47.16	18	300
Train	*106*	*53.8*	*31.92*	*10*	*240*
Time (off-peak)	60	55.1	37.5	10	240
Time (peak)	46	52.2	23.09	15	120

2.8 Summary of data used in the model

Table 2.15 summarises the data that was used in the modelling exercise undertaken by OXERA and reported below. In general, the data was as expected: bus prices are (or are perceived to be) lower than train prices; and in-vehicle journey time is, or is perceived to be, less for trains.

Even this initial review of the data raised concerns in the context of a choice modelling exercise. In particular, the fact that bus users considered the price of their journeys to be less than that of the train, together with the finding that total journey times were shorter when taking the bus (mostly due to the shorter access and egress times), suggested that respondents were not faced with a situation in which trading between the modes was a viable option. Were an average bus user to switch, they would face not only a higher price for the journey, but also a longer journey time. It would therefore make little sense for that average person to switch away from the bus.

Table 2.15: Summary of actual and alternative data

Variable	Observations	Price (pence)	Total journey time (minutes)	In-vehicle time (minutes)	Headway (minutes)	Access and egress (minutes)
Bus as actual	106	101.3	51.3	28.9	13.3	13.8
Train as alternative	106	156.1	53.8	20.7	23.9	32.8
Train as actual	89 or 90	242.5	47.0[1]	23.5	22.3	20.3
Bus as alternative	90	173.6	80.1	46.4	19.7	24.6

Note: [1] 89 train users answered total journey time.

3. Ease of Switching and Diversion Rates

3.1 Ease of switching

In addition to the information on journey characteristics outlined above, the survey was used to collect information on the perceived ease of switching between the mode of choice and the alternative, the transfer prices and times (ie, the amount that prices would have to rise to induce respondents to switch), as well as information on respondents' diversion factors, a measure of what they would do, if they were not to continue to use their current mode of public transport. This sub-section describes the data on ease of switching; sections 3.2 and 3.3 examine the transfer price data and the diversion rates.[5]

Respondents were asked how easy or difficult they would find it to switch to the alternative mode. Table 3.1 shows that bus users, in particular, would find it difficult to switch to trains. Of bus users, 55% would find it difficult to switch, compared with 33% of train users who would find it difficult to switch. This may be due to the wider variety of destinations offered by bus routes.

Looking at those respondents who travelled during peak times, similar overall patterns are observed for those who would find it difficult to switch. However, more peak than off-peak train users would find it easy to switch. The converse was found for bus users.

[5] The information in this section is derived from the sample of 196. It may therefore not be representative of the wider NOP sample.

Table 3.1: Ease of switching

	Total sample	Peak users	Off-peak users
All respondents			
Difficult (%)	44.9	42.6	47.1
Easy (%)	33.2	36.2	30.4
Neutral (%)	20.9	21.3	20.6
Total (N)	196	94	102
Bus users			
Difficult (%)	54.7	52.2	56.7
Easy (%)	25.5	21.7	28.3
Neutral (%)	18.9	26.1	13.3
Total (N)	106	46	60
Train users			
Difficult (%)	33.3	33.3	33.3
Easy (%)	42.2	50.0	33.3
Neutral (%)	23.3	16.7	31.0
Total (N)	90	48	42

Tables 3.2 to 3.6 describe ease of switching broken down into the supplied demographics. Table 3.7 highlights the sub-groups of respondents that would find it proportionately more difficult to switch than the average of the sample.

Table 3.2: Ease of switching, by age (%)

	15–24	25–34	35–44	45–54	55–64	65+	Total
Difficult	55.3	39.5	36.6	37.9	52.9	58.8	44.9
Easy	38.3	39.5	34.1	31.0	29.4	11.8	33.2
Neutral	6.4	20.9	29.3	31.0	17.6	29.4	20.9
	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Share of sample	24.2	22.2	21.1	14.9	8.8	8.8	100.0

Table 3.3: Ease of switching, by occupational status (%)

	Employed full-time	Employed part-time	Looking after home/ family	Permanently retired	Unemployed and seeking work	Full-time higher education	Attending school or full-time education	Permanent sick or disabled	Total
Difficult	42.0	45.0	33.3	56.5	37.5	45.0	80.0	66.7	44.9
Easy	35.0	20.0	33.3	17.4	62.5	55.0	20.0	16.7	33.2
Neutral	23.0	35.0	33.3	26.1	0.0	0.0	0.0	16.7	20.9
	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Share of sample	51.5	10.3	6.2	11.9	4.1	10.3	2.6	3.1	100.0

Table 3.4: Ease of switching, by income band (%)

	Under £10,000	£10,000–£19,999	£20,000–£29,999	£30,000–£39,999	£40,000–£49,999	£50,000–£59,999	£60,000–£99,999	£100,000+	Total
Difficult	55.9	45.3	40.8	75.0	33.3	16.7	25.0	0.0	44.9
Easy	29.4	35.8	30.6	12.5	44.4	50.0	75.0	100.0	33.2
Neutral	14.7	18.9	28.6	12.5	22.2	33.3	0.0	0.0	20.9
	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Share of sample	19.8	30.8	28.5	9.3	5.2	3.5	2.3	0.6	100.0

Table 3.5: Ease of switching, by gender (%)

	Male	Female	Total
Difficult	35.0	52.6	44.9
Easy	43.8	26.3	33.2
Neutral	21.3	21.1	20.9
	100.0	100.0	100.0
Share of sample	41.2	58.8	100.0

Table 3.6: Ease of switching, by journey purpose (%)

	Going to work	Taking children to/from school	Going to college	Shopping for food	Shopping for non-food items	Personal business	Leisure trips	Going out in the evening	Total
Difficult	37.0	100.0	35.7	83.3	47.4	60.0	51.4	27.3	44.9
Easy	39.7	0.0	57.1	8.3	28.9	10.0	31.4	36.4	33.2
Neutral	23.3	0.0	7.1	8.3	23.7	30.0	17.1	36.4	20.9
	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Share of sample	37.6	0.5	7.2	6.2	19.6	5.2	18.0	5.7	100.0

Table 3.7 summarises the information in the ease of switching tables above, highlighting groups that would find it relatively more difficult to switch—for example, the group of 15–24-year olds

was 10.4 percentage points more likely to find it difficult to switch than the overall sample (ie, 44.9% + 10.4% = 55.3%).

Table 3.7: Sub-groups finding it difficult to switch

Group/sub-group	
Total sample	44.9%
	Percentage point difference from total sample:
15–24 age group	+10.4
55–64 age group	+8
65+ age group	+13.9
Retired	+11.6
Sick/disabled	+21.7
<£10,000 income	+9.8
£30,000—£40,000 income	+28.9
Female	+7.8

3.2 Transfer prices

Respondents were asked: 'What is the most you would pay for the same ticket before you would stop using the [bus or train, as appropriate]?' The response has been divided by the average number of trips the respondent made using that ticket in order to infer a single-journey maximum price that the respondent would pay before switching. Subtracting the actual price paid per trip gives the maximum price increase a consumer would accept for a single journey before switching to the alternative mode.

In this analysis, any negative responses have been excluded, and only respondents who would have switched from bus to train, or train to bus have been included.

Table 3.8 shows the maximum increase in price that a respondent would accept before switching mode for bus and train users.

Table 3.8: Maximum increase in price before switching (pence)

	Observations	Mean	Standard deviation	Min.	Max.
All users	123	47.50	78.39	0.71	625
Bus users	61	42.87	85.38	0.71	625
Train users	62	52.05	71.26	2.86	500

Train users appear to accept a higher increase in price before switching than bus users, although this is likely to be related to higher average train fares compared with bus fares.

3.3 Diversion rates

Respondents were asked: 'If you did stop using the [bus or train, as appropriate] for that journey, what would you do instead?' To identify differences between the diversion rates of bus users and train users, the figures are presented separately for each breakdown. Table 3.9 presents information on diversion rates overall, Table 3.10 for peak users and Table 3.11 for off-peak users.

Table 3.9: Diversion rates by mode (%)

	Train	Bus	Total
Use the bus instead	63.3	n/a	30.2
Switch operator	n/a	18.2	9.5
Use the train instead	n/a	40.9	21.4
Use the underground instead	1.7	4.5	3.2
Use car, motorbike or scooter	31.7	21.2	26.2
Walk or cycle	1.7	9.1	5.6
Make the journey less often	0.0	1.5	0.8
Not make the journey	1.7	1.5	1.6
Travel elsewhere	0.0	3.0	1.6
	100	100	100
Share of sample	46.9	53.1	100

Table 3.10: Diversion rates by mode, peak hours (%)

Peak times	Train	Bus	Total
Use the bus instead	54.8	n/a	27.0
Switch operator	n/a	n/a	11.1
Use the train instead	n/a	31.3	15.9
Use the underground instead	3.2	6.3	4.8
Use car, motorbike or scooter	35.5	18.8	27.0
Walk or cycle	3.2	12.5	7.9
Make the journey less often	0.0	0.0	0.0
Not make the journey	3.2	3.1	3.2
Travel elsewhere	0.0	3.1	1.6
	100	100	100
Share of sub-sample	49.2	50.8	100

Table 3.11: Diversion rates by mode, off-peak hours (%)

Peak times	Train	Bus	Total
Use the bus instead	72.4	n/a	27.0
Switch operator	n/a	13.9	11.1
Use the train instead	n/a	47.2	15.9
Use the underground instead	0.0	2.8	4.8
Use car, motorbike or scooter	27.6	22.2	27.0
Walk or cycle	0.0	5.6	7.9
Make the journey less often	0.0	2.8	0.0
Not make the journey	0.0	0.0	3.2
Travel elsewhere	0.0	2.8	1.6
	100	100	100
Share of sub-sample	44.6	55.4	100

These tables show that a lower proportion of peak-time train users (54.8%) would switch to use the bus than off-peak users (72.4%), with most of those not switching to the bus switching to a car, motorbike or scooter instead, regardless of the time of day. For bus users, the diversion patterns are more complex. A much smaller proportion of bus users would switch to use the train (40.9%, compared with the 63.3% of train users who would use the bus). Furthermore, a lower proportion would use private motorised transport as an alternative, and a higher proportion would either cycle or walk. This reflects the generally shorter nature of bus journeys, as well as different patterns of car ownership among bus and train users. Among bus users, 18.2% would switch to use another operator's bus service.[6]

Tables 3.12 to 3.19 show the split between train users who would switch to bus and bus users who would switch to train, broken down by the supplied demographics.

Table 3.12: Diversion rates for bus users, by age (%)

	15–24	25–34	35–44	45–54	55–64	65+	Total
Switch operator	26.1	16.7	0.0	30.0	0.0	0.0	17.6
Use the train instead	34.8	55.6	50.0	10.0	50.0	0.0	39.7
Use the underground instead	8.7	0.0	0.0	10.0	0.0	0.0	4.4
Use car, motorbike or scooter	17.4	22.2	21.4	20.0	50.0	0.0	20.6
Walk or cycle	4.3	5.6	14.3	20.0	0.0	0.0	8.8
Make the journey less often	0.0	0.0	7.1	0.0	0.0	0.0	1.5
Not make the journey	0.0	0.0	0.0	0.0	0.0	100.0	1.5
Travel elsewhere	4.3	0.0	7.1	0.0	0.0	0.0	2.9
	100	100	100	100	100	100	100
Share of sample	33.8	26.5	20.6	14.7	2.9	1.5	100

Table 3.13: Diversion rates for train users, by age (%)

	15–24	25–34	35–44	45–54	55–64	65+	Total
Use the bus instead	75.0	52.9	53.8	88.9	42.9	100.0	63.3
Use the underground instead	0.0	0.0	7.7	0.0	0.0	0.0	1.7
Use car, motorbike or scooter	25.0	47.1	38.5	11.1	28.6	0.0	31.7
Walk or cycle	0.0	0.0	0.0	0.0	14.3	0.0	1.7
Not make the journey	0.0	0.0	0.0	0.0	14.3	0.0	1.7
	100	100	100	100	100	100	100
Share of sample	20.0	28.3	21.7	15.0	11.7	3.3	100.0

[6] Information on the proportion of routes on which actual bus competition currently takes place would be needed to assess the closeness of competition. Many of those who responded that they would switch to the train may not currently be able to switch to another operator's bus service.

Table 3.14: Diversion rates for bus users, by occupational status (%)

	Employed full-time	Employed part-time	Looking after home/family	Permanently retired	Unemployed and seeking work	Full-time higher education	Attending school or full-time education	Permanent sick or disabled	Total
Switch operator	17.6	28.6	12.5	0.0	0.0	22.2	100.0	0.0	17.6
Use the train instead	32.4	42.9	62.5	50.0	75.0	33.3	0.0	33.3	39.7
Use the underground instead	5.9	0.0	0.0	0.0	0.0	11.1	0.0	0.0	4.4
Use car, motorbike or scooter	23.5	28.6	0.0	0.0	25.0	22.2	0.0	33.3	20.6
Walk or cycle	11.8	0.0	25.0	0.0	0.0	0.0	0.0	0.0	8.8
Make the journey less often	0.0	0.0	0.0	0.0	0.0	0.0	0.0	33.3	1.5
Not make the journey	0.0	0.0	0.0	50.0	0.0	0.0	0.0	0.0	1.5
Travel elsewhere	5.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.9
	100	100	100	100	100	100	100	100	100
Share of sample	50.0	10.3	11.8	2.9	5.9	13.2	1.5	4.4	100

Table 3.15: Diversion rates for bus users, by occupational status (%)

	Employed full-time	Employed part-time	Looking after home/family	Permanently retired	Unemployed and seeking work	Full-time higher education	Attending school or full-time education	Permanent sick or disabled	Total
Use the bus instead	64.7	50.0	0.0	75.0	50.0	75.0	66.7		63.3
Use the underground instead	0.0	12.5	0.0	0.0	0.0	0.0	0.0		1.7
Use car, motorbike or scooter	35.3	25.0	100.0	0.0	50.0	25.0	33.3		31.7
Walk or cycle	0.0	12.5	0.0	0.0	0.0	0.0	0.0		1.7
Not make the journey	0.0	0.0	0.0	25.0	0.0	0.0	0.0		1.7
	100	100	100	100	100	100	100		100
Share of sample	56.7	13.3	1.7	6.7	3.3	13.3	5.0	0.0	100

Table 3.16: Diversion rates for bus users, by gender (%)

	Male	Female	Total
Switch operator	28.0	11.6	17.6
Use the train instead	28.0	46.5	39.7
Use the underground instead	4.0	4.7	4.4
Use car, motorbike or scooter	12.0	25.6	20.6
Walk or bicycle	12.0	7.0	8.8
Make the journey less	4.0	0.0	1.5
Not make the journey	0.0	2.3	1.5
Travel elsewhere	8.0	0.0	2.9
	100	100	100
Share of sample	36.8	63.2	100

Table 3.17: Diversion rates for train users, by gender (%)

	Male	Female	Total
Use the bus instead	58.1	69.0	63.3
Use the underground instead	0.0	3.4	1.7
Use car, motorbike or scooter	38.7	24.1	31.7
Walk or cycle	0.0	3.4	1.7
Not make the journey	3.2	0.0	1.7
	100	100	100
Share of sample	51.7	48.3	100

Table 3.18: Diversion rates for bus users, by journey purpose (%)

	Work	Going to school/college	Food shopping	Non-food shopping	Personal	Leisure	Evening	Total
Switch operator	11.5	37.5	0.0	18.2	25.0	15.4	33.3	17.6
Use the train instead	46.2	37.5	66.7	9.1	25.0	53.8	33.3	39.7
Use the underground instead	0.0	0.0	0.0	9.1	0.0	7.7	33.3	4.4
Use car, motorbike or scooter	26.9	12.5	0.0	36.4	50.0	15.4	0.0	23.5
Walk or cycle	7.7	0.0	0.0	9.1	0.0	7.7	0.0	5.9
Make the journey less often	0.0	0.0	33.3	0.0	0.0	0.0	0.0	1.5
	100	100	100	100	100	100	100	100
Share of sample	38.2	11.8	4.4	16.2	5.9	19.1	4.4	100

Table 3.19: Diversion rates for train users, by journey purpose (%)

	Work	Going to school/college	Food shopping	Non-food shopping	Personal	Leisure	Evening	Total
Use the bus instead	60.0	100.0		61.5	0.0	57.1	100.0	63.3
Use the underground instead	0.0	0.0		0.0	0.0	7.1	0.0	1.7
Use car, motorbike or scooter	40.0	0.0		30.8	100.0	28.6	0.0	31.7
Walk or cycle	0.0	0.0		7.7	0.0	0.0	0.0	1.7
Not make the journey	0.0	0.0		0.0	0.0	7.1	0.0	1.7
	100	100		100	100	100	100	100
Share of sample	41.7	6.7	0.0	21.7	1.7	23.3	5.0	100

Table 3.20 summarises the diversion rate information, showing which sub-groups have a higher propensity than average to switch from train to bus and from bus to train. From a comparison of the switching directions (bus to train and train to bus), it appears that there are few systematic similarities between the characteristics of those who would switch modes.

Table 3.20: Sub-groups with higher propensity to switch between bus and train

Group/sub-group	From train to bus	From bus to train
Total sample	63.3	40.9
	Percentage point difference from total sample:	
15–24 age group	+11.7	-
25–34 age group	-	+15.9
35–44 age group	-	+10.3
45–54 age group	+25.6	
55–64 age group	-	+10.3
Looking after home/family	-	+22.8
Retired	+11.7	+10.3
Unemployed and seeking work	-	+35.3
Full-time higher education	+11.7	-
Female	+5.7	+6.8
Going to work	-	+6.5
Leisure	-	+14.1

4. Choice Modelling Results

4.1 Correlations

Before starting the modelling exercise, correlations were run to identify any relationships between the variables that may have hindered the subsequent modelling exercise. If correlations between any two variables are low, this suggests that there is little, if any, relationship between them. However, correlations that are close to zero can introduce problems of collinearity. Table 4.1 shows the correlations between the variables that were used in the modelling exercise.

C*hoice of mode* is a dummy variable representing the actual mode that respondents chose.

Table 4.1: Correlations

	Choice of mode	Price	In-vehicle time	Headway	Access and egress	Time of day	Age	Income	Gender
Choice of mode	1								
Price	0.0308	1							
In-vehicle time	–0.1403	0.354	1						
Headway	–0.1965	0.1069	0.2455	1					
Access and egress	–0.3172	0.0807	0.2917	0.2813	1				
Time of day	0.0027	0.0696	–0.0167	0.0129	–0.0778	1			
Age	0.0334	–0.1177	–0.0824	–0.0431	0.032	–0.2519	1		
Income	0.0605	0.0338	–0.0076	0.0201	–0.0032	0.0458	–0.0182	1	
Gender	0.0013	–0.1052	–0.0577	–0.0742	–0.0081	–0.0392	0.0855	–0.0701	1

Note: The correlation table uses data on the price of bus and train, and actual and alternative modes.

The correlations in Table 4.1 indicate that the most important factors determining choice relate to the characteristics of the journey (in-vehicle time, headway, and access and egress time) rather than the demographics. The demographic factors all had low correlations with choice. It was also notable that price had a positive but low correlation with the choice variable.

4.2 Modelling approach

The main focus of interest in this exercise centred on establishing the degree to which rail and bus are substitutes. A methodology to examine the competition between them was therefore needed. In this context, an appropriate and well-established approach is to analyse the choices that individuals make between these two alternatives. Given that there are only two alternatives, the standard logit procedure is appropriate, which involves explaining the probability of choosing a particular option as a function of the travel characteristics of the two—in particular, price, in-vehicle time, headway, and access and egress time.

How individuals respond to variations in these travel characteristics is a function of their personal and situational characteristics, such as income level, or whether the journey is for commuting or leisure purposes. The standard logit model can accommodate such variations by specifying incremental terms, of the form of dummy variable interactions, to allow the sensitivity to, say, cost to vary with income level, or time to vary with journey purpose.

Given the main focus of the research, and the nature of the information collected, the standard logit procedure was considered the most appropriate model to estimate. The logit model applied is described in the Technical Appendix.

4.3 Model estimation

In order to estimate a model that was not being driven by outlying observations, cut-off points for several variables were defined. Observations with a journey time longer than 180 minutes, a price higher than £30, or an access and egress time longer than 120 minutes were excluded. This left a sample size of only 196 respondents who had answered all of the necessary questions. This is below the usual minimum for estimating a choice model. Choice models require much larger sample sizes than conventional econometric models because the binary dependent variable which proxies utility contains much less information than a continuous variable and does not give any indication of the level of difference in utility, only that one set of characteristics yields a higher utility than the alternative.

The four factors included in the choice model (price, in-vehicle time, headway, and access and egress time) are those considered crucial in determining the utility of an individual when choosing between the two modes of transport. This expectation was supported by the correlations that were run, with the exception of price, which was found to have a low correlation with respondents' choices. These explanatory factors capture the characteristics of each mode that are expected to influence the individual's decision between modes. Due to the high proportion of respondents who did not answer some of the questions, the sample size restricts the explanatory power of the model. Had the dataset contained a richer selection of data, more control variables, such as peak and off-peak users, could have been included to derive elasticities specific to each group.

The aggregate model that was estimated yielded the coefficients and standard errors in Table 4.2.

Table 4.2: Choice model

	Price	In-vehicle time	Headway	Access and egress	ASC (bus)
Coefficient	0.00023	–0.03308	–0.03021	–0.06936	0.05448
Standard error	0.00068	0.01108	0.01400	0.01382	0.27492
z	0.34	–2.98	–2.16	–5.02	0.20
P>|z|	0.73	0.00	0.03	0.00	0.84
Log likelihood	–95.97				
N	196				

Note: ASC, alternative-specific constant (see Technical Appendix).

The log-likelihood test for the joint significance of the coefficients shows them to be jointly significant.

The coefficients in the model only indicate the relative importance of each factor in determining respondents' utility; they do not have a direct interpretation of their own. Elasticities derived using these coefficients are presented in section 5.1.

The negative values of the coefficients on the time, headway, and access and egress variables show that increases in these variables all reduce utility. These estimates are significant at the 5% level.

No effect was found for price in determining utility, as the coefficient is insignificant and very close to zero. This insignificance means that, in this model, price does not have a statistically significant impact on utility. Several categories of respondent were excluded to test the consistency of this result, including respondents who reported a zero cost (in general, concessionary-fare travellers), and those with high-cost journeys; however, the overall result was not affected. Although, in theory, a negative coefficient was to be expected on the coefficient on price (because increases in price are expected to reduce utility), none of the formulations modelled produced a negative coefficient, and none of the models produced a statistically significant result. The potential reasons for this result are explored in section 4.6 below.

4.4 Modelling peak and off-peak differences

The time of day that journeys are taken can be expected to make a difference to the respondents' decisions on travel choices. For example, if the duration of a journey by bus is expected to be affected by congestion, whereas the duration of the journey by train is not expected to be affected by congestion, this could affect the decision taken. Furthermore, the characteristics of the travellers may mean that their tastes, and hence their demand, for transport differ.

Although the sample that can be used for modelling (even in aggregate) is small, the feasibility of identifying statistically significant differences in the demand elasticities between peak and off-peak times has been explored.[7] The two approaches adopted to explore the peak-time effects were to estimate separate models for peak and off-peak times; and to estimate a combined model, but introducing interactive variables on the determinant factors (eg, a peak-price variable), thereby enabling the incremental effects of the variable on peak-time travel to be estimated.

Of these two approaches, the second represents the more parsimonious, and more likely to generate results. Nevertheless, the results of the first approach are presented in Table 4.3 below.

