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NATIONAL MULTI-MODAL TRAVEL FORECASTS

LITERATURE REVIEW

AGGREGATE MODELS

Stephen Clark

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NATIONAL MULTI-MODAL TRAVEL FORECASTS

LITERATURE REVIEW

AGGREGATE MODELS

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CONTENTS

ABSTRACT

This paper reviews the current state-of-the-art in the production of **National Multi-Modal Travel Forecasts**. The review concentrates on the UK travel market and the various attempts to produce a set of accurate, coherent and credible forecasts. The paper starts by a brief introduction to the topic area. The second section gives a description of the background to the process and the problems involved in producing forecasts. Much of the material and terminology in the section, which covers modelling methodologies, is from Ortúzar and Willumsen (1994). The paper then goes on to review the forecasting methodology used by the Department of Transport (DoT) to produce the periodic National Road Traffic Forecasts (NRTF), which are the most significant set of travel forecasts in the UK. A brief explanation of the methodology will be given. The next section contains details of how other individuals and organisations have used, commented on or attempted to enhance the DoT methodology and forecasts. It will be noted that the DoT forecasts are only concerned with road traffic forecasts, with other modes (rail, air and sea) only impacting on these forecasts when there is a transfer to or from the road transport sector. So the following sections explore the attempts to produce explicit travel and transportation forecasts for these other modes. The final section gathers together a set of issues which are raised by this review and might be considered by the project.

1 INTRODUCTION

The production of reliable estimates of future travel demand within the UK has obvious benefits, not least the planning of various forms of infrastructure investments in order to meet this demand. If these forecasts include exogenous variables then these variables can be varied, so as to assess the sensitivity of their level on the forecasts.

There are two basic travel markets considered in this paper, passengers and freight. The **passenger market** is composed of many different modes, the more common of which are : private car; bus (and other stage stop services ie light rapid transit); taxi; bicycle; walk; rail; coach and air. Some of these modes are in direct competition with each other at some market level (ie inter city rail with long distance car travel). The task of forecasting is not only to predict the size of the passenger travel market but also the share which each mode takes of this market. Whilst many mode specific models exist for the prediction of the demand within each mode (many of which are described in this paper) account needs to be taken of the competition between modes. Thus the addition of a single car owner may decrease the number of annual bus/train journeys (or bus/train kilometres) by a fixed amount but increase the annual number of car journeys (or car kilometres) by a differing (probably greater) amount. The effect on the use of available road space may also need to be taken into account. Figure 1 attempts to describe some of these mode interactions. The text accompanying each arrow describes the factors which may cause a move from one mode to another. Thus an increase in incomes may cause a move from bus to car travel whilst, conversely, a decrease in incomes may cause the opposite movement. Some of the movements are relatively *easy* to induce (bus into car) whilst others are more *problematic* (car into train).

The **freight market** has the following modes: heavy goods vehicles; light goods vehicles; rail; inland water-ways; sea transport and air. The attributes traditionally associated with each of these modes are:

HGV : Flexible; Good for medium size loads; Cost-effective.
LGV : Very flexible; Good for small size loads;
RAIL: Cost-effective; Good for large (bulk) loads; Inflexible;
INLAND: Very cost-effective; Good for large size loads; Very inflexible; Slow
SEA: Cost-effective; Good for very large size loads; Very inflexible; Slow
AIR: Quick; Capacity for small size loads only; Expensive.

To an extent the commodities within each mode are captive.

2 TRANSPORT MODELLING

"All models are wrong but some are useful" G.E.P. Box

Modelling of anything other than the most simple of processes is an imperfