DEMAND FOR RAIL TRAVEL AND THE EFFECTS OF EXTERNAL FACTORS

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Abstract

This paper estimates an enhanced model for forecasting railway demand and to explain the high levels of growth experienced in the 1990's in Great Britain. The problems with previous forecasting methods and research findings are outlined. The key driver of demand is found to be GDP, but variations in car journey times, fuel costs, car ownership levels, population and a post-privatisation time trend have also made significant contributions. The estimation makes use of two large data sets obtained from recorded ticket sales and from travel surveys. The estimated models are in use within the rail industry in Great Britain and have been able to successfully predict rail demand levels experienced since 1998.

Keywords: Railways, Demand Forecasting, External Factors, GDP Elasticities

1. INTRODUCTION

Although factors external to the rail industry, such as the level of economic activity and competition from other modes, are beyond its control, their fundamental importance to future revenue streams and strategic business planning has over many years yielded a large body of empirical evidence. This is no more evident than in Britain where there is a long tradition of research in this area (Tyler and Hassard, 1973; Glaister, 1983; Jones and Nichols, 1983; Fowkes et al., 1985; Owen and Phillips, 1987; Phillips, 1987; TCI, 1997; Wardman, 1997a; CEBR, 1998; Wardman and Dunkerley, 1999; NERA, 1999; Steer Davies Gleave, 1999). Despite this, serious forecasting inaccuracies emerged in the late 1990's and it became clear that there was a need to update the parameters and framework used to forecast the effects of external factors. The research reported here contributes an improved understanding in the context of non-commuting rail travel in Great Britain through the analysis of both rail ticket sales data and travel survey data.

The structure of this paper is as follows. Section 2 outlines the forecasting framework and parameters which, until recently, were widely used in the railway industry in Great Britain. It demonstrates their inability to explain the demand growth of the 1990's and addresses trends in a range of factors that contributed to the higher than predicted demand growth. Section 3 summarises the causes of the forecasting problem. Fresh empirical evidence is reported based on the analysis of ticket sales data in section 4 and on the analysis of travel survey data in section 5. The resulting models are used to forecast subsequent demand growth and a comparison of actual and forecast growth is covered in section 6. Concluding remarks are provided in section 7.

2.   BACKGROUND

2.1   The Forecasting Procedure

The Passenger Demand Forecasting Handbook (PDFH) contains a forecasting framework and parameters that have long been used in the railway industry in Great Britain and from time to time it is updated (BRB, 1986, 1989; ATOC, 1997, 2002). The version in use prior to the most recent (4th) edition (ATOC, 2002) forecast the effect of external factors on the volume (V) of rail demand as:

$$\frac{V_{new}}{V_{base}} = \left(\frac{GDP_{new}}{GDP_{base}} \right)^{g} (1 + t)^{n} \tag{1}$$

where g is the elasticity to gross domestic product (GDP), t is an annual time trend and n is the number of years between the new and base time periods. The forecasting framework and parameters have their origins in the work of Owen and Phillips (1987), Phillips (1987) and BRB (1988).

The GDP elasticity represents the positive impacts of economic activity on business trips and income on leisure trips. The time trend represents the net effect of: increases in car ownership; improvements to the road network; falling real motoring costs; changes in demographic factors and land use; and trends in marketing. It does <u>not</u> include major competitive impacts; econometric models took explicit account of key events such as coach deregulation, new motorways and the introduction of air shuttle services. Given model calibration to data for the 1970's and 1980's, when car ownership growth was strong but traffic congestion was not widespread, the estimated trends had the expected negative sign.

The recommended GDP elasticities and annual time trends in the 3rd edition of PDFH for non-commuting trips were 1.5 and -2½% for London based inter-urban flows, 1.5 and -2% for Non London inter-urban flows, 1.0 and -1½% for non London suburban flows and 1.2 and -2% for flows in the South East. For Great Britain's historic GDP growth rate of around 2% per annum, the forecast annual increases in demand vary between 0.36% for South East non-commuting trips and 0.95% for Non London inter-urban trips.

2.2   Recent Trends and Forecasting Performance

Over the period 1970 to 1990, in which time rail network in Britain has been roughly constant, PDFH provides a reasonably accurate account of trends in rail demand due to external factors. However, the relationship breaks down in the 1990's. GDP growth has exceeded the historic average which, when combined with limited growth in trunk road length and car ownership and large increases in car costs, has caused unprecedented levels of rail demand growth which cannot be explained.

Table 1 illustrates the scale of the problem across a number of routes for which data was supplied for the analysis reported in section 4. The actual gross growth figures are taken from the railway industry's CAPRI ticket sales recording system, and standard elasticities from the 3rd edition of the PDFH have been used to calculate the net growth after the removal of the effects of fare and service quality changes on each flow. The pricing up that occurred in shorter distance markets is apparent, as is the more widespread availability of cheaper but restricted tickets for longer distance travel. The fare and service quality changes have themselves been the cause of large variations in demand.

GDP increased by 19.2% between 1990 and 1998, an average of 2.22% per annum, which provides forecast growth over the period ranging between 5.0% and 10.7%. In all cases the actual net growth exceeded the forecast growth by a substantial amount, whilst there are also noticeable differences in forecasting performance across flows. Examination of trends in key external factors could provide explanations of the poor forecasting performance and differential growth rates.