[7] During the course of this research, it was suggested to OXERA that it would be possible to model any peak and off-peak difference using a hierarchical, nested logit model. However, such a model has no role in this binary choice context because its purpose is to overcome the common cross-elasticity properties of the logit model when more than two alternatives are examined. It would only serve a purpose in this binary choice context, if different datasets were being combined and it is necessary to allow for different scales between the two. An example of this is the combined analysis of revealed- and stated-preference data.

In principle, it is possible to extend the analysis to the joint choice of mode and time of departure. This would require a hierarchical logit approach, given the possibility that the cross-elasticities are not equal. The alternatives might be peak travel by train, off-peak travel by train, peak travel by bus, and off-peak travel by bus. However, to implement such an approach would have demanded the collection of additional information relevant to the choice of time of travel, particularly the amount of schedule delay involved for each alternative and the degree of arrival-time flexibility. In any event, this would have to be restricted to choices within a particular journey purpose. For example, the time of travel choice for the journey to work could be examined, but the choice of whether to travel to work or to make a leisure trip is not relevant to the current inquiry.

Table 4.3: Separate peak and off-peak model results

	Price	In-vehicle time	Headway	Access and egress	ASC (bus)
Peak					
Coefficient	–0.00015	–0.051	–0.051	–0.080	.0048
Standard error	0.00082	0.018	0.021	0.022	0.40
z	–0.19	–2.89	–2.42	–3.68	0.01
P>|z|	0.85	0.004*	0.015*	0.00**	0.99
Log likelihood	–42.58				
N	94				
Off-peak					
Coefficient	0.0018	–0.021	–0.011	–0.068	0.21
Standard error	0.0019	0.015	0.021	0.019	0.40
z	0.98	–1.34	–0.53	–3.57	0.52
P>|z|	0.33	0.18	0.60	0.00**	0.60
Log likelihood	–50.81				
N	102				

Note: * significant at 5% confidence level; ** significant at 1% confidence level.

Although the log-likelihood tests of these separate models do indicate that the coefficients are jointly significant, the models suffer from the small number of observations—in particular that for off-peak travel, which has produced particularly weak results in statistical terms. Of the explanators in the off-peak model, only access and egress is found to be significant. As for the combined model, the coefficient on price is both wrongly signed and insignificant.

The peak model performs better in terms of the individual coefficients. As in the combined model presented in Table 4.2, the coefficients on in-vehicle time, headway, and access and egress time journey are all correctly signed and statistically significant at the 95% level. While the coefficient on price is correctly signed, the significance tests show that no reliance should be placed on this figure.

Table 4.4 presents the results of the second model run to explore the peak and off-peak effects. As described above, this involves modelling the base variables as well as dummy variables that were interacted with each of the other variables. These dummy interaction variables represent the incremental effects of taking the journey at peak times; the base variables represent the off-peak effects.

Table 4.4: Modelling with peak dummy interaction results

	Price	In-vehicle time	Headway	Access and egress	ASC (bus)
Main coefficients					
Coefficient	0.0017	–0.01814	–0.01354	–0.06885	0.10790
Standard error	0.0018	0.01350	0.02059	0.01875	.28519
z	0.94	–1.34	–0.66	–3.67	.38
P>|z|	0.35	0.18	0.51	0.00**	.71
Peak interactions					
Coefficient	–0.00184	–0.03544	–0.03589	–0.01043	–
Standard error	0.00198	0.01870	0.02827	0.02851	–
z	–0.93	–1.90	–1.27	–0.37	–
P>|z|	0.35	0.06*	0.20	0.72	–
Log likelihood	–93.46				
N	196				

Note: * significant at 10% confidence level; ** significant at 1% confidence level.

The results presented in Table 4.4 do not provide a statistically justified basis for deriving separate elasticities for peak and off-peak travel. While the log-likelihood test is passed, showing that the coefficients are jointly significant, only the estimated coefficient for access and egress time is significant at the 5% level; the incremental variable for peak-time in-vehicle time is significant at 10%. None of the other estimates is statistically significant.

A further model was run with only an incremental peak effect on price. Although this again produced no price effect, for completeness, the results of that model are presented in Table 4.5.

Table 4.5: Choice model with peak price variable

	Price	Peak price	In-vehicle time	Headway	Access and egress	ASC (bus)
Coefficient	0.00157	–0.00154	–0.03381	–0.03045	–0.07073	0.09143
Standard error	0.00177	0.00189	0.01122	0.01403	0.01397	0.27987
z	0.89	–0.82	–3.01	–2.17	–5.06	0.33
P>|z|	0.373	0.414	0.00**	0.03*	0.00**	0.74
Log likelihood	–95.94					
N	196					

Note: * significant at confidence 5%; ** significant at 1% confidence level.

Given the lack of significant findings in relation to the peak variables, the preferred model is therefore that which is presented in Table 4.2, which produced significant results in relation to the time-related factors, but did not produce any significant price effect. As this price result was unexpected, it was therefore necessary to explore the data in more detail to try to understand why no price effect appeared.

4.5 Modelling total time variant

As an alternative to modelling all of the time-related factors separately, the following two variants of the model were estimated using data from the question relating to total journey time. In the first model estimated, headway was included as a separate explanatory variable; in the second, headway was excluded and assumed to be subsumed within respondents' answers in relation to total door-to-door journey time.

Tables 4.6 and 4.7 present the results of these two models, and show that the inclusion of headway does have the effect of marginally reducing the coefficient on door-to-door time. However, consistent with the results outlined above, price is not found in either model to have any significant impact on utility.

Table 4.6: Choice model for door-to-door elasticities, including headway

	Price	Door-to-door time	Headway	ASC (bus)
Coefficient	0.00035	–0.02819	–0.04234	0.24432
Standard error	0.00051	0.00631	0.01307	0.19564
z	0.68	–4.47	–3.24	1.25
P>|z|	0.494	0	0.001	0.212
Log likelihood	–109.28			
N	195			

The model reported in Table 4.7, excluding headway, enabled an additional 30 observations to be included.

Table 4.7: Choice model for door-to-door elasticities, excluding headway

	Price	Door-to-door time	ASC (bus)
Coefficient	0.00026	–0.034	0.51
Standard error	0.00050	0.0063	0.16
z	0.51	–5.46	3.08
P>|z|	0.607	0	0
Log likelihood	–130.06		
N	225		

Elasticities derived from modelling total door-to-door journey time are reported in section 5.3 below.

4.6 Investigating the lack of a price effect

In modelling transport choices, it is unusual not to find an effect for price on individual's utility, and the lack of any statistical finding warrants further investigation. There are several reasons why price may not appear to affect utility using this data and model specification. For example, a significant proportion of the respondents faced no price incentive between different modes of transport. Of the 196 respondents, 45 (or 23%) would have paid the same price regardless of which mode they used. The presence of these respondents in the model will therefore have muted any price effect in the model. This compares with 11 respondents who faced the same journey time on the actual and alternative modes, and 18 on access and egress time.

The lack of price variation is emphasised in the figures below, which present the difference between actual and alternative values for both price and in-vehicle journey time. As these show, the price difference exhibits relatively little variation when compared with in-vehicle journey time. Also, the high proportion of respondents who experience no price effect is shown by the height of the central bar in Figure 4.1.

Therefore, while the difference between prices behaves as expected, with bus being on average less expensive than train (see also Table 2.8), the variable exhibits insufficient variation to be able to model its effects with significance. This does not imply that price does not influence utility, only that the survey has not identified a sufficient proportion of respondents for whom bus and train are close substitutes to extract information on demand responses to price.

