THE DEMAND FOR LONGER DISTANCE RAIL TRAVEL IN GREAT BRITAIN: SOME NEW EVIDENCE

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ABSTRACT

This paper presents an analysis of the demand for longer distance rail travel in Great Britain between 1989 and 2003. Key findings are as follows:-

- Demand was strongly and positively correlated to the level of GDP.
- Demand for reduced fare travel was significantly more price sensitive than demand for full fare travel.
- Demand was relatively price sensitive on routes where air services competed strongly with rail services.
- The entry of low cost airlines tended to reduce the demand for rail travel.

1. INTRODUCTION

This paper presents an analysis of the demand for longer distance rail travel in Great Britain. Our findings are based on the application of time series econometric methods to a data set containing the volumes of journeys and of revenues from ticket sales, disaggregated by 4-weekly periods, between the London Travelcard Area (the London TCA) and each of a set of twenty major provincial centres.[2] The data cover the period from April 1989 to March 2003.[3]

The work has been prompted by several factors:-

- the perception that the market conditions affecting the demand for longer distance rail travel in Great Britain may have changed significantly during the 1990s;
- the possibility of studying the impact of market entry by low cost airlines on routes serving Scotland and the North of England; and
- the wish to explore different bases for disaggregating the demand for longer distance rail travel than those used in previous studies.

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[2] Bath, Birmingham, Bristol, Cardiff, Carlisle, Edinburgh, Glasgow, Leeds, Leicester, Liverpool, Manchester, Newcastle, Nottingham, Norwich, Plymouth, Preston, Stockport, Swansea, Swindon, York
[3] Services to the provincial centres served by the East Coast main line (Leeds, York, Newcastle and Edinburgh) were affected by electrification works during the early stages of the period up to late 1990, and the subsequent introduction of new rolling stock. In these cases, equations were estimated over the period from April 1992 onwards (April 1991 in the case of Edinburgh), by which time it was judged new services had fully settled down.

Two previous published studies have used a broadly similar approach to our own to examine the factors affecting the demand for longer-distance London-based rail travel. Jones and Nichols (1983) estimated individual demand equations for 17 of the 20 flows considered in the present study for periods varying from 1969 or 1971 to 1976 or 1977, using 4-weekly ticket sale and revenue data similar to those employed in the present study. The measure of demand used by Jones and Nichols was total ticket sales aggregated over all types of ticket, and the price variable was average revenue per ticket, defined as total revenue divided by total ticket sales in each 4-weekly period. As well as estimating the effect of price on demand, these authors also studied the effects on rail travel of variations in GDP, cyclical economic activity, rail service levels, service levels on competing modes of transport, and seasonal factors.

Subsequently, Owen and Phillips (1987) analysed demand for rail travel on each of the 20 London-based flows examined in the present study, using the same data base of 4-weekly ticket sales and revenues employed by Jones and Nichols. Partial adjustment models were estimated over the period from 1973 to 1984 for demand between London and each regional centre aggregated over all ticket types and also disaggregated into first and second class ticket sales. For the aggregate models, the price variable was defined in the same way as in the Jones-Nichols paper. For the disaggregated analysis, the price was defined as the average revenue per ticket for tickets sold in each disaggregated ticket category. Like Jones and Nichols, Owen and Phillips also studied the effects on demand of macroeconomic activity, rail service levels, service levels on other modes of transport, and seasonal factors.

Most recently, a paper by Wardman (2006) has studied the demand for rail travel across a range of markets, including longer distance routes between London and provincial centres, for the period 1990 to 1998. Although the data source used by Wardman is similar to that used in the present study, Wardman only reported results obtained by panel estimation methods, so that no estimates are available for individual flows. In addition, Wardman's estimates were obtained by constraining all so-called "external" parameters other than GDP to predetermined values derived from other studies. Finally, it is unclear how the set of long distance London based flows for which results are reported in Wardman's paper compare to the set used in the present study. As a result, the findings in Wardman's paper are difficult to relate to those reported below, and are not considered further in this paper.

The results presented below therefore update the estimates obtained in the earlier studies by Jones and Nichols and Owen and Phillips in respect of the sensitivity of rail travel to changes in key economic variables. They also expand the scope of the earlier analyses in the following ways:-

- First, we examine how demand parameters, especially the price elasticity of demand, vary between flows within the sample. We relate these variations to journey characteristics which might affect the level of competition and hence the degree of substitutability between rail and other modes of transport.

- Second, we present results for ticket sales disaggregated into full fare tickets (whether First or Standard Class) and reduced fare tickets. We argue that these groupings are more soundly based in consumer demand theory than the disaggregation into first and second class ticket sales used by Owen and Phillips. We also examine whether we would expect to find significant differences between the key demand parameters for full fare and reduced fare journeys, and whether the empirical findings are consistent with our a priori expectations.

The remainder of the paper is organised as follows:-

- We begin by describing the data used in the modelling work, and our choice of explanatory variables.
- We then discuss our approach to model estimation.
- We go on to present the results of our estimations.
- Finally, we assess the implications of our findings for public policy.

2. EMPIRICAL METHODOLOGY AND DATA

2.1 A Model of Rail Demand

Our model of rail demand follows directly from the previous studies undertaken by Jones and Nichols and Owen and Phillips. It is estimated within a single equation framework which assumes that price is exogenous, for reasons discussed in the section on estimation and econometric issues below. The factors that are considered to be potentially important determinants of rail demand are: real income, economic activity, rail fares and levels of service, price and quality characteristics of alternative transport modes, and seasonal factors.