Table 1: Actual and Forecast Growth in Non Season Tickets 1990-98

Flows	Sample of Flows	Growth in Regional per capita GDP	Change in Regional % of Households With a Car	Growth in Regional Population	Forecast Demand Growth	Actual Gross Demand Growth	Actual Net Demand Growth
To London 20-100 miles	43	13.4%	0.71→ 0.78	3.8%	6.3%	38.3%	52.9%
To London 100-200 miles	238	11.8%	0.67→ 0.73	2.3%	6.3%	48.0%	59.4%
To London > 200 miles	139	10.5%	0.62→ 0.68	1.0%	6.3%	63.0%	53.6%
From London 20-100 miles	86	12.9%	0.61→ 0.64	4.3%	6.3%	20.8%	31.9%
From London 100-200 miles	203	12.9%	0.61→ 0.64	4.3%	6.3%	35.3%	39.7%
From London > 200 miles	130	12.9%	0.61→ 0.64	4.3%	6.3%	59.6%	38.7%
Non London <20 miles	222	11.6%	0.65→ 0.71	2.4%	5.6%	6.6%	11.3%
Non London 20-100 miles	1014	12.0%	0.65→ 0.71	2.1%	10.7%	8.6%	18.2%
Non London 101-200 miles	934	12.8%	0.67→ 0.73	2.4%	10.7%	33.7%	33.9%
Non London > 200 miles	1169	12.6%	0.65→ 0.71	2.4%	10.7%	34.8%	28.4%
SE to London >20 miles	43	20.9%	0.76→ 0.81	4.2%	5.0%	10.5%	23.1%
SE from London >20miles	205	12.9%	0.61→ 0.64	4.3%	5.0%	30.4%	43.6%
SE Non London >20 miles	137	20.9%	0.76→ 0.81	4.2%	5.0%	11.6%	17.7%

The forecasts in Table 1 are based on national GDP but variations at a more disaggregate level might provide a better explanation of differential rates of demand growth. Regional GDP per capita growth relating to the origin station ranges from 20.9% for South East England to 8.3% for North East England. Inspection of regional GDP growth suggests that it does not provide the main explanation of differential growth rates.

The petrol and oil price index increased by 23.2% in real terms between 1990 and 1998 (DTLR, 2001). Steer Davies Gleave (1999) reviewed British evidence and concluded that the cross elasticities of rail demand with respect to car cost were 0.1 and 0.3 for inter-urban business and leisure trips and 0.25 and 0.35 for suburban business and leisure trips. The fuel cost increases would therefore be expected to increase business and leisure rail trips by 2.1% and 6.5% respectively in the inter-urban market and by 5.4% and 7.6% in the suburban market. Business travel forms around 40% and 15% respectively of trips on London and Non London inter-urban flows whilst a figure of around 10% can be taken as broadly representative of suburban flows (ATOC, 2002). We would therefore expect rail demand growth of around 4.7%, 5.8% and 7.4% on these three sets of flows. Fuel price increases will therefore have contributed to the strong 1990's demand growth but not to the differential growth rates across routes.

Temporal data on road journey times is poor in quality and coverage. The best evidence for inter-urban travel is provided by large scale 'floating car' surveys undertaken in 1995 and 1998 (DETR, 1999). Car journey times increased substantially in more congested circumstances, such as in built-up areas, peak periods and London and the South East, but were generally much less in the off-peak and non built-up areas. The Steer Davies Gleave (1999) review also covered car journey time cross elasticities and concluded that 0.3 was representative of both business and leisure inter-urban travel with a figure of 0.25 for suburban travel. Whilst there is considerable uncertainty about car journey times, average annual increases of 2½% on London flows, 1½% on Non London inter-urban flows and 2% on suburban flows across the period seem reasonable. These translate into rail demand increases of 6.1% for London based trips, 3.6% for Non London trips and 4.0% for suburban trips. Moreover, there may be additional impacts insofar as the greater congestion increased car unreliability. It would seem that differences in journey time increases across areas have contributed to the larger demand growth on London routes. One might also expect those resident in London and the South East to be more adept at avoiding traffic congestion in that area which would contribute to the higher growth rates in long distance trips to London than from London.

A principal cause of the forecasting inaccuracy lies in the treatment of car ownership and particularly the failure to allow for recent growth being lower as ownership reaches saturation than when the recommended time trends were formulated. In successive ten year periods between 1958 and 1998 the increases in the number of cars per adult (DTLR, 2001) were 0.14 (108%), 0.10 (37%), 0.10 (28%) and 0.08 (16%). Steer Davies Gleave (1999) reviewed the British evidence and concluded that a suitable elasticity within the leisure market was -0.7 with respect to the proportion of households with a car. Between 1990 and 1998, the 7.5% growth in the proportion of households with a car would therefore have led to a 4.9% demand reduction in the rail leisure market. Using the business and leisure travel shares cited above for London, Non London and suburban flows, and assuming ownership to have saturated in the business market, demand would be reduced by 2.9%, 4.2% and 4.4% on these flows. Contrast these with between 11.4% and 18.3% reductions forecast by the recommended time trends cited in section 2.1. Whilst these car ownership effects will have contributed to the higher growth on London routes, they do not explain the stronger growth on flows to than from London.

Population exhibited modest growth of 2.9% between 1990 and 1998. The growth has been larger in the South of England than in the Midlands which in turn has exceeded the North, Scotland and Wales (ONS, 2001). That population growth has been greatest for regions nearer to London does not explain why demand growth has been highest on the longer distance London based routes whilst, as is apparent in Table 1, population growth on routes from London is generally somewhat greater than on routes to London yet it is the latter which have experienced higher demand growth.

3. CAUSES OF THE FORECASTING PROBLEM

A range of factors came together in the 1990's to cause rail demand to increase in excess of that forecast using industry standard procedures. The strong negative time trend, which had represented the effects of falling motoring costs, gradual improvements in the road network and increasing car ownership, is clearly no longer appropriate, and instead explicit account needs to be taken of changes in the costs and times of rail's main competitor, the private car. Furthermore, there are several reasons for expecting the rail GDP elasticity to have increased over time.

There is some evidence (DTLR, 2001) to support an upward trend in the proportion of income that is spent on transport in recent years. It is only when incomes become relatively high that rail can be 'indulged in' and the 'luxury' benefits of usable time and freedom from the stresses and efforts of driving can be purchased. Income growth in the 1990's was above trend, and this 'windfall' might have impacted more on groups who are relatively predisposed to rail, such as young urban singles, whilst 'unexpected' increases in discretionary income could support luxury spending. As far as business trips are concerned, the growth in GDP is now driven much more by service industries and these generate more travel, particularly of the 'briefcase' type where rail does well, so that the rail GDP elasticity could now be higher than has historically been the case.

Even if the income elasticity of overall trip making has not grown over time, we would expect the estimated rail income elasticity to increase if rail captures larger shares of new trips and the causes of this are not adequately allowed for in models[1]. Even if key variables such as car costs and times were entered into the rail demand model to discern their effects rather than attributing them to GDP, a trend increase in the GDP elasticity could still occur as a result of more stressful driving conditions and greater variability of car journey times which are not readily accounted for or simply because there is insufficient road capacity to accommodate the additional traffic. Furthermore, if the rail market is made up of various sub-markets with different GDP elasticities, there will be a tendency for the overall GDP elasticity to increase over time as the faster growing segments form a larger proportion of the total.