Figure 4.1: Distribution of difference in price between actual and alternative modes (pence)

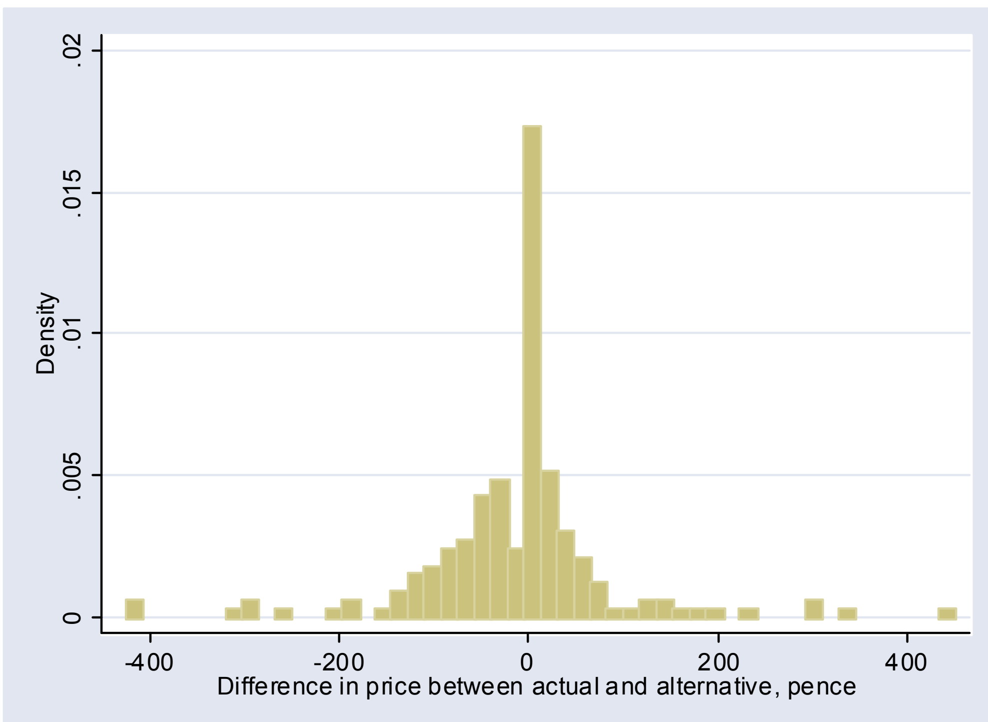


Figure 4.2: Distribution of difference in journey time between actual and alternative modes (minutes)

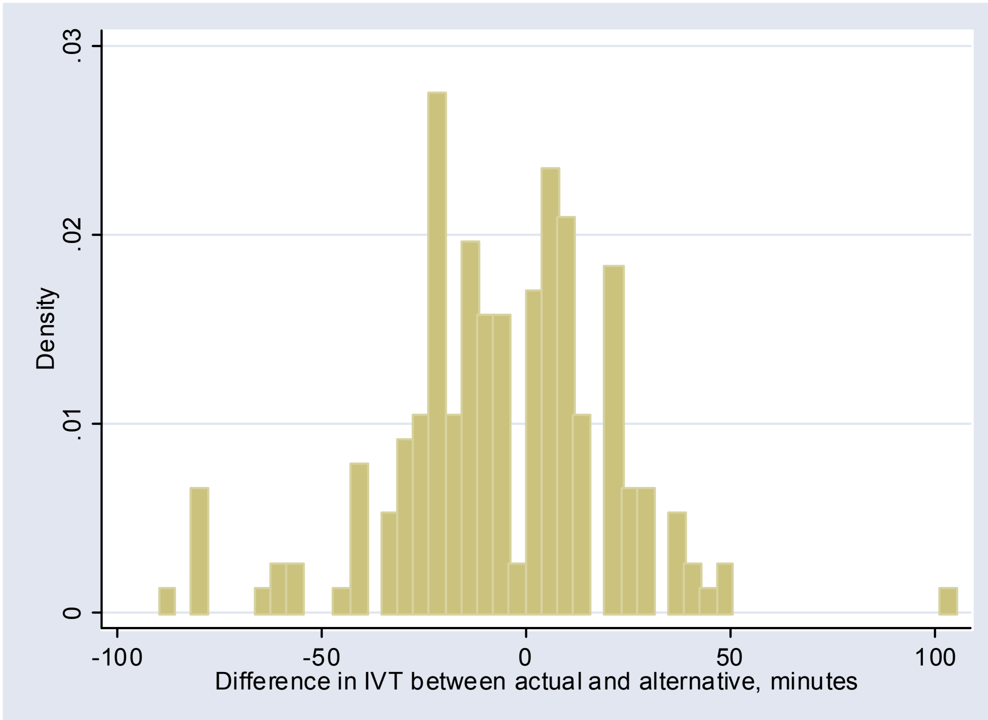


Figure 4.3: Distribution of difference in access and egress time between actual and alternative modes (minutes)

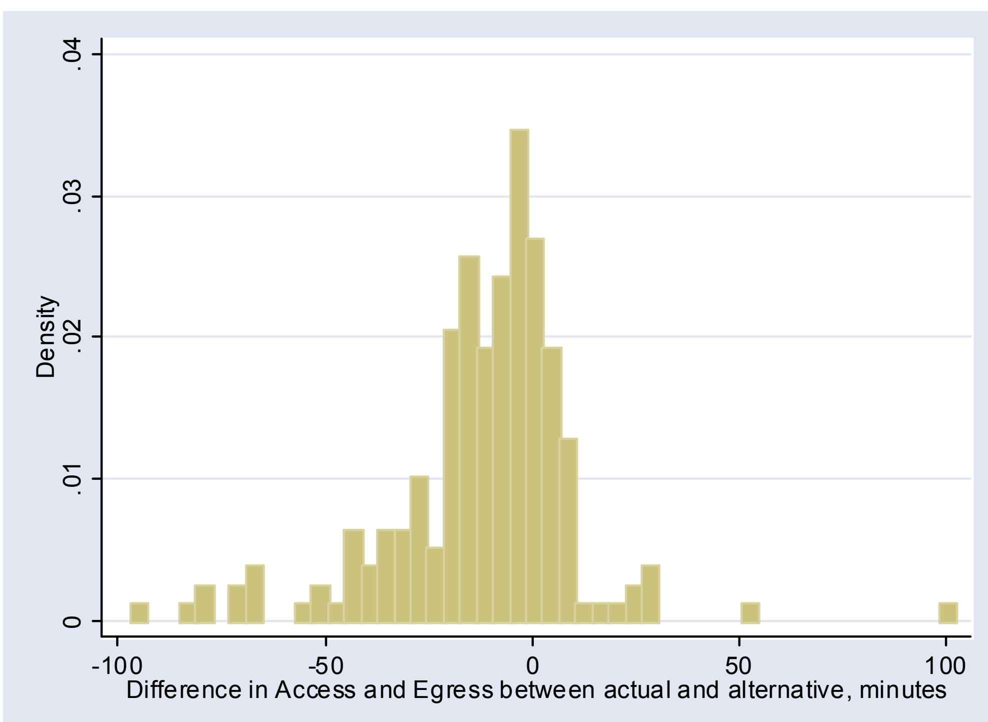


Table 4.8 demonstrates that, on average, those respondents who would find it difficult to switch face a higher price for the alternative than the actual. Conversely, those respondents who would find it easy to switch face a lower price for the alternative than their actual journey. This indicates that price may influence how people perceive the ease of switching from one mode to another.

Table 4.8: Average difference in price by ease of switching (pence)

Ease of switching	Average price difference between actual and alternative
Difficult	–15.89
Easy	15.78
Neutral	21.10
Total (weighted average)	**2.02**

Further investigation of the data indicates that a significant minority of the sample answered questions relating to an alternative journey that was not only more expensive than the actual mode they used, but also took longer overall. This was the case for 15 of the 46 peak-time bus users; 19 of the 60 off-peak bus users; 12 of the 48 peak-time train users, and eight of the 42 off-peak train users. Overall, this represents 54 of the 196 respondents used in the model. In choice modelling terms, this means that these respondents were ‘non-traders’—in other words, while they faced an alternative, the alternative was worse than the actual in several ways, and therefore was not a feasible choice. This attribute of the data can create problems when modelling choices in identifying with precision the values of the coefficients of the relevant attributes. This problem was exacerbated by the fact that a further 45 respondents faced no price effect whatsoever. This meant that, of the total sample of 196 respondents, 99 faced either no price incentives or price incentives that would have constrained their switching behaviour.