Putting these factors together, the model of rail demand can be expressed in its most generic form as:

$$D_{ij} = f(Y, EA, P_{ij}, GJT_{ij}, SQ_{ij}, AM_{ij}, S, T) \qquad (1)$$

Where:

- D_{ij} is the level of demand for rail travel between a pair (i,j) of zones
- Y is real income
- EA is an index of economic activity
- P_{ij} is the price of rail travel between i and j
- GJT_{ij} is the generalised journey time between i and j, defined as the planned average journey time between principal stations plus half the time between trains
- SQ_{ij} is the service quality on rail between i and j
- AM_{ij} is the set of performance factors (price, journey time etc) for alternative transport modes between zones i and j
- S is the seasonal effect
- T is a time trend

The precise formulation of our economic model has been shaped by the dataset we have been able to construct and is discussed below.

2.2 Data

Several sources were used to assemble the dataset used for our analysis. Table 1 provides a summary of the main data sources for each variable.

Table 1
Summary of Data Sources

Variables	Data source
Demand (D_{ij})	CAPRI, number of journeys
Price (P_{ij})	CAPRI, revenue per journey
Generalised journey time (GJT_{ij})	Strategic Rail Authority (SRA)[4]
Real GDP (Y)	Office of National Statistics (ONS), UK GDP at factor cost at 1995 prices
Economic activity (EA)	ONS
Alternative modes (AM_{ij})	DTI petrol prices

2.2.1 Demand and prices

Rail passenger demand data have been drawn from the Computer Analysis of Passenger Revenue Information (CAPRI) database, which is the successor to the NPAAS database used in the previous studies by Jones and Nichols and Owen and Phillips. The database contains four-weekly data on the number of tickets sold and the revenue associated with each ticket type for each journey. The data we have used covers 20 individual London-based flows and includes all four-weekly periods from April 1989 to March 2003, so that there are observations for 182 time periods and up to 14 ticket types on each flow.

The price variable we use is average revenue, defined as the total revenue for each ticket type, or grouping of ticket types, divided by the number of journeys for each ticket type or grouping of ticket types. This variable is converted to constant 1995 prices using the RPI series drawn from the ONS.

A number of adjustments were made to the CAPRI data prior to analysis. First, some periods were omitted due to strike activity. During these periods, it is possible that the number of ticket sales represented the level of capacity rather than the level of demand. Second, an adjustment factor was applied to the data to take into account the fact that these periods, which occurred in either the first or the 13th period of a year, contained more or less than 28 days. The adjustment factor we applied to both journeys and revenue was simply 28/N, where N is the number of days in the period. Third, we omitted a number (generally 8) of periods following the Hatfield rail crash in October

[4] Now part of the Department for Transport.

2000, when it was clear that the raw CAPRI data were seriously misreporting the number of journeys and/or revenue in a period. The problems with data recording during this episode appeared to affect all of the flows in the sample.

2.2.2 Level of aggregation by ticket type

The Capri data for each flow contained ticket sales data for 14 product codes. Like Owen and Phillips, we have estimated demand equations both for demand aggregated over all ticket types, as well as for disaggregated groupings of ticket types. Our approach to disaggregation has been to combine First and Standard full fare tickets into a single group. This group is characterised by the twin features that choice of journey time is fully flexible, enabling journeys to be undertaken at any time, including peak travel times when demand is most intense, and that no advanced booking is required prior to travel. In contrast, tickets within the other ticket type grouping, which includes all reduced fare travel, will only be available outside specified peak times, and will often need to be booked in advance. At a theoretical level, the choice between full and reduced fare ticket bundles can be characterised as a high level decision on when to travel (or when to book). Choice within the each of the two groups is then a lower level decision contingent on the prior decision between product groups. Our prior expectation was that demand for full fare travel would be less price elastic than demand for reduced fare travel, first, because it is likely to be characterised by a lower proportion of more optional travel, and, second, because service quality standards on alternative modes, especially car or coach, would be lower during peak travel periods due to higher congestion on roads (and at airports).

We therefore believe that this approach to disaggregation is likely to generate more homogenous product groups than the approach to disaggregation used by Owen and Phillips, which was based on a division between all First and all Standard class tickets, since the second group, in particular, would include a mixture of both full and reduced fare tickets.

We considered the estimation of disaggregated demand equations containing both the "own" price of the ticket category concerned and the price of the other ticket category. This approach would have enabled the estimation of cross-price elasticities. We found during our initial examination of the data that multicollinearity would be a severe problem in estimating equations of this kind, because of the very high correlations observed between the prices of the two groups of tickets. When equations containing both the own price and the price of the other ticket category were estimated, we found that the coefficients on the other price were in general either highly insignificant or incorrectly signed.[5] In light of this finding, we decided to focus on estimation of equations with just the own price of the relevant ticket grouping in the set of explanatory variables.

2.2.3 Generalised journey time

[5] Similar findings are reported both by Owen and Phillips and by Wardman and Toner (2003).

Generalised journey time (GJT_{ij}) is defined as the average timetabled journey time between stations i and j, plus half of the service interval between trains. Generalised journey time may therefore vary either as a result of a change in the point-to-point journey time, or because of a change in train service intervals. Both Jones and Nichols and Owen and Phillips found that reductions in rail journey times resulting from the introduction of the High Speed train (HST) in the 1970s and 1980s were associated with significant increases in the demand for rail travel.

By contrast, between 1989 and 2003, there were no significant changes in scheduled journey times between London and any of the major provincial centres covered in our data set, except for the period immediately following the Hatfield accident in October 2000, when temporary timetables were introduced, usually incorporating increased journey times. However, as noted above, we found major issues of data integrity in the CAPRI data for six months or more following the accident, and, we therefore omitted these periods from our analysis. By the time data integrity had been restored, timetables had generally returned to pre-accident scheduled times. So, although there were increases in service frequencies on some routes, especially during the period from 1997/98 to 2002/03, there was very little variability in the measure of GJT on any of the sample flows in the period once the immediate post-Hatfield observations had been removed, and hence no opportunity in practice to estimate GJT elasticities.