A number of other unaccounted factors could have influenced rail demand between 1990 and 1998. There have been gradual improvements to stations, on-board facilities, rolling stock, and information and booking systems, but these are offset by the increased crowding resulting from demand growth and by perceptions of worsening reliability. There is, however, one outstanding factor. This is the stimulus to rail demand through improved marketing, innovative pricing, better fare enforcement and more dynamic management in the post privatisation period brought about by the strong incentive for train companies to grow sales aggressively to offset the sharply declining subsidy profiles which were a feature of many of the franchise agreements.

Fresh empirical research is therefore clearly required, not only to provide up-to-date parameters but also to enhance the forecasting framework to cover a wider range of factors. Two independent opportunities presented themselves. The first was to estimate updated and enhanced models to rail ticket sales data and the second was to analyse data from the National Travel Survey (NTS).

Rail ticket sales data is, as is clear from the numerous studies, that which typically supports the analysis of external factors in Great Britain. It is, in principle, well suited to this task of providing up-to-date parameter estimates, particularly since data for the period where the forecasting problems emerged was available. Nonetheless, other evidence is always welcome. Whilst disaggregate mode choice models can and do yield cross-elasticity estimates, we are not aware of convincing income elasticity evidence from such models and it is this which is the key demand driver. A potentially more profitable line of analysis in this context is the analysis of NTS data. It can provide independent evidence against which to assess elasticities derived from ticket sales data, especially regarding the critically important impact of income, and enhance our understanding by covering a wider range of socio-economic variables. The results of these two independent pieces of analysis are then assessed in the light of their ability to forecast subsequent rail demand trends.

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[1] For example, morning peak arrivals into Central London increased by 10% between 1995 and 1998 whereas due to the congested road conditions the increase in rail traffic was 13% (Steer Davies Gleave, 1999).

4. EMPIRICAL EVIDENCE: ANALYSIS OF TICKET SALES DATA

4.1 Method

The enhanced rail demand model estimated here replaces the time trend of equation 1 with car ownership, population, car travel time and fuel cost. The volume of rail demand between stations i and j in time period t is therefore specified as:

$$V_{ijt} = \mu_{ijt} F_{ijt}^{\alpha} GJT_{ijt}^{\beta} G_{it}^{\gamma} P_{it}^{\delta} T_{ijt}^{\kappa} C_{ijt}^{\lambda} H_{it}^{\theta}$$

(2)

F, T and C represent the fare, car time and car cost on a route whilst GJT is generalised journey time covering the timetable related service quality aspects of journey time, frequency and interchange. G, P and H relate to the origin levels of per capita GDP, population and the proportion of households with a car. The parameters are all elasticities except μ which is a size effect representing the generating potential of origin stations not accounted for by income and population and the attracting potential of destination stations. Coach and air competition varied little in the period and could thus be ignored.

To avoid specifying variables to represent effects which are not of interest here, we can instead examine changes in demand between two time periods (1 and 2) and assume that μ_{ij} is effectively constant. The model then takes the form:

$$\frac{V_{ij2}}{V_{ij1}} = \left(\frac{F_{ij2}}{F_{ij1}}\right)^{\alpha} \left(\frac{GJT_{ij2}}{GJT_{ij1}}\right)^{\beta} \left(\frac{G_{i2}}{G_{i1}}\right)^{\gamma} \left(\frac{P_{i2}}{P_{i1}}\right)^{\delta} \left(\frac{T_{ij2}}{T_{ij1}}\right)^{\kappa} \left(\frac{C_{ij2}}{C_{ij1}}\right)^{\lambda} \left(\frac{H_{i2}}{H_{i1}}\right)^{\theta}$$

(3)

The base year (1) is taken as 1998 and a logarithmic transformation of equation 3 is estimated by multiple regression. The variance of its error term (ε_{ij}) is:

$$Var(\varepsilon_{ij}) = \frac{1}{V_{ij1}^2} Var(V_{ij1}) + \frac{1}{V_{ij2}^2} Var(V_{ij2}) - \frac{2Cov(V_{ij1}V_{ij2})}{V_{ij1}V_{ij2}}$$

(4)

Weighted least squares is used to correct for the variation in the error variance across observations. Observations were removed where year-on-year demand more than doubled or halved. This reduced the data by only 2% overall but removed the worst excesses of data inaccuracy.

4.2 Data

We were supplied with annual CAPRI ticket sales data for 5010 flows for the period 1990 to 1998, excluding 1994 which was affected by serious industrial action. Season ticket sales were not included and thus the journeys are largely for non-commuting purposes. Flows were removed in areas where CAPRI does not give a full account of travel because of the widespread use of multi-modal local authority Travelcards.

We were also supplied with revenue per trip and GJT. Given the resources available to the study, the population, GDP and car ownership figures were restricted to a regional level of disaggregation. The greatest uncertainty relates to car journey times. In consultation with others involved in the study, and bearing in mind the DETR (1999) speed survey and evidence in section 4.4 below supporting larger

increases in the second half of the 1990's, a series of judgements were made[2]. On flows to and from London, it was assumed that the rate of increase was 2½% per year up to 1995 and 4% thereafter within 40 miles of London and 1¼% and 1½% respectively for beyond 40 miles. The latter two figures were used for Non London inter-urban flows. For the remaining journeys within urban areas, the figures were 1½% up to 1995 and 2% thereafter.

4.3   The Co-linearity Problem

A key problem faced in estimating the effects of external factors on rail travel demand is that of serious co-linearity. This problem has plagued the results of several recent studies that attempted to provide revised parameters for equation 1 in the light of the highlighted poor forecasting performance. (TCI, 1997; Wardman, 1997b; CEBR, 1998; Steer Davies Gleave 1999) For example, TCI (1997) estimated GDP and trend parameters to ticket sales data over a period where their correlation exceeded 0.9. Unsurprisingly, the correlation between the estimated GDP elasticities and time trends was –0.83 across seventeen models for different routes. Indeed, there were five instances of negative GDP elasticity estimates and in all but one case the time trend was positive. Nor is this a recent phenomenon as is apparent in the results of Owen and Phillips (1987) and Phillips (1987) upon which PDFH recommendations have largely been based. Whilst it can be argued that as long as the pattern of correlation is maintained in the future it will not be a problem for forecasting, we have seen that this has not proved to be the case in the past and it is unlikely to be so in the future. That most studies made no serious attempt to overcome the problem, and indeed some failed to recognise it, is alarming.

The problems of co-linearity are here compounded since equation 3 contains more external factors than equation 1. For example, in the data set of long distance London based flows, the correlations between GDP and each of car time, fuel and car ownership all exceed 0.9. However, these do not enter the logarithmic transformation of equation 3 which is that estimated. Taking ratios will alter the pattern of correlation, and indeed transformations such as this could be adopted as a possible solution to co-linearity in some circumstances. The correlations between the logarithm of the ratio of GDP and the logarithms of the ratios of car time, fuel and car ownership were 0.97, 0.95 and 0.64. The problem therefore remains, and is reflected in the correlations of estimated coefficients. The correlations between the estimated GDP elasticity and the car time, fuel, and car ownership elasticities were -0.80, -0.59 and -0.49 whilst the correlations between the estimated car ownership and car time elasticities and the fuel cost and car time elasticities were -0.51 and -0.54.

The results of analysis of the 5636 observations of long distance London based flows illustrate the consequences of these correlations. Although the GJT elasticity of -0.89 (±0.07) and the fare elasticity of -0.99 (±0.03) are remarkably similar to the PDFH recommended values of -0.9 and around -1.0 respectively, and the goodness of fit when an intercept was included of 0.65 is respectable, more unsatisfactory parameter estimates for the external factors could hardly be envisaged despite the precision with which they have been estimated. The GDP elasticity can reasonably be expected to be larger than 0.21 (±0.18) on London flows whilst the population elasticity of -0.94 (±0.14), car ownership elasticity of 0.64 (±0.10) and car cost cross elasticity of -0.48 (±0.12) were all wrong sign and the car journey time cross elasticity of 4.37 (±0.39) is far from believable. A series of much simpler models was estimated, which contained only a single external factor in addition to GDP, yet the problem remained.

A solution to the co-linearity problem is to constrain sufficient parameters to predetermined values so that reliable values can be obtained for the remaining freely estimated parameters. Unfortunately, the parameters of <u>all</u> external factors other than GDP had to be constrained to equal the best available evidence if sensible results were to be obtained.

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[2] The main purpose of a study subsequent to this (Steer Davies Gleave, 2003) was to specifically address the impact of car congestion on rail demand. It failed to discern significant effects, concluding that, "there are significant shortcomings in the data sources available for measuring road congestion".

4.4 Results: Estimation of Enhanced Models

Table 2 reports the results of estimating the parameters of equation 2 for long distance London based flows, Non London flows and flows in the South East and Table 3 provides illustrative implied GDP elasticities by route and distance. The railway industry in Britain invariably distinguishes between these three sets of flows because of their uniquely different user characteristics, supply side features and competitive environments. The constraints for the car time and fuel cost cross-elasticities and the car ownership elasticity were taken from the review of Steer Davies Gleave (1999) and discussed in section 2 whilst the origin population elasticity is constrained to equal 1 so that rail trips grow in line with population. For each flow, a base GDP elasticity is estimated to which is added incremental amounts denoting the post privatisation effect, whether the journey was to London or did not involve London at all and an interaction with distance which allows the GDP elasticity to increase with distance. A number of interesting findings have emerged.

Table 2: Models Estimated to Rail Ticket Sales Data

	London	Non London	South East
GDP	1.15 (38.1)	0.30 (21.0)	0.92 (8.4)
Incremental GDP effects			
+Post95	0.42 (15.9)	0.08 (5.2)	0.35 (3.1)
+To London	0.77 (35.5)	-	0.61 (4.4)
+Non London	-	-	-0.27 (3.0)
+Distance	0.0015 (8.6)	0.0060 (24.6)	-
GJT	-1.08 (27.1)	-0.61 (32.8)	-0.9
Fare	-0.83 (40.1)	-0.59 (64.8)	-0.49 (6.1)
Car Time	0.30	0.30	0.30
Car Cost	0.22	0.27	0.24
Car Ownership	-0.42	-0.60	-0.53
Adjusted R^2	0.64	0.29	0.33
Observations	5636	23206	2610

Note: Regression coefficients with t statistics in parentheses. The constrained parameters taken from the Steer Davies Gleave (1999) review are weighted by the indicative journey purpose splits taken from ATOC (2002) for the flow type in question.

Table 3: Implied GDP Elasticities

	25 Miles			75 Miles			150 Miles			250 Miles		
	Pre 95	Post 95	%	Pre 95	Post 95	%	Pre 95	Post 95	%	Pre 95	Post 95	%
To London	1.96	2.38	+21.4	2.03	2.45	+20.7	2.15	2.57	+19.5	2.30	2.72	+18.3
From London	1.19	1.61	+35.3	1.26	1.68	+33.3	1.38	1.80	+30.4	1.53	1.95	+27.5
Non London	0.45	0.53	+17.8	0.75	0.83	+10.7	1.20	1.28	+6.7	1.80	1.88	+4.4
SE to London	1.53	1.88	+22.9	1.53	1.88	+22.9	-	-	-	-	-	-
SE from London	0.92	1.27	+38.0	0.92	1.27	+38.0	-	-	-	-	-	-
SE Non London	0.65	1.00	+53.8	0.65	1.00	+53.8	-	-	-	-	-	-

Firstly, rail travel can in many instances be regarded as a 'luxury' good with an income elasticity in excess of one. Leisure trips to London and short breaks which supplement annual holidays may still be widely regarded as luxury goods. More generally, rail travel may be seen as a luxury given the high costs of car ownership but low marginal costs of use.

Secondly, the GDP elasticities are higher on London than Non London flows. This could stem from higher GDP elasticities for business travel which forms a much higher proportion of travel on London routes. Rail business trips are largely made up of 'briefcase' travellers from the commercial, legal and technology sectors where growth has tended to outpace the national average and these sectors are well represented in London and major regional centres. Congestion problems are also greater on London routes and would inflate the income elasticity if rail captures a larger proportion of newly generated than existing trips.

Thirdly, the GDP elasticities are somewhat larger for trips to than from London. We have specified the car journey time increases to be the same for trips to and from London yet those resident outside London may be less able to take steps to moderate the impact of car journey time increases. It may well be that rail performs best at capturing newly generated trips on London based flows given this is where the congestion problems are worst. The increasing dominance of London as a destination for business and leisure travel will also have contributed to the larger growth to than from London. A further contributory factor, conditional upon business travel having a higher GDP elasticity, is that the proportion of travel that is for business is greater on flows to than from London.

Fourthly, there is evidence that the GDP elasticity increases with distance. In part this could reflect a trend towards longer distance journeys, but it is also conceivable that we have understated the cross elasticities with respect to car time for longer journeys since there is evidence (Wardman, 2001) that the value of car travel time increases at a faster rate with distance than does the value of rail travel time. The distance effect is much stronger for Non London flows. This may be because, in contrast to London based flows, rail only becomes an attractive option to those with a car available over longer distances where driving becomes a more onerous task and the advantages rail possesses offset the significant deterrents involved in accessing the rail network. Although there was no significant distance effect on South East flows, the range of distances is here much more limited.

Finally, and of particular interest, are the higher GDP elasticities on all routes from 1995. If this is a one-off impact of privatisation it needs to be isolated from the underlying GDP effect. Table 3 shows that the post 1995 effect on the GDP elasticity is quite pronounced, but we do not find it reasonable that the 'pure' GDP elasticity could vary so much over such a short period. We note that the post 1995 effects are larger on the long distance London flows and on the South East flows. It is on these routes where we suspect that the congestion problem could possibly be worse than here specified but also where the post privatisation marketing abilities and efforts, tackling of fare evasion and dynamic management have been greatest.

We explored whether the post 1995 GDP effect was a function of higher car journey time increases after 1995 than we had specified. Anecdotal evidence and figures for car journey to work times (DTLR, 2001) support larger car journey time increases in the second half of the decade. The post 1995 annual rates of growth in car journey times that were just sufficient to remove the post 1995 GDP effect were 8.3, 2.6 and 6.7 times those initially used for London, Non London and South East flows. These would imply implausibly large increases in car journey times. We must therefore conclude that significant underestimation of the car time effect is not the principal cause of the post 1995 increase in the GDP elasticity. Our view is that these are primarily residual trend effects of a one-off nature due to privatisation which, through correlation, have been discerned by the GDP elasticity, and possible gradual increasing of the GDP elasticity for the reasons discussed in section 3.

The elasticities to fare and GJT are generally satisfactory. GJT varied little on flows in the South East and reliable estimates could not be obtained. The GJT elasticity was therefore constrained to PDFH recommendations in order to isolate the effects that were present. However, the goodness of fit obtained (for models containing an intercept) varies considerably, from quite respectable levels for the London based flows to levels where there is clearly a large amount of noise in the data. Heteroscedasticity is taken account of by using weighted least squares based on equation 4. Although there is evidence of first order autocorrelation, with Durbin-Watson statistics of 0.71, 0.61 and 0.94 for London, Non London and South East flows respectively, we did not proceed to correct for this given the high level of precision with which the coefficients are estimated.

5. EMPIRICAL EVIDENCE: ANALYSIS OF NATIONAL TRAVEL SURVEY DATA

Relatively little use has been made of National Travel Survey (NTS) data for modelling purposes. It here serves a valuable purpose of providing a separate set of income, trend and car ownership effects, which turn out to suffer less from co-linearity problems, that can corroborate or challenge the results of the ticket sales analysis. It can also provide insights into the effects of various socio-economic factors which cannot be obtained through analysis of rail tickets sales data.

5.1 Data

The NTS provides information on individuals' travel patterns recorded in a 7 day travel diary. NTS data was available for the years 1985/6, 1988 through to 1993 and 1995 through to 1997 covering 96027 individual records spread fairly evenly across years. NTS data also contains information on a range of socio-economic and demographic characteristics of individuals and their households. Since trip information is only available for the chosen mode, the data is not suited to mode choice analysis.

5.2 Method

The data was aggregated to represent average rail trip rates of individuals in various categories of five variables. These were: gender; whether the household owned a car; household structure, which could take the form of single person households (*Struc1*), two person households (*Struc2*), three person households with children (*Struc3*) and three person households without children (*Struc4*); age groups of under 30 (*Age1*), between 30 and 50 years (*Age2*) and over 50 (*Age3*); and the socio-economic groups of semi and non skilled manual (*SEG1*), professional and managerial (*SEG2*), clerical (*SEG3*) and skilled manual (*SEG4*). The analysis of the grouped NTS data took the basic form:

$$T_{ijklmt} = \mu e^{\sum_{i=2}^{I} \alpha_i C_{it}} e^{\sum_{j=2}^{J} \beta_j G_{jt}} e^{\sum_{k=2}^{K} \gamma_k H_{kt}} e^{\sum_{l=2}^{L} \delta_l A_{lt}} e^{\sum_{m=2}^{M} \lambda_m S_{mt}} Y_{ijklmt}^{\psi} W_{ijklmt}^{\tau} \qquad (5)$$

T_{ijklmt} is the number of trips per head in year t in a particular category and C, G, H, A and S are dummy variables denoting various categories of car ownership, gender, household structure, age group and socio-economic group respectively. Given n categories of a variable, n-1 dummy variables can be specified and the exponentials of their coefficients (α_i, β_j, γ_k, δ_l and λ_m) denote the proportionate effect on rail trip rates of a particular category relative to the arbitrarily omitted category. Additionally the mean income (Y) and mean walk time to the station (W) of those in each category were included in the model and their parameters (ψ and τ) represent elasticities. Although income is correlated with socio-economic group and to a lesser extent age and household structure, there may well be variations in the propensity to travel and to choose rail which are driven by different attitudes, lifestyles, preferences, and requirements and ability to travel rather than income per se.

This aggregate procedure was adopted because the models are then directly comparable with those estimated to ticket sales data and their parameters can be easily interpreted and applied. Moreover, grouping data across individuals nets out a large amount of random error that exists at the level of weekly individual trip making.

5.3 NTS Model Results

The total number of combinations of each category of the socio-economic and demographic variables is 192 for each year. This yields a maximum of 1920 observations across the 10 available years. However, cases where there are no trips in a category are removed from the estimated model, leaving

815 observations for leisure travel and 462 observations for business trips[3]. The models are reported in Table 4.

The income elasticity and car ownership effect in the leisure model are plausible and precisely estimated, although we might expect the former to be lower than the income elasticities of conventional rail demand models since the latter do not include socio-economic group[4]. The car ownership parameter implies that those without a car make around twice as many leisure rail trips independent of income and a car ownership elasticity of –0.55 for the 72% of households in 1998 who owned a car. The former is consistent with the trip rate data collected by Steer Davies Gleave (1999) which, for journeys over 5 miles, also found that those without a car in the household were about twice as likely to make a rail trip whilst the car ownership elasticities in the two studies are not greatly different. Whilst there is, as we have seen, a very high correlation between the proportion of households with a car and GDP, the correlation between whether an individual is in a household with a car and the level of household income can be expected to be and actually is much lower. The correlation between the estimated coefficients for income and car ownership in Table 4 is only 0.256. Indeed, when separate leisure models were estimated for each year, the correlation between the 10 coefficients for income and whether there is a car in the household was actually zero!

Those aged over 50 (*Age3*) make considerably fewer leisure rail trips whilst males tend to make many more. The omitted socio-economic category is the semi and non skilled manual group and we would expect, and indeed find, that other socio-economic groups make more rail trips. Most rail trips are made by the professional and managerial category (*SEG2*), followed by the clerical (*SEG3*) and the skilled manual categories (*SEG4*). Households containing children (*Struc3*) make by far the fewest leisure rail trips, presumably because of the cost and other advantages of using car for group travel, with a smaller negative effect associated with three person households without children (*Struc4*). The walk time elasticity seems much too large and may be subject to simultaneity bias because those who make a large number of rail trips choose to live nearer to rail stations.

Table 4: NTS Rail Leisure Trip Rate Models

	Leisure		Business	
	Coeff (t)	Effect	Coeff (t)	Effect
Constant	n.s.		-6.039 (2.3)	
Age3	-0.723 (7.4)	*0.49	-0.355 (3.0)	*0.70
Male	0.344 (4.3)	*1.41	0.469 (4.6)	*1.60
SEG2	1.166 (7.9)	*3.21	2.159 (7.7)	*8.66
SEG3	0.955 (7.6)	*2.60	1.387 (5.0)	*4.00
SEG4	0.476 (3.5)	*1.61	1.536 (5.2)	*4.65
Struc2	n.s.		-0.394 (2.8)	*0.67
Struc3	-0.692 (7.2)	*0.50	-0.475 (3.2)	*0.62
Struc4	-0.164 (1.8)	*0.85	-0.291 (1.9)	*0.75
Car	-0.759 (9.8)	*0.47	n.s.	
Walk	-1.234 (10.9)		-1.934 (9.8)	
Income	0.688 (4.9)		n.s.	
Trend	0.022 (2.2)		n.s.	
GDP	n.s.		1.950 (3.5)	
Adjusted R^2	0.43		0.41	
Observations	815		462	

Note: Regression coefficients with t statistics in parentheses. The R^2 for the leisure model relates to a model containing the constant term. The effect denotes the proportionate change relative to the base category.

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[3] The reason for this is that logarithms cannot be taken of zero trips. Nonetheless, a purely additive model produced similar results regardless of whether zero trips were removed or not.

[4] When the SEG variables were removed, the income elasticity increased to 1.40 (±0.22)

The temporal dimension allows a time trend term to be specified. The trend could discern differences between time series and cross sectional income elasticities as well as the effects of other variables not in the model. The time trend denotes that rail trips are growing by 2.2% per annum quite separate from any income and car ownership variation. Fortunately, the correlations between the time trend estimate and the coefficients for income and car ownership are both less than 0.1, explaining why the impact of including the trend on the income and car ownership coefficients was negligible. Using GDP in the place of a time trend produced a worse fit. There was some support for the income elasticity increasing with the level of income. However, it was only a very modest increase from 0.68 in 1985 to 0.76 in 1998 and therefore we did not persist with it. .

Turning now to business travel, income did not have a significant influence upon rail business trip rates. When included, the income elasticity was 0.08 with a t ratio of 0.3. In contrast with the leisure models, socio-economic characteristics play a very much more important role in explaining variations in business trip rates. When the SEG variables were removed, the income elasticity was 0.93 and significant (t=4.4) but the adjusted R^2 fell appreciably to 0.32. Males make 60% more business trips than females whilst those aged over 50 make 30% fewer trips. All household types make fewer business trips by rail than single person households whilst the walk time elasticity is again too high. Whether there was a car available to the household did not influence the number of business trips.

Business trips are driven by the level of economic activity, represented by GDP. This variable, which discerns only temporal effects, has a significant influence upon business trip rates and its elasticity is 1.95. There might be additional temporal effects and thus a time trend was specified. When both GDP and time trend were included, neither were significant due to the large correlation of -0.96 between their coefficients. Including just the time trend revealed a 4.1% annual growth but a slightly worse fit than the GDP model. Analysis failed to detect support for a growing GDP elasticity over time.

The goodness of fit of each model is respectable given the expected large amount of random error in surveyed weekly rail trips and the absence of variables relating to the fare and service quality of rail and competing modes. The Durbin-Watson statistics for the leisure and business models of 1.79 and 1.89 indicate that first order autocorrelation is not a problem. A Breusch-Pagan test (REF) found that the error variance in the leisure model depended upon *Struc3*, *Age3* and *SEG4* and in the business model the significant influences were *Age3*, *SEG2*, *SEG3* and *SEG4*. Whilst the Chi-Squared test of the null hypothesis of homoscedasticity could be rejected in each case, both the error regression models achieved R^2's around 0.06 and did not imply a great deal of variation around a constant error variance. Indeed, using weighted least squares to correct for the identified form of heteroscedasticity hardly impacted upon the results.