A final explanation may be that the sample selection methodology (random number dialling in postcode areas with a train station) has not identified respondents with feasible alternatives. However, the consistency of the time-related elasticities reported in section 5 with those in previous studies suggests that this is not a significant factor.

5. Estimating Elasticities

The approach outlined in the Technical Appendix generates a respondent-specific elasticity that can then be summarised to show the average elasticity for bus and train users.

5.1 Price elasticities

As the calculations of elasticity rely on finding a statistically significant coefficient on the explanatory variable in the model, it is not possible to calculate either own- or cross-price elasticities on the basis of the data modelled above.

5.2 Time elasticities

Own- and cross-elasticities have been calculated with respect to each of the explanatory factors related to time described above and used in the modelling. Those related to in-vehicle time, headway, and access and egress time are presented, as well as elasticity related to the measure of total time used in the model presented in section 4.5.[8]

5.2.1 Journey time elasticities

Table 5.1 shows the distribution of elasticities with respect to journey time for bus and train users. The elasticities are presented as distributions, with means, standard deviations and minimum and maximum figures also provided. This is because they are calculated by taking the average of the estimates of each individual's elasticity in the sample, given the predicted coefficient in the model in Table 4.2.

The interpretation of the elasticity estimates is that, for all users, a rise of 1% in journey time would lead to a fall of 0.54% in demand. This data shows that bus demand is more sensitive to journey time than train demand.

Table 5.1: Distribution of own-elasticities with respect to journey time

	Mean	Standard deviation	Min.	Max.
All	–0.54	0.67	–4.96	0.00
Train	–0.41	0.55	–4.96	0.00
Bus	–0.66	0.76	–3.76	0.00
N	196			

Table 5.2 presents the relevant cross-elasticities, both of which are positive, as expected, indicating that bus and train are substitutes for each other. These cross-elasticities also indicate that the

[8] In this form of discrete choice model where there is binary choice between two modes, there is no leakage to other modes of transport other than bus to train and train to bus. Therefore, the own-elasticities estimated using these techniques represent a lower bound for own-elasticities. If switching to other modes could be incorporated into the model, own-elasticities would be higher than estimated. However, this feature of the model does not affect the cross-elasticities that are most relevant for the purposes of assessing the impact of the merger.

demand for trains is more responsive to changes in bus journey times than bus demand is for changes in train journey times.

Table 5.2: Distribution of cross-elasticities with respect to journey time

	Mean	Standard deviation	Min.	Max.
Demand for train with respect to journey time of bus	0.56	0.38	0.00	2.59
Demand for bus with respect to journey time of train	0.41	0.55	0.00	4.96
N	196			

Table 5.3 presents the estimates of the elasticities in a slightly different format, and provides information on the upper and lower bounds of the elasticity estimates.[9] This was to take into account the fact that the coefficients used to calculate the elasticities are themselves estimates derived from the modelling process. The coefficient estimates are therefore associated with standard errors that give a numerical range within which it is possible to be 95% confident that the 'true' value of the coefficient lies. The upper and lower bounds of the elasticities in Table 5.3 (and in equivalent tables that follow for the other time-related factors) are calculated using the top and bottom of the estimated range for the coefficients.

Table 5.3: Upper and lower bounds of journey time elasticities

	Lower bound	Mean	Upper bound
Own-elasticities			
All	–0.18	–0.54	–0.89
Train	–0.14	–0.41	–0.68
Bus	–0.23	–0.66	–1.10
Cross-elasticities			
Demand for train with respect to journey time of bus	0.19	0.56	0.92
Demand for bus with respect to journey time of train	0.14	0.41	0.68
N	196		

5.2.2 Headway elasticities

This section presents elasticity information for headway in the same format as for the in-vehicle journey time in the preceding section. Table 5.4 shows the distribution of elasticities with respect to headway. Caution needs to be applied when interpreting these values, as they are derived from grouped data, as described in section 2.6.

[9] The Commission specifically requested that the estimates be presented in this form.

Table 5.4: Distribution of elasticities with respect to headway

	Mean	Standard deviation	Min.	Max.
All	–0.33	0.36	–2.27	0.00
Train	–0.41	0.38	–2.27	0.00
Bus	–0.25	0.32	–2.14	0.00
N	196			

As headway is the only statistically significant variable that will be under the control of the merged company, the elasticities of demand with respect to the alternative mode are of particular interest. Table 5.5 indicates that a 1% increase in the headway of bus services will lead to a 0.24% increase in train demand. However, a 1% increase in train headway would lead to a 0.41% increase in bus use. This indicates that users are more sensitive to the frequency of trains than of buses.

Table 5.5: Distribution of cross-elasticities of demand with respect to headway

	Mean	Standard deviation	Min.	Max.
Demand for train with respect to headway time of bus	0.24	0.24	0.00	1.97
Demand for bus with respect to headway time of train	0.41	0.38	0.00	2.27
N	196			

Table 5.6 presents the upper and lower bounds of headway elasticities in the same format as for journey time elasticities in Table 5.3.

Table 5.6: Upper and lower bounds of headway elasticities

	Lower bound	Mean	Upper bound
Own-elasticities			
All	–0.03	–0.33	–0.63
Train	–0.04	–0.41	–0.78
Bus	–0.02	–0.25	–0.49
Cross-elasticities			
Demand for train with respect to headway time of bus	0.02	0.24	0.45
Demand for bus with respect to headway time of train	0.04	0.41	0.78
N	196		

5.2.3 Access and egress time elasticities

Table 5.7 shows the distribution of elasticities with respect to access and egress time. These elasticity estimates are higher than those relating to in-vehicle time. This indicates that the proximity of start and end points of the mode to the origin and destination points of the individual are more important in determining demand than in-vehicle journey time. This is seen in the larger negative coefficient on access and egress time in the utility function. Respondents dislike an increase in access and egress time more than they dislike an increase in journey time.

Table 5.7: Distribution of elasticities with respect to access and egress time

	Mean	Standard deviation	Min.	Max.
All	–1.01	1.37	–8.32	0.00
Train	–1.25	1.53	–8.32	0.00
Bus	–0.77	1.14	–6.93	0.00
N	196			

Table 5.8: Distribution of cross-elasticities of demand with respect to access and egress time

	Mean	Standard deviation	Min.	Max.
demand for train with respect to access and egress time of bus	0.53	0.46	0	2.56
demand for bus with respect to access and egress time of train	1.25	1.24	0	8.32
N	196			

Table 5.9 presents the upper and lower bounds of access and egress elasticities in the same format as for journey time elasticities in Table 5.3.

Table 5.9: Upper and lower bounds of access and egress time elasticities

	Lower bound	Mean	Upper bound
Own-elasticities			
All	–0.61	–1.01	–1.40
Train	–0.76	–1.25	–1.74
Bus	–0.47	–0.77	–1.07
Cross-elasticities			
Demand for train with respect to access and egress time of bus	0.33	0.53	0.74
Demand for bus with respect to access and egress time of train	0.76	1.25	1.74
N	196		

5.3 Estimating door-to-door journey time elasticities

In order to obtain elasticities relating to door-to-door journey times, total journey time was included in the model. As described above, two variants of this total time model were run, including and excluding headway. Table 5.10 presents elasticities derived from the model where headway was excluded as a separate explanator.

Table 5.10: Distribution of elasticities with respect to door-to-door journey time

	Mean	Standard deviation	Min	Max
All	–1.15	1.72	–20.54	0.00
Train	–1.04	1.48	–18.49	0.00
Bus	–1.26	1.93	–20.54	0.00
N	225			

Table 5.11: Distribution of cross-elasticities of demand with respect to door-to-door journey time

	Mean	Standard deviation	Min.	Max.
Demand for train with respect to door-to-door time of bus	0.89	0.51	0.00	3.82
Demand for bus with respect to door-to-door time of train	1.04	1.49	0.00	18.49
N	225			

Table 5.12 presents the upper and lower bounds of total time elasticities.