Apart from changes in generalised journey time, variations in other attributes of rail service quality, notably train reliability (measured as the proportion of scheduled train miles that were actually run) and punctuality, might affect the demand for rail travel. Although data on reliability and punctuality were collected throughout the period over which we estimated the models, the service groupings in respect of which they were collected were more highly aggregated than the particular point-to-point flows covered by the CAPRI data, especially in the period prior to rail privatisation in 1996/97.[6] In the absence of data relating to specific flows, we felt unable to assess the effects of wider service quality factors on the demand for rail travel.

2.2.4 Attributes of alternative transport modes

The price and service levels of non-rail modes of transport can be expected to affect the demand for rail travel where there are possibilities for substitution between the modes. On the large majority of routes in our sample, the principal substitutes for rail travel are cars and intercity coach services. Both Jones and Nichols and Owen and Philips found that the demand for rail travel on some routes had been reduced either following motorway openings, which led to more intense competition both from car and coach, or following the deregulation of coach services. However, Jones and Nichols also found that variations in the price of petrol did not appear to have had a significant effect on the demand for rail travel.

[6] More detailed data, linked to the development of the performance incentivisation regime, were published following rail privatisation.

On four of the routes (Manchester, Newcastle, Glasgow and Edinburgh), rail services faced substantial competition from domestic air services, and the studies by both Jones and Nichols and Owen and Philips found that improvements in domestic air services had led to a reduction in the demand for rail travel on the London-Glasgow and London-Edinburgh flows.

Our analysis of the direct effects on the demand for rail travel of changes in the strength of competition from other modes of transport has been shaped by the nature of the changes that have occurred in the prices and levels of service on the other modes during the period covered by the data, and the availability of data on price and service quality on other modes. In contrast to the earlier studies, there were no major changes in the levels of coach service, and no major motorway openings on routes that might compete with rail services during this period. However, there has been a potentially significant change in competitive conditions on the three long distance flows between London and Newcastle, London and Glasgow and London and Edinburgh, as a result of the entry of low cost carriers onto these routes, in competition with the existing scheduled airlines, BA and BMI.

The key entry events were as follows:-

- Glasgow: entry by easyJet (Glasgow-Luton) and Ryanair (Prestwick-Stansted) in late 1995; subsequent entry by Go (Glasgow-Stansted) in 2000.
- Edinburgh: entry by easyJet (Edinburgh-Luton) in early 1995, with subsequent service openings by Go (Edinburgh-Stansted) in 1997 and by easyJet (Edinburgh-Gatwick) in 2001.
- Newcastle: entry by Go (Newcastle- Stansted) in late 2000.

In each case, market entry by the low cost carriers led to significant reductions in air fares for both business and leisure travellers, and this, in turn, greatly stimulated air traffic volumes.[7]

We investigated the effects of changes in one element of the generalised cost of road travel in the form of petrol prices, where we used a monthly index of the national average price of premium unleaded petrol, obtained from the Department of Trade and Industry. We converted the price data to 1995 prices, and adjusted the monthly time series to convert them into four-weekly periods.

We examined the effects of the entry of low cost airlines on the demand for rail travel by means of dummy variables, taking the value zero for the period prior to commencement of service and one thereafter. Where, as in the case of Edinburgh, for example, several distinct episodes of market entry occurred, we also experimented with multiple dummy variables to take account of these effects.

2.2.5 Real GDP

[7] See Civil Aviation Authority (2005)., *UK Regional Air Services*, CAP 754, February 2005.

The measure of real GDP in our dataset is UK GDP at factor cost at 1995 prices, drawn from the Office of National Statistics (ONS). The UK GDP series is available on a quarterly basis. The data were converted into four-weekly periods corresponding to the demand and revenue data by interpolating the quarterly series.

We considered using regional GDP data. We rejected this option, first, because regional GDP data are only available on an annual basis, and, second, because the regional GDP data were highly correlated with the national data series.

2.2.6 Economic activity

The level of cyclical economic activity may affect the level of demand for rail travel independently of the level of GDP. Thus, an economic downturn, although consistent with stable GDP, could cause significant reductions in company profits, new business etc, and a reduction in consumer confidence, leading to a reduction in the demand for both business-related and non-business rail travel.

We examined two possible measures of economic activity.

- An index based on the ratio of GDP to an estimated trend level of GDP. The estimation of the GDP trend values was derived from a regression of GDP data against time during an estimation period that started and finished at comparable points in the economic cycle (ie peaks during the second quarter of 1973 and the third quarter of 2000).[8]
- The level of unemployment in both Great Britain and London. The data were derived from the ONS NOMIS data base. They were supplied on a monthly basis and adjusted to a four-weekly basis by interpolation.

We found that the index measure of economic activity was highly negatively correlated (r = -0.96) with the unemployment measure over the period covered by our traffic data.

2.2.7 Seasonal variation

Seasonal variations in travel behaviour, which are a significant feature of rail travel in the UK, were examined through the use of 12 dummy variables for the 13 four-weekly periods in a year.

2.2.8 Time trend

Owen and Phillips included a linear time trend variable in their model to capture the effects of a range of external factors, such as car usage and local economic activity for which reliable monthly data were not available. Owen and Phillips found that the estimated time trend was generally negative and significant, and implied an average annual rate of decline of over 3 per cent in total demand. We too have tested for the

[8] Variations in such an index were found to contribute significantly to the explanation of variations in the demand for rail travel in the study by Jones and Nichols (1983).

presence of a time trend, although, as discussed below, we have obtained different results to those reported by Owen and Phillips.

3. MODEL ESTIMATION

The objective of our study has been to estimate long run elasticities of demand for rail travel for each of the flows in our sample. We have estimated separate equations using OLS for sales of all types of ticket, for all full fare tickets (first and standard class) and for all types of reduced fare tickets.

In doing so, we have assumed that the price variable was exogenous. If it was not exogenous, for example, if price was raised during periods when demand was high, then the estimated price elasticity would be biased, in this case, towards zero. Removing such bias would require the use of more complex estimation methods, based on the use of Instrumental Variables.