6.   COMPARISON OF ELASTICITIES AND POST 1998 VALIDATION

We here compare the elasticities obtained from the analysis of the ticket sales and the NTS data and, more importantly, validate the forecasts produced by the two methods against out-turn demand in time periods beyond the calibration period.

For journeys to and from London and the average distance of 100 miles, the GDP elasticity from the ticket sales model reported in Table 2 is 1.69, increasing to 2.11 with the inclusion of the post 1995 effect. The corresponding figures for Non London routes are 0.90 and 0.98 and for South East routes are 1.03 and 1.38. The share of non-season ticket volume between London, Non London and South East operators was around 10%, 34% and 56% in 1998[5]. This would imply an overall GDP elasticity of 1.05, increasing to 1.32 with the post 1995 effect. The analysis of NTS data yielded a business travel GDP elasticity of 1.95 and a leisure travel income elasticity of 0.69. Using business shares for the three sets of routes of 40%, 15%, and 25% (ATOC, 2002), a representative NTS average would be 0.98.

Such a close degree of correspondence of the overall income elasticities from the two data sources is most encouraging. Although it could be argued that increases in fuel costs and car times could have

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[5] Data supplied by the Strategic Rail Authority.

been discerned by the GDP elasticity in the NTS business model, it should be noted that the effects of these across the entire period of the NTS data used here were much less than across the period of the ticket sales analysis. In the leisure model the trend would have discerned some of these effects. Relatively little of the NTS data covers the post privatisation period so its effect should have only a very minor bearing on this comparison of income elasticities.

We have already seen that the car ownership effect in the NTS data is not greatly different from that provided by a review of previous evidence. The time trend in the NTS leisure model indicates that rail demand would have increased by around 19% between 1990 and 1998 independent of income and car ownership effects. In section 2, growth attributed to fuel price and car time increases in the leisure market was estimated at 13.0%, 10.3% and 11.9% in the inter urban London, inter urban Non London and suburban markets. We would have liked the two approaches to produce more similar figures, although the extent to which the NTS trend discerns improvements in rolling stock, station facilities and marketing, and greater environmental concerns, would contribute to this difference.

Finally we turn to a comparison of the forecasts both across methods and with reference to actual rail demand growth in the period after 1998. We have no detailed data along the lines of Table 1 for post 1998. Data is however available on the volume of non-season tickets in total (SRA, 2003). The Hatfield accident of October 2000 resulted in widespread speed restrictions being imposed throughout the network which had an adverse but unknown impact on rail demand. Data prior to this event has therefore been used. We have also made use of more recent data when the network had largely recovered from the post Hatfield service disruptions.

Table 5 lists the actual year-on-year growth in the volume of non-season ticket sales for 6 financial quarters. Changes in fares and service quality were minor and can be ignored. The strong demand growth in the years leading up to 1998 is repeated. GDP growth was generally above average, with the slightly lower GDP per capita growth implying around a ½% per annum growth in population. The proportion of households with a car was 0.72 in 1998 and 1999 and 0.73 in 2000, and we have assumed growth of 0.005 per annum. Car times have been assumed to increase by 2½% on London routes and 1½% on Non London routes whilst the cost of fuel increased by 5.5% between 1998 and 1999 and by 7.0% between 1999 and 2000.

Table 5: Forecast and Actual Demand for Non Season Tickets 1998-2000 and 2002-2003

	Actual	GDP	PDFH3 London	PDFH3 NonLon	PDFH3 S East	Ticket Sales London	Ticket Sales Non London	Ticket Sales South East	NTS Business	NTS Leisure
99 Q1 v 98 Q1	6.5%	1.64%	-0.1%	0.4%	-0.1%	4.2% - 4.7%	3.0% - 3.1%	3.4% - 3.9%	3.2%	2.9%
99 Q2 v 98 Q2	6.9%	2.30%	0.9%	1.4%	0.7%	5.3% - 6.1%	3.6% - 3.8%	4.3% - 4.9%	4.5%	3.3%
99 Q3 v 98 Q3	4.6%	2.75%	1.5%	2.1%	1.2%	6.1% - 7.1%	4.0% - 4.2%	4.8% - 5.7%	5.4%	3.7%
99 Q4 v 98 Q4	6.5%	3.04%	2.0%	2.5%	1.6%	6.9% - 8.1%	4.7% - 4.9%	5.5% - 6.5%	6.0%	3.9%
00 Q1 v 99 Q1	6.9%	3.31%	2.4%	2.9%	1.9%	7.4% - 8.7%	5.0% - 5.2%	5.9% - 6.9%	6.6%	4.0%
00 Q2 v 99 Q2	8.6%	2.74%	1.5%	2.1%	1.2%	6.4% - 7.4%	4.4% - 4.6%	5.1% - 6.0%	5.4%	3.6%
Mean	6.7%	2.63%	1.4%	1.9%	1.1%	6.1% - 7.0%	4.1% - 4.3%	4.8% - 5.7%	5.2%	3.6%
03 Q2 v 02 Q2 London	3.8%	2.11%	0.6%	-	-	3.7% - 4.6%	-	-	3.9%	
Non London	4.1%	2.11%	-	1.1%	-	-	1.5% - 1.7%	-	3.8%	
South East	2.3%	2.11**%**	-	-	0.5%	-	-	2.2% - 3.4%	3.8%	

Note: Q denotes quarter within the financial (April-March) year. The 03 Q2 v 02 Q2 figures for London flows exclude the West Coast route where a major upgrade caused very serious disruptions to services and demand.

As expected, the forecasts (PDFH3) based on the third edition of PDFH (ATOC, 1997) for each of London, Non London and South East flows fall woefully short of what actually happened. This remains so if fuel price and car journey time effects are included, whereupon the average forecast increases are 3.5%, 3.8% and 3.1%.

The ticket sales model is based on the estimated and constrained parameters set out in Table 2 for an average distance of 100 miles. Two sets of forecasts are provided, according to whether the post 1995 effect is included or not. The NTS leisure travel forecasts also incorporate population growth

alongside the income, car ownership and time trend effects in Table 4 whilst the NTS business travel forecasts are based solely on overall GDP.

Using the shares for each flow type cited above, the average of the ticket sales based forecasts ranges between 4.7% and 5.4% compared to the mean actual growth of 6.7%. These are dramatically better forecasts than the PDFH3 forecasts and would seem to support a continuation of the post-privatisation effect in this period.