Table 5.12: Upper and lower bounds of door-to-door journey time elasticities

	Lower bound	Mean	Upper bound
Own-elasticities			
All	–0.74	–1.15	–1.56
Train	–0.67	–1.04	–1.41
Bus	–0.81	–1.26	–1.72
Cross-elasticities			
Demand for train with respect to door-to-door time of bus	0.57	0.89	1.21
Demand for bus with respect to door-to-door time of train	0.67	1.04	1.41
N	225		

5.4 Indicative elasticities by sub-sample

The above elasticities have been calculated for the complete sample, based on discrete choices between bus and train. While, by definition, all the respondents to this survey had this choice between bus and train, the data reported in section 3.3 showed that switching from bus to train or vice versa would not be their first choice. This section reports the results of the analysis of whether elasticities vary depending on the alternative form of transport that the respondents would have taken.

As the modelling has not enabled statistically robust estimates of coefficients for these different sub-groups, these elasticities should be considered indicative only, and should not be relied on as statistically robust results.

Table 5.13: Elasticities by mode of diversion

	Price[1]	In-vehicle time	Headway	Access and egress	Door-to-door journey time
Use a bus instead		–0.61	–0.35	–0.84	–0.84
Use another company's bus		–0.60	–0.40	–1.09	–1.37
Use the train instead		–0.41	–0.26	–0.93	–0.83
Use the underground instead[2]		–0.34	–0.24	–0.80	–0.52
Use car, motorbike or scooter		–0.56	–0.32	–0.90	–0.85
Walk or cycle		–0.37	–0.45	–1.94	–0.90
Make the journey less often[3]		–0.08	–0.12	–0.71	–0.30
Not make the journey[3]		–0.41	–0.23	–0.83	–0.63
Travel elsewhere[3]		–0.22	–0.51	–0.67	–0.41
Total		**–0.54**	**–0.33**	**–1.01**	**–1.15**

Note: **1** Confidential data. **2** Price, in-vehicle time, headway, access and egress, and door-to-door journey time figures based on fewer than 10 responses. **3** Price, in-vehicle time, headway, and access and egress figures based on fewer than 10 responses.

As this data shows, for total journey time there is little difference between the indicative elasticity estimates for those switching from bus to train, train to bus, and either bus or train to car. It is also notable that those bus users who answered that they would use another company's bus appear to have higher elasticities than others in the sample. This reflects the fact that, where there is head-to-head competition between buses, the competing bus operator is likely to be a closer alternative than a switch to train.

Undertaking comparable analysis for peak and off-peak journeys shows that for in-vehicle journey time and headway, there is virtually no difference in the indicative elasticities. For access and egress and door-to-door time, off-peak travellers exhibit a higher elasticity than peak-time travellers.

Table 5.14: Elasticities by peak and off-peak

	Price[1]	In-vehicle time	Headway	Access and egress	Door-to-door journey time
Off-peak		–0.54	–0.32	–1.11	–0.98
Peak		–0.53	–0.34	–0.90	–0.87
Total		**–0.54**	**–0.33**	**–1.01**	**–1.15**

Note: **1** Confidential data.

6. Additional Modelling

6.1 Transfer price modelling

To obtain a measure of the responsiveness of demand to changes in price, the transfer price data was investigated further. Calculating by how much the price would have to rise before an individual switched to the other mode gives a direct measure of consumer surplus. The following transfer price model was estimated:

$$TP = \alpha_0 + \alpha_1(\text{Price}_{alt} - \text{Price}_{actual}) + \alpha_2(Time_{alt} - Time_{actual}) + \alpha_3(A\&E_{alt} - A\&E_{actual})$$

where:

- *TP* is the transfer price to switch from the chosen mode;
- *Price* is the price of each mode for a single journey;
- *Time* is the in-vehicle time for the journey;
- *A&E* is the access and egress time for the journey.

The model was run only for those respondents who would switch to either the bus or train from their current mode. This was because the model is seeking to identify the impact that the difference of each of the key characteristics has on switching behaviour between bus and train. This left a sample of 77 observations. As the dependent variable is a continuous variable, ordinary least squares regression is used, which is less sensitive to small sample bias than logit modelling.

The model produced the coefficients shown in Table 6.1.

Table 6.1: Transfer price model

	Constant	Price	Time	Access and egress
Coefficient	–2.298	–0.16	0.78	1.28
t-ratio	0.16	4.49	1.87	1.15

The model has the correct sign on the coefficients for time, and access and egress, although the latter is insignificant at 5%. However, the price variable has the wrong sign. If price were an important factor in determining this set of respondents' utility, the coefficient on the difference in price (alternative–actual) should be positive and close to 1. The negative significant value may be due to spurious correlations in the data or the lack of close substitution between bus and train. The model does not explain the price effect any more than the logit model.

6.2 Generalised cost modelling

6.2.1 Modelling approach

In the previous choice modelling, the drivers of utility were the price faced by the consumer and the factors that affected the length of time that the journey would take (in-vehicle time, access and egress, and headway). The choice modelling predicts which mode individuals will take based on the characteristics of each mode and how they affect utility. This imposes a constraint that the value of time is the same across all individuals, and that all individuals respond in the same way to changes in the characteristics of the mode. A more flexible assumption would be that individuals' values of time vary according to their socioeconomic characteristics.

Applying a generalised cost function allows each demographic segment of the sample to have their own value of time figure, which is then multiplied by the observed length of time for the door-to-door journey. This puts the observed value of door-to-door journey time in money-metric terms, which are specific to the demographic segment of that individual. By adding the money-metric measure of the time taken for the journey to the fare paid, a 'generalised cost' figure is arrived at for each individual. This generalised cost can then be used to replace the existing explanators (price and total door-to-door journey time). The elasticity then obtained from the generalised cost model is an aggregate elasticity of both price and time effects. These effects can be separated out using the average proportion of price to money-metric journey time in order to give separate measures of the price and journey time elasticity. The method outlined below follows that used by Lythgoe and Wardman in creating a generalised cost model for 'Modelling Passenger Demand for Parkway Rail Stations'.[10] (For a more detailed description of generalised cost modelling, see Ortúzar and Willumsen.)[11]

6.2.2 Values of time

To obtain a total value of time for each respondent's journey, values of time were obtained from a report by Mackie et al.[12] Using Tables 25 and 26 in that report, a weighted value of time was constructed by income bands and journey purpose. The values of time reported were for end-1997 values and prices. These were updated to be comparable with the NOP survey using the Office of National Statistics Average Earnings index.[13] The weighted, updated values of time are shown in Table 6.2.

Table 6.2: Weighted and updated values of time by income and journey purpose (pence per minute)

Income band (£)	Commuting	Other
<17,500	3.37	3.88
17,500–35,000	4.99	4.84
35,000+	6.99	5.77

Source: OXERA calculations.

These values of time were applied to the NOP data using the income bands and journey purpose questions in the survey. The income bands do not match exactly, but once earnings growth has been taken into account, the bands are of similar size.

The money-metric measure of journey time is calculated by multiplying the appropriate value of time by the door-to-door journey time, in minutes. The generalised cost is calculated by adding the money-metric value of the journey time to the price paid by the individual for the journey (or the hypothetical price and journey time in the case of the alternative).

[10] Lythgoe, W.F. and Wardman, M. (2004), 'Modelling Passenger Demand for Parkway Rail Stations', *Transportation*, **31**:2, May.
[11] Ortúzar, J. de D. and Willumsen, L.G. (1999), *Modelling Transport*, second edition, John Wiley & Sons, p. 153.
[12] Mackie, P.J., Wardman, M., Fowkes, A.S., Whelan, G. and Nellthorp, J. (Institute for Transport Studies, University of Leeds) and Bates, J. (John Bates Services), (2003), 'Values of Travel Time Savings in the UK', report to the Department for Transport, January.
[13] Office of National Statistics (2004), 'Average Earnings Index 1963–2004'.

6.2.3 Generalised cost model

The generalised cost model is still a choice model, but instead of utility being explained by the components of the journey, it is explained by the aggregated generalised cost measure defined above. The regression uses data from 197 individuals and passes the log-likelihood ratio test that the coefficients are jointly significant. The regression is reported in Table 6.3.