The problem of simultaneity almost certainly does not affect our model. First, seasonal demand effects are netted out through the use of seasonal dummy variables. Second, in the pre-privatisation period, fares were set annually by British Rail. Following privatisation, fares were adjusted more frequently, in January, May and September. However, at no time is there any evidence over this period that train operators set fares in response to demand conditions in the same (or immediately previous) four-weekly period. We have therefore felt justified in estimating single equation models using OLS.

We have adopted a partial adjustment approach to estimating long run elasticities. This approach assumes that rail users do not adjust their demand for rail travel instantaneously in response to changes in the price of rail travel, or to changes in other factors, such as real income, that affect demand. Instead, demand adjustment takes place over several time periods.

It follows that in any time period t, there is a long run equilibrium level of demand, D^*_t, associated with the actual level of the variables that determine demand, including price, P_t, and GDP, Y_t, which can be written as

$$D^*_t = \alpha_0 + \alpha_1 P_t + \alpha_2 Y_t + u_t \qquad (2)$$

where u_t is a random disturbance term. It is assumed that the change in the level of demand between time periods t and (t-1) is proportional to the difference between the equilibrium level of demand in t, D^*_t, and the actual demand in (t-1), D_{t-1}.

$$D_t – D_{t-1} = \lambda(D^*_t – D_{t-1}) \qquad (3)$$

(3) may be rewritten as:

$$D_t = \lambda D^*_t + (1-\lambda)D_{t-1} \qquad (4)$$

Demand in the current period t is thus the weighted average of the desired level of demand in t, D^*_t, and actual demand in (t-1), D_{t-1}. The higher is λ, the greater is the weighting attached to demand in the current period, and thus the more rapidly does demand adjust to any exogenous shock, such as a change in price or income.

Substituting in (2) from (1) and rearranging gives actual demand in t as

$$D_t = \lambda\alpha_0 + (1-\lambda)D_{t-1} + \lambda\alpha_1 P_t + \lambda\alpha_2 Y_t + \lambda u_t \qquad (5)$$

When equation (5) is estimated in logarithmic form, the coefficients $\lambda\alpha_1$, $\lambda\alpha_2$ etc give the estimates of short run elasticities. Long run elasticities are obtained by dividing the coefficients on P_t etc by λ, which is derived from the regression coefficient on D_{t-1} in equation (4).

The full set of explanatory variables described in Section 2 above was tested for inclusion in the final models. The process involved testing variables to assess their contribution to explaining the variance of demand and discarding those found to be insignificant. During this process of refinement, our measures of economic activity, generalised journey time, the price of petrol and the time trend were found to be insignificant in all of the demand models.

We therefore estimated demand equations of the following kind for each of the London-based flows in our sample for total ticket sales, for all reduced fare ticket sales and for sales of full fare first and standard class tickets. The models were estimated for the period from April 1989 to March 2003, with the exception of flows on the East Coast main line, which as noted earlier, were affected by major engineering works during the early years of the period.

$$\ln D_t = \beta_0 + \beta_1 \ln D_{t-1} + \beta_2 \ln P_t + \beta_3 \ln Y_t + \sum_{i=4}^{i=15} \beta_i S_{it} + \varepsilon_t \qquad (6)$$

where

- $D_{t,t-1}$ = Volume of single journeys between London and provincial centre in t and (t-1)
- P_t = Real average revenue/fare per journey in t
- Y_t = Real GDP at 1985 factor cost in t
- S_{it} = Seasonal 0/1 dummy variables (12 in all[9])
- ε_t = random error term

In the equations for the three flows where there was market entry by low cost carriers, we also included a further dummy variable, taking the value 0 prior to the time of entry and 1 thereafter.[10]

[9]Using the level in the March period as the base.
[10] In the cases of Edinburgh and Glasgow, where there was more than one potentially significant entry event, we experimented with the use of two or more such dummy variables.

Formulated in this double logarithmic form, the coefficients on P and Y are short run elasticities, and long run fare and GDP elasticities are derived as (β_2/(1- β_1)) and (β_3/(1-β_1)).

Models with lagged dependent variables on the right hand side are biased in small samples but consistent (Greene, 2003). The bias is of the order of 1/T, where T is the sample size. In the present case, the sample size (c180) is sufficiently large to ensure that the finite sample bias is negligible. In addition, the use of the Durbin-Watson d statistic to test for the presence of autocorrelation is invalid when the regression equation contains lagged dependent variables. To address this issue, we have tested the null hypothesis of non-autocorrelated disturbances using Durbin's h statistic[11], calculated as

$$(1- D/2)\sqrt{(N/(1-N.var(\beta_1))}$$

where

D = Durbin-Watson statistic
N = sample size
β_1 = coefficient of the lagged dependent variable.

4. ESTIMATION RESULTS

We begin by presenting results for overall goodness-of-fit and autocorrelation. We then discuss the estimates of long run fare and GDP elasticity, and the evidence on the effects of market entry by low cost airlines.

4.1 Overall goodness of fit

Table 2 shows coefficients of determination corrected for degrees of freedom (Adjusted R^2) and Durbin's h statistic for each of the 60 equations.

With the exception of the Carlisle and Swindon flows, all of the Adjusted R^2 values for the equations for total journeys and for reduced fare journeys are greater than 0.79. The Adjusted R^2 values are somewhat lower in the models explaining variations in demand for full fare journeys. The hypothesis of non-autocorrelation in the residuals was rejected at the 5% level in just 10 of the 60 equations. Taken together, the summary statistics indicate that the models are well-specified and have a high degree of explanatory power.