Again using the shares across routes and the journey purpose splits cited above, the mean increase in demand forecast by NTS is 4.1%[6]. Even though the NTS forecasts will have discerned very little post 1995 effect, these forecasts are farther from the actual demand increases than the ticket sales based forecasts without the post 1995 effect. Given the NTS data covers years in the 1980's when car congestion is not regarded to be as serious and when car fuel costs were actually falling, the GDP elasticity in the business model and the trend in the leisure model will not have discerned as large an effect due to these variables as if they had been estimated purely to 1990's data, thereby partially explaining the lower forecasts. Inclusion of the same car time and cost effects as the ticket sales based forecasts would yield business and leisure forecasts of 6.5% and 6.1% and an overall forecast of 6.2% which is very close the actual growth.

Moving to the most recent post-Hatfield quarter available, data supplied to us by the Strategic Rail Authority indicated that the increase in ordinary tickets on London based, Non London and South East train companies was 3.8%, 4.1% and 2.3% between the second quarters of 2002 and 2003.

GDP growth was 2.1% whilst fuel prices fell by 2.9% and we have assumed the same increases in car journeys times as for the other forecasts. Car ownership and population growth were small and the net effect on rail demand can reasonably be taken to be negligible.

The ticket sales models can predict the London and the South East flows very well, particularly if we assume that the post-privatisation effect has run its course. However, the relatively large increase on Non London flows cannot be explained. On these flows, the fuel price reductions will have a larger forecast effect than elsewhere whilst car journey times were specified to increase at a lower rate. It is tempting to attribute the forecasting inaccuracy to a belated post privatisation effect. Even though the former Regional Railways companies were in a weaker managerial position at the time of privatisation, and therefore took longer to adopt new managerial practices and innovative marketing methods, this argument is too speculative. Instead, we regard this large growth on Non London routes to be a temporary 'aberration', and note that a number of other studies back up the findings of this study by indicating that demand growth due to external factors would be expected to be somewhat stronger on London than Non London routes (Palomo, 1996; Wardman 1997b; Ahmed, 1998; NERA, 1999; Wardman and Whelan, 2004).

The NTS forecasts replicate the demand changes reasonably well: using the shares of each route cited above, the average demand increase was 3.1% which is not greatly different from the average NTS forecast of 3.8%. However, the forecasts are counter to those based on ticket sales since Non London demand growth is explained well but the growth on South East flows is not.

7.   CONCLUSIONS

This study has examined both ticket sales data and survey based data to provide an improved understanding of the impact of external factors on the demand for rail travel in Great Britain. Although the models predict appreciably larger growth than previous forecasting procedures, we can take encouragement in the fact that the results obtained from independent analysis of two somewhat different data sets provide broadly consistent findings and that the models were able to forecast subsequent rail demand growth reasonably accurately. A number of important findings have emerged from this study.

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[6] Although the NTS models can predict demand changes stemming from different socio-economic and household characteristics, these would hardly vary within these timescales.

Firstly, we have developed models which can explain demand levels far better than those which the industry had previously been using. In part this is because of the estimation of more up-to-date parameters and in part due to the use of an enhanced forecasting framework. These models are being used by the Strategic Rail Authority to forecast background growth and more generally have had a major bearing on the recommended GDP elasticities used in the most recent edition of the Passenger Demand Forecasting Handbook (ATOC, 2002) which is widely used in the rail industry in Britain.

Secondly, the problem of co-linearity in previous studies has been recognised and addressed in order to isolate the effects of a range of variables which, in future years, will correlate differently. We have demonstrated that the process of constrained estimation was here essential to obtaining sensible results and disentangling the effects of a range of variables, although admittedly uncertainties remain about the cross elasticity terms and in particular the extent of car journey time increases. The contribution to rail demand growth between 1990 and 1998, on average, of each of the variables considered in this study is set out in Table 6. The critical importance of GDP to rail demand growth is quite clear. Car time and fuel cost had broadly similar effects but in some areas rail demand will have benefited much more from population growth. Except on the Non London flows, the post 1995 effect made a significant contribution to growth second only to GDP in importance. The future pattern of variation in the various external factors will differ from that apparent in the 1990's, which in turn differed from previous periods, and it is therefore important to distinguish between their separate effects to forecast future demand growth. The abolition of the fuel duty escalator removes a strong inflationary pressure on car costs whilst population is forecast to stagnate and we have argued that the post 1995 trend was largely a transient effect. Moreover, recent growth in and future projections of GDP are lower than the sustained high rates of much of the 1990's whilst the pressure on the road network may lead to more serious congestion problems.

Table 6: Impact of External Variables on 1990-1998 Rail Demand Growth

	London	Non London	South East
GDP	1.301 (1)	1.196 (1)	1.149 (1)
Car Time	1.043 (4)	1.031 (4)	1.067 (3)
Fuel Cost	1.045 (3)	1.056 (2)	1.049 (5)
Population	1.038 (5)	1.022 (6)	1.055 (4)
Car Ownership	0.975 (6)	0.951 (3)	0.972 (6)
Post 1995 Trend	1.119 (2)	1.033 (5)	1.092 (2)
Total	1.606	1.307	1.440

Thirdly, we have shown the complementarity of survey and ticket sales data. Although both can provide important insights into the demand effects of external factors, the former provides estimates of the effects of socio-economic and demographic factors not achievable by the latter whilst the latter is well suited to the analysis of changes in rail service quality and fare which the former is unable to do. Our preference is to use the elasticities based on the ticket sales analysis since it is a much larger data set, disaggregates by flow type and distance, and covers a wider range of external factors, although the NTS income elasticities are similar and it is income which is the key demand driver.

Fourthly, there is clear support for strong variation in the GDP elasticity across routes, with higher values on London than Non London flows and increasing with distance. With the exception of local and short distance Non London trips, the GDP elasticities support the notion of rail travel being a luxury good. There is also support for the GDP elasticity increasing over time.

Finally, there is evidence of an otherwise unaccounted for stimulus to demand resulting from privatisation. It is here concluded that it is better to isolate this and regard it as a temporary phenomenon rather than allowing its effect to be built into forecasts in perpetuity.

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