Table 6.3: Generalised cost model

	Generalised cost	ASC (bus)
Coefficient	–0.0088	0.5219
Standard error	0.0016	0.1788
z	–5.42	2.92
P>|z|	0.000	0.004

When using the generalised cost measure, a negative and significant impact is found on the overall cost of the journey (including time and price).

6.2.4 Deriving elasticities

Estimates of the elasticity with respect to the generalised cost are found in the same way as the elasticities for the choice model were derived (more detail is available in the Technical Appendix). The average elasticity for the generalised cost is –1.35 and can be split by train and bus users, as in Table 6.4.

Table 6.4: Distribution of elasticities with respect to generalised cost

	Mean	Standard deviation	Min.	Max.
All	–1.35	1.94	–20.38	0.00
Train	–1.10	1.48	–15.93	0.00
Bus	–1.59	2.29	–20.38	0.00
N	197			

Table 6.4 shows an aggregate elasticity relating to the combined effect of price and journey time. To disaggregate the price and time effects, the elasticity can be apportioned according to the average proportion of price to journey time, since they are both in units of pence, although these results do not imply that a significant price effect was found. The generalised cost model indicates that the generalised cost of the journey (including price and time) has a significantly negative effect on the utility of individuals and that part of that negative effect is the price of the mode. Table 6.5 below shows the distribution of price and time elasticities using this method.

Table 6.5: Distribution of disaggregated elasticities with respect to generalised cost

	Mean	Standard deviation	Min.	Max.
Price				
All	–0.47	0.67	–7.08	0.00
Train	–0.38	0.51	–5.53	0.00
Bus	–0.55	0.80	–7.08	0.00
Time				
All	–0.88	1.27	–13.30	0.00
Train	–0.72	0.96	–10.40	0.00
Bus	–1.04	1.49	–13.30	0.00
N	197			

The elasticities relating to the door-to-door journey time found in Table 6.5 are of a similar magnitude to those found in the choice model in Table 5.6.

7. Conclusions

The discrete choice modelling undertaken during the course of this research has produced estimates of time elasticities that, in general, comply with estimates previously obtained in relation to bus and train travel.

Time elasticities

The statistically significant own- and cross-elasticities derived from the aggregate model are presented in Table 7.1.

Table 7.1: Mean elasticities

	In-vehicle journey time	Headway	Access and egress time	Door-to-door journey time
Own-elasticities				
All	–0.54	–0.33	–1.01	–1.15
Train	–0.41	–0.41	–1.25	–1.04
Bus	–0.66	–0.25	–0.77	–1.26
Cross-elasticities				
Demand for train with respect to bus characteristics	0.56	0.24	0.53	0.89
Demand for bus with respect to train characteristics	0.41	0.41	1.25	1.04
N	196			

In relation to in-vehicle time, the evidence from previous studies suggests an elasticity in the range –0.6 to –0.8, although evidence from the two Scotland studies suggests values outside this range: in one case above, and in the other below.[14] The own-elasticities estimated by OXERA in this research are at the low end of the estimates from previous studies of in-vehicle time elasticity.

This research has added to the previous literature and has produced some new estimates of cross-elasticities on which little evidence has been previously available. For example, new estimates of cross-elasticities have been produced with respect to the different time components. The estimates for the separate time components are preferred as they provided richer information than those for total door-to-door journey time, and enable focus to be placed on the aspects that the company could manipulate strategically after the merger (especially headway).

Furthermore, the elasticities estimated in this research are based on information that is specific to the localities most likely to be affected by the merger, and they relate specifically to bus–train interactions, which are at the core of the Commission's assessments.

Price elasticities

No price effect was found, despite a wide range of options being explored. The generalised cost approach provided some indicative values, suggesting that bus price elasticities were greater than train price elasticities.

[14] The literature is summarised in a separate paper provided by OXERA to the Commission, and is available at www.competition-commission.org.uk.

The results of that previous literature on fare elasticities show that short-run bus fare elasticities are in the range –0.35 to –0.5, increasing to around –1 in the long-run. There is relatively limited specific evidence on Scotland, but the evidence that is available suggests that elasticities for trips taken within Scotland are slightly higher than the British average.

Short-run rail elasticities seem to be in the range –0.5 to –0.7, increasing to –0.75 to –1.0 in the long run. Scottish market studies are broadly consistent with these conclusions; although there is some evidence to suggest that long-run own-price elasticities are slightly higher than the British average.

There is mixed evidence on cross-elasticities. Modelling work by OXERA suggests a cross-price elasticity of rail demand to bus costs of around 0.45 (with no discernible further long-term effects), while two studies of bus and rail demand in Scotland found this elasticity to be smaller. For the cross-price elasticity of bus demand to rail costs, the opposite pattern holds, with the OXERA evidence pointing to 0.08 in the short run and 0.15 in the long run, with a piece of Scottish evidence showing higher sensitivities of bus demand to rail cost (0.35).

Appendix: Technical Appendix

Choice modelling approach

To model respondents' choice between bus and train journeys (and ultimately derive relevant elasticities), a discrete choice model has been adopted. The generic model that was initially estimated predicted the probability that an individual takes the train rather than the bus, based on responses given to the questions on the price, journey time, frequency and access/egress time of both the mode that the respondent actually took, and the equivalent data for the alternative mode that they did not take.

The development of the models is based on the multinomial logit (below).

$$P_i = \frac{\exp(U_i)}{\sum_n \exp(U_n)}$$

where:

- exp is the exponential function;
- P_i is the probability that the individual will choose mode i, where i equals bus or train;
- n is the number of modes to choose between—in this model, two;
- U_i is the utility of choosing mode i, which is a function of the characteristics of the individual and the attributes of the mode.

The attributes of the mode include price, journey time, frequency and access/egress time, as defined in section 2.

Theoretically, it would be possible to extend the generic model to control for income effects, journey purpose and peak versus off-peak travel. In the current modelling exercise, the sample size has not allowed robust exploration of these categories of transport user.

Intuitively, the choice model takes each respondent's actual and alternative mode and assumes they choose the mode that maximises their utility. The absolute level of utility is irrelevant in this context; only the relative valuations of the two choices are of concern.

By maximising the utility function, the model finds optimal values for the coefficients on each of the variables.

In the choice model, a constant is attached to one or other of the modes in order to capture the average effect on utility of all factors not included in the model. This is commonly referred to as an 'alternative-specific constant'.

Deriving elasticities

Although it is usual to report price elasticities, as the coefficient on price is insignificant, price elasticities have not been reported here. An elasticity based on an insignificant result is unlikely to be robust in significance or accuracy.

Elasticities with respect to time, headway, and access and egress times can, however, be calculated. Below is an example of how to calculate the elasticity of demand with respect to time.

In a discrete choice model, the elasticity with respect to time describes the change in the probability that an individual chooses an alternative, given a one-unit change in time. Assuming that representative utility is linear in price, the elasticity for train demand with respect to time can be calculated as:

$$\mathrm{E}_{t,P} = \beta_1 P_t (1 - p(b))$$

where:

- $E_{t,P}$ is the elasticity of train journeys with respect to the time of train journeys;
- P_t is the level of the time of train journeys;
- β_1 is the coefficient on the time of train journeys;
- *p(b)* is the probability of taking the alternative (bus).

A similar approach will be taken to estimate the elasticity for bus use, replacing the price of train journeys with the price of bus journeys, and the probability of choosing the bus with the probability of choosing the train.

Using the formula above, an elasticity of –0.5 would indicate that a 1% increase in train journey times would lead to a 0.5% decrease in train demand.

Cross-time elasticities between train and bus modes are calculated in a similar way using the following formula:

$$\mathrm{E}_{BT} = -p(t)\beta_1 T_t$$

where:

- E_{BT} is the cross-time elasticity of bus journeys with respect to the time of train journeys;
- T_t is the time of the train journeys;
- β_1 is the coefficient on the time of train journeys;
- $p(t)$ is the probability of taking the train.