Table 2

Summary Statistics

Centres	Total		Reduced		Full fare	

[11] See Dougherty (2002)

	journeys		fare journeys		journeys	
	AdjR^2	**h**	**AdjR^2**	**h**	**AdjR^2**	**h**
Bath	**0.91**	**1.40**	**0.92**	**-1.05**	**0.69**	**-3.21**
Birmingham	**0.94**	**1.59**	**0.98**	**-0.07**	**0.81**	**1.63**
Bristol	**0.92**	**-0.29**	**0.94**	**0.58**	**0.62**	**1.55**
Cardiff	**0.85**	**1.88**	**0.87**	**-0.90**	**0.63**	**0.71**
Carlisle	**0.69**	**1.53**	**0.73**	**4.82**	**0.56**	**1.20**
Edinburgh	**0.93**	**-0.15**	**0.95**	**1.13**	**0.75**	**0.10**
Glasgow	**0.86**	**-0.52**	**0.88**	**-0.40**	**0.74**	**0.18**
Leeds	**0.93**	**-1.25**	**0.95**	**-1.88**	**0.70**	**-0.52**
Leicester	**0.89**	**0.88**	**0.84**	**1.60**	**0.80**	**-1.55**
Liverpool	**0.79**	**2.20**	**0.82**	**0.62**	**0.48**	**0.00**
Manchester	**0.88**	**-0.03**	**0.92**	**-1.56**	**0.63**	**0.10**
Newcastle	**0.87**	**2.16**	**0.89**	**1.25**	**0.77**	**2.83**
Norwich	**0.89**	**-3.34**	**0.87**	**-0.75**	**0.85**	**0.11**
Nottingham	**0.92**	**-0.11**	**0.93**	**-4.96**	**0.64**	**ND**
Plymouth	**0.84**	**0**	**0.87**	**0.87**	**0.75**	**0.95**
Preston	**0.89**	**0.26**	**0.92**	**-0.33**	**0.65**	**1.16**
Stockport	**0.79**	**-1.46**	**0.85**	**-1.65**	**0.61**	**-0.30**
Swansea	**0.80**	**0.51**	**0.86**	**1.97**	**0.43**	**2.73**
Swindon	**0.72**	**1.57**	**0.72**	**1.77**	**0.72**	**1.75**
York	**0.93**	**1.59**	**0.94**	**2.10**	**0.71**	**1.28**

4.2 Long Run Fare Elasticities

Table 3 shows the estimated long run own fare elasticities of demand for all tickets, for all types of reduced fare tickets, and for all full fare tickets for the 20 flows covered in the study. The table also gives the t-statistics for each of the coefficients.

The following points can be made about the results reported in Table 3.

- All of the coefficients in respect of total journeys and journeys on reduced fare tickets are correctly signed, and almost all are significant at the 1% level.
- Eighteen of the twenty coefficients on full fare journeys are correctly signed, and ten are significant at the 1% level, with a further five significant at the 5% level. The differences in the robustness of the results between the two ticket groupings may reflect the fact that the market for full fare journeys on some of the flows is relatively "thin" with demand heavily dominated by travel on reduced fare tickets.
- The median values of the elasticities for each type of journey indicate that the demand for reduced fare journeys was around 80% more price (fare) elastic than the demand for full fare journeys. This is a substantially wider differential than was estimated by Owen and Phillips between the fare elasticities of demand for travel on first and second class tickets. We examine the significance of the differences between the fare elasticities of demand for full and reduced travel further below, but note that the

finding is consistent with a priori expectations, for the reasons explained set out in Section 2 above.

- We note that the median value of the long run fare elasticity of demand for all types of ticket is strikingly similar to that obtained by Owen and Phillips.[12]

Table 3

Long Run Own Fare Elasticities
Journeys between London and Provincial Centres

Centre	Total Journeys		Reduced Fare Journeys		Full Fare Journeys	
	Elasticity	t-Statistic	Elasticity	t-Statistic	Elasticity	t-Statistic
Bath	-1.33	5.74	-0.98	5.53	-0.99	3.17
Birmingham	-0.77	3.14	-2.20	15.52	-0.27	2.31
Bristol	-0.99	3.75	-1.28	5.99	-0.40	2.02
Cardiff	-0.17	0.78*	-0.06	0.42*	-0.44	2.02
Carlisle	-1.07	7.15	-1.02	7.41	-1.03	5.61
Edinburgh	-2.03	7.30	-2.35	9.01	-2.10	6.48
Glasgow	-2.01	9.96	-2.40	13.29	-3.06	5.78
Leeds	-1.16	4.06	-1.05	3.88	-0.77	1.46*
Leicester	-1.45	9.37	-1.85	3.76	-0.47	1.59*
Liverpool	-0.68	6.01	-1.44	10.08	-0.44	2.78
Manchester	-0.59	3.63	-1.30	5.64	-0.47	2.60
Newcastle	-1.51	9.75	-1.37	8.01	-1.30	2.57
Norwich	-1.34	5.29	-1.61	6.13	-1.20	4.77
Nottingham	-0.99	6.06	-0.95	5.45	-0.12	0.41*
Plymouth	-1.37	7.52	-1.88	6.53	-1.85	8.10
Preston	-0.90	6.33	-1.90	7.74	0.31	1.50*
Stockport	-0.92	3.27	-1.19	2.00	0.15	0.67*
Swansea	-0.78	4.16	-1.00	6.99	-1.17	5.77
Swindon	-1.52	7.28	-1.87	8.83	-0.80	2.73
York	-1.19	7.13	-1.61	6.56	-1.09	2.86
Median	-1.07		-1.37		-0.77	

*****Not significant at the 5% level.

4.3 Differences in Long Run Fare Elasticities between Flows

Our results indicate that there are apparently wide variations in the estimated fares elasticities between flows within the sample. Whilst the fares elasticity of demand for

[12] Owen and Phillips reported a median value of fare elasticity for all journeys of -1.08.

total journeys was less than -1.0 for nine of the twenty flows, it exceeded -1.5 for four of the flows. Wide variations are also observed within the sample in respect of the fare elasticity of demand for reduced fare journeys and for full fare journeys. We have therefore examined whether the variation between flows in the estimated elasticities may be related systematically to variations in the competitive environment facing train operators in each of the distinct geographical markets concerned.

Each of the previously cited studies of demand for rail travel between London and the set of provincial centres in our sample reported evidence of competitive interaction between rail services and other modes of transport. Jones and Nichols found that both major motorway openings and the subsequent upgrading of coach services and the introduction of so-called Shuttle air services in the early and mid 1970s had significant negative effects on the demand for rail travel on routes where the upgraded services competed directly with rail services.[13] Similarly, Owen and Phillips found evidence that improved services in the wake of the deregulation of interurban coach services led to a reduction in the demand for rail services on many of the flows in their sample. They also found that on the three flows where air services already competed strongly with rail (Newcastle, Glasgow and Edinburgh) there was evidence of a permanent shift of demand away from rail following the disruptions to rail services that occurred as a result of strikes in 1982.

In examining the relationship between the strength of intermodal competition and the level of the fare elasticity of demand we hypothesised that competitive conditions facing train operators would differ between very long distance markets (journey lengths over 275 miles), where the train operator faced competition from domestic air services, and those shorter distance journeys where consumers would be choosing between rail and either private car or interurban coach services. Defined in this way, the set of very long distance markets consists of the flows between London and Edinburgh, Glasgow and Newcastle.[14] The set does not include the London – Manchester flow, despite the fact that there are good air connections between Manchester and London. However, compared to other regional centres, a relatively high proportion of the traffic on the London – Manchester services is connecting, or interlining traffic, making onward air journeys via the major UK hub airport at Heathrow (see, CAA (2005), op cit). We judged that rail and air would not be as close competitors for journeys of this kind as for point to point journeys between London and a provincial centre.

We examined this hypothesis by estimating simple regression equations of the following kind:

$$E_i = \beta_0 + \beta_1 D_i + \varepsilon_i \qquad (7)$$

where

E_i = estimated long run own fare elasticity on flow i

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[13] Improvements in the level of service on road would also mean that the use of a private car would become a closer substitute for rail travel.

[14] Carlisle is also located over 275 miles from London, but there is no regional airport in the vicinity.

D_i = dummy variable taking the value 1 if there is air competition, zero otherwise
ε_i = random error term

We expected the co-efficient on the dummy variable to be negative, for two reasons. First, we would anticipate that the availability of a mode offering faster journey time than rail would attract a high proportion of business travellers, who are relatively time sensitive but less price sensitive than most non-business travellers. As a result, the proportion of business travellers using rail would be lower than on routes where there was no air alternative. Second, we would expect that air travel, especially if low cost air services are available, would offer a closer substitute to rail than would be offered by intercity coaches, since the journey time penalty associated with coach travel is very substantial, even on shorter distance routes.

The results of this analysis are shown in Table 4.

Table 4

Differences in Long Run Own Fare Elasticities

All journeys

Co-efficient	Estimated Value	t-Statistic
β_0	-1.01	12.09**
β_1	-0.84	3.87**

Reduced fare journeys

Co-efficient	Estimated Value	t-Statistic
β_0	-1.36	10.72**
β_1	-0.84	2.07*

Full fare journeys

Co-efficient	Estimated Value	t-Statistic
β_0	-0.65	4.49**
β_1	-1.48	3.95**

** Significant at 1% level
* Significant at 5% level

The results in Table 4 indicate that the demand for all journeys, for reduced fare journeys and for full fare journeys on the three very long distance flows where there was strong competition from domestic air services was significantly more price (fare) elastic than was the demand on those routes where there was either no viable domestic air service or where domestic air services cater principally for interlining passengers.[15] The difference was especially marked in the case of full fare journeys, where the "average" fare elasticity on air-competitive flows was over twice as high as on other flows.

We have also examined whether there was any evidence that the demand for rail travel on flows where the journey time difference between rail and private car was relatively small, so that private car might compete strongly with rail, was more fare elastic than on other flows where rail enjoyed a relatively large advantage in journey time over car travel. To do so, we again used regression analysis, adding a second dummy variable taking the value 1 if the estimated journey time difference between rail and road was 1 hour or less, and zero otherwise.[16] However, in this case, we found that although the coefficients on the short distance dummy variable were correctly signed, they were not significant.

4.4 Differences in Long Run Fare Elasticities between Full and Reduced Fare Journeys

For the reasons discussed in Section 1 above, we expected to find that the demand for reduced fare journeys was more fare elastic than the demand for full fare journeys, and we have noted above that the median value of the long run own fare elasticity for reduced fare journeys was around 80% higher (more price elastic) than the median value of the long run own fare elasticity for full fare journeys. We have examined the significance of the differences in estimated elasticities between the two disaggregated demand categories more rigorously by estimating the t-statistic for the differences in estimated mean values between the two categories of demand in respect of the 17 flows (giving 16 degrees of freedom) where there was no substantial air competition. We found an estimated t value of 4.24. This is significant at the 1% level on a one-tailed test, which is appropriate in this case. Our empirical findings in respect of the differences between the price sensitivity characteristics of our disaggregated groupings of ticket sales are therefore entirely consistent with our a priori expectations.

4.5 Long Run GDP Elasticities

Table 5 shows the estimated long run elasticities of demand with respect to UK Gross Domestic Product (GDP) for all tickets, for all types of reduced fare tickets, and for all full fare tickets for the 20 flows covered in the study. The table also gives the t-statistics for each of the coefficients.

Taken together with the absence of any time trend, these results provide evidence of a major shift in demand conditions for rail travel between London and provincial centres compared to those prevailing at the time of both the previously cited studies. Briefly, although Jones and Nichols found evidence of a strong relationship in the early-mid 1970s between the demand for rail travel and the level of cyclical activity in the economy, measured in terms of the deviation of GDP from its trend level, they found no

[15] As is the case for Manchester.

[16] We compared the difference between the scheduled journey time on rail with the indicative journey time shown on the AA website (http:///www.theAA.com) for journeys between the provincial centre and a specified zone in Central London.

evidence of any relationship, either positive or negative, between the demand for rail travel and the actual level of GDP. Subsequently, using data from the late 1970s to the mid 1980s, Owen and Phillips found evidence of a positive relationship between the demand for rail travel and UK GDP on the majority of the flows in their sample[17], but this positive GDP effect operated alongside a strongly negative time trend. Assuming trend growth in GDP of around 2 – 2.25% per annum, the combination of the two effects would mean a trend decline in demand of around one half of one per cent per annum.

Table 5

Long Run GDP Elasticities
Journeys between London and Provincial Centres

Centre	Total Journeys		Reduced Fare Journeys		Full Fare Journeys	
	Elasticity	t-Statistic	Elasticity	t-Statistic	Elasticity	t-Statistic
Bath	1.74	8.49	2.14	8.97	1.12	3.39
Birmingham	2.51	5.95	3.14	13.01	1.39	6.10
Bristol	1.80	6.74	2.27	8.59	0.44	2.74
Cardiff	1.33	7.06	1.80	6.81	0.47	2.68
Carlisle	0.37	1.52	0.90	5.17	0.66	2.86
Edinburgh	1.00	2.31	1.30	2.99	0.80	2.07
Glasgow	-1.12	5.53	-1.62	8.46	0.84	1.46
Leeds	1.74	5.07	2.56	4.75	1.22	4.17
Leicester	1.61	10.35	2.12	4.77	1.09	3.77
Liverpool	1.38	9.75	1.91	10.62	0.53	1.79
Manchester	2.17	6.64	3.02	7.54	1.34	3.84
Newcastle	0.66	2.23	2.47	5.85	-1.28	5.43
Norwich	1.62	7.28	1.47	7.28	1.76	7.46
Nottingham	1.99	9.04	2.02	7.69	1.14	4.13
Plymouth	0.59	4.85	1.35	6.37	0.01	0.11
Preston	2.15	8.07	3.94	8.36	-1.10	3.11
Stockport	2.39	4.48	2.88	2.71	0.25	0.65
Swansea	0.98	6.84	1.14	9.57	0.59	3.95
Swindon	1.85	7.59	2.37	8.89	1.35	4.56
York	1.56	6.79	1.75	4.88	1.31	5.20
Median	1.61		2.02		0.80	

Jones (2001) has suggested that the change in demand conditions facing passenger rail operators may be linked to several factors affecting the level of competition from private car use.

[17] Although the coefficients on GDP were not significantly different from zero in around a third of their estimated equations.

- A slowdown in the rate of growth of the car stock, which fell from just under 3% per annum in the 1980s to around 1.5% per annum in the 1990s.
- Increases in real petrol prices; whereas petrol prices declined by over 1% per annum in real terms in the 1980s, in the 1990s they increased by nearly 3% per annum.
- A dramatic reduction in the rate of growth of private vehicle traffic, from 5.5% per annum in the 1980s to 1% per annum in the 1990s.
- Finally, there was evidence from AA data of a deterioration in the service quality available on the road network as reflected in the frequency and extent of major traffic incidents.

Jones noted that because the volume of travel by private car is so much greater than by rail, a relatively small diversion of demand from car to rail might result in a disproportionately large increase in the demand for rail.

The data in Table 5 also indicate that there quite wide variations in long run GDP elasticities both as between different geographical markets and between reduced and full fare journeys. We examine each of these aspects in turn.

4.6 Differences in Long Run GDP Elasticities between Flows

We examined whether the availability of a "superior" (higher price/faster journey time) mode of public transport in the form of domestic air services might tend to reduce the responsiveness of the demand for rail travel to the level of GDP. To do so, we used a similar approach to that employed in analysing differences in the long run fare elasticity of demand between flows where the rail operator faced effective competition from domestic air services and those where it did not. Specifically, we estimated equations of the form

$$E_i = \beta_0 + \beta_1 D_i + \varepsilon_i \qquad (8)$$

where

E_i = estimated long run GDP elasticity on flow i
D_i = dummy variable taking the value 1 if there was air competition, zero otherwise
ε_i = random error term

As shown in Table 6, the coefficients on the air competition dummy variable are negative and significant in the total journeys equation (at the 1% level), and in the equation for reduced fare journeys (where it is significant at the 5% level). The co-efficient in the equation for full fare journeys is also negative, but is not significant. Taken together, these results suggest that, as hypothesised, the presence of competition from domestic air service tended to reduce the GDP elasticity of demand for rail travel in the period covered by our data.

Table 6

Differences in Long Run GDP Elasticities

All journeys

Co-efficient	Estimated Value	t-Statistic
β_0	1.59	9.63**
β_1	-1.41	3.87**

Reduced fare journeys

Co-efficient	Estimated Value	t-Statistic
β_0	2.16	8.77**
β_1	-1.45	2.27*

Full fare journeys

Co-efficient	Estimated Value	t-Statistic
β_0	0.80	4.30**
β_1	-0.69	1.44

** Significant at 1% level
* Significant at 5% level

4.7 Differences in Long Run GDP Elasticities between Full and Reduced Fare Journeys

We had no strong a priori expectations about the differences between the long run GDP elasticities for full and reduced fare journeys, although the median value of the long run GDP elasticity for reduced fare journeys was over twice as high as the median value of the long run GDP elasticity for full fare travel. We have examined the difference between the mean values for the seventeen flows with no or limited air competition using a t test. In this case we estimated a t-statistic of 5.02 for the difference between the means, which is significant at the 1% level on a one-tailed test. To the extent that a higher proportion of journeys made on reduced fare tickets than on full fare tickets are linked to leisure activities, our findings would indicate that the demand for leisure travel on rail was relatively GDP elastic compared to the demand for business or work-related travel, which is more heavily focussed on peak travel times, and hence tends to be made on full fare tickets.

4.8 The Effects of Changes in the Level of Air Competition

Between 1995 and 2003, new services were opened by the new generation of low cost airlines (notably Ryanair, easyJet and Go) on the three routes (Glasgow, Edinburgh and Newcastle) where BA and or BMI already competed with rail services. We examined the impact of these new services on the demand for rail travel using either a single dummy variable, or, where there was more than one potentially significant entry event, as in the case of the Glasgow and Edinburgh flows, two dummy variables. Each of the dummy variables took the value 0 prior to the entry event and 1 thereafter.

Our analysis indicated that the initial market entry by the low cost carriers did not appear to have had a significant effect on the demand for rail travel on either the Glasgow or Edinburgh flows, with the coefficients being either incorrectly signed or not significant. On the Newcastle flow, however, market entry by easyJet at around the time when rail services were being disrupted by the aftermath of the Stevenage accident, appeared to have a significant negative effect on rail travel, especially on the demand for reduced fare journeys.

The finding that rail lost traffic to air following a major service disruption is similar to the results obtained by Owen and Phillips, who found that there was a loss of demand for rail travel on very long distance routes following disruptions caused by strike action on the rail network in 1982. We therefore re-estimated the equations for both Glasgow and Edinburgh with the air competition dummy variable set to 0 prior to the Stevenage accident, and 1 following the accident.

The estimation results for the air competition dummy variables specified in this way are shown in Table 7.

Table 7

Long Run Impacts of Market Entry by Low Cost Carriers

Edinburgh

Journey type	Percentage Change in demand	t-Statistic
All journeys	-20	2.76
Reduced fare journeys	-16	2.35
Full fare journeys	-29	3.32

Glasgow

Journey type	Percentage Change in demand	t-Statistic
All journeys	+2	0.41
Reduced fare journeys	-2	0.42
Full fare journeys	-15	1.41

Newcastle

Journey type	Percentage Change in demand	t-Statistic
All journeys	-8	2.12

Reduced fare journeys	**-19**	**3.82**
Full fare journeys	**+5**	**1.13**

We see that in seven of the nine equations, the coefficients are correctly signed (indicating a loss of traffic from rail to air). In three cases, the coefficients are significant at the 1% level, and at the 5% level in two others. The impact of air competition appears to have been especially marked on the Edinburgh flow, where the post-Stevenage disruption coincided with a major upgrade to air services in the form of the opening of a new Edinburgh – Gatwick service by easyJet, which might have been particularly attractive for business passengers[18]. The market entry of easyJet, probably combined with the effects of rail service disruption, also appears to have had a significant negative effect on demand for reduced fare journeys between Newcastle and London.

5. SUMMARY OF KEY RESULTS AND CONCLUSIONS

The principal findings of the research can be summarised as follows:-

- In contrast to the earlier studies, by Jones and Nichols and by Owen and Phillips, we find that during the period covered by our data, the demand for rail travel between London and most of the major provincial cities in our sample was strongly and positively associated with the level of UK Gross Domestic product (GDP).
- We find no evidence of the kind of negative time trend identified by Owen and Phillips working to counteract the positive GDP effect.
- Consistent with our a priori expectations, we find evidence that the demand for full fare rail travel was significantly less price elastic than the demand for reduced fare travel.
- We also find evidence that the long run price elasticity of demand varied systematically with journey length, in a manner which we believe is related to the level of competition faced by rail services from other modes of transport, in particular, domestic air services.
- We find evidence that the long run elasticity of demand with respect to the level of GDP was significantly higher for travel on reduced fare tickets than it was for travel on full fare tickets.
- We find some evidence that the entry of low cost airlines, such as easyJet and Ryanair, onto domestic routes that compete with intercity rail services, has significantly reduced the level of demand for rail travel.

Taken together, the findings in respect of the relationship of demand to GDP and the absence of any negative time trend confirm the evidence of a major shift in market conditions for longer distance rail travel in Great Britain noted by Jones (2001, op cit). Like Jones, we believe that the most plausible explanation for the shift in market conditions is linked to changes in the level of service available on the interurban road network, as a result of higher levels of congestion and delay as demand presses

[18] Hence, the particularly sharp negative impact on full fare travel.

increasingly on capacity, especially at peak times. We would therefore expect to find that, in the absence of major increases in capacity and levels of service on the road network, and of increases in the average level of rail fares in real terms, demand for London-based intercity rail travel will continue to increase at around one and a half to two times the rate of trend GDP growth, except on the very long distance routes (such as London-Glasgow and London-Edinburgh) where domestic air services will continue to offer a close substitute for rail travel, both for business and leisure travellers.

Our findings in relation to the long run elasticity of demand for total journeys with respect to fares can be compared directly with those obtained by Owen and Phillips. The median values of long run fares elasticity in the two studies are strikingly similar - - 1.07 in the present study and -1.08 in the earlier study. However, whereas Owen and Phillips' estimates are clustered relatively closely around the median value, with a range between upper and lower quartile means of just 0.49, our results indicate a greater diversity of local market conditions, with a range of 1.1 between the upper and lower quartile means. In large part, this difference relates to the much higher estimates of fare elasticities we have obtained in our demand equations for the three very long distance flows that now face stiff air competition from both low cost and conventional carriers.

Our estimates of the elasticity of demand with respect to fares for travel on full and reduced fare tickets suggest that on many short and medium distance routes, operators have clear incentives to widen the fares differential between the two types of ticket. In principle, their ability to do so may be weakened if full fare tickets were subject to price regulation, and by consumers' ability to reschedule journey timings to take advantage of lower reduced fare ticket prices. It might be enhanced by the greater use of airline-style online booking and demand management arrangements.

Finally, we note that our findings in respect of fares and GDP elasticities demonstrate the limitations of any "official" guidelines[19] to demand conditions in very broadly defined geographical markets. We have found striking evidence of wide variations in both parameters that indicate the need for careful study of demand conditions in particular geographical markets as a basis both for commercial policy decisions by franchised rail operators and for public policy, especially in relation to fares regulation and the provision of capacity.

Overall, we believe that the results obtained in the present study demonstrate once again that the application of standard and well-tried models of consumer demand are able to give a robust and convincing explanation of the key factors driving the demand for longer distance London-based rail travel.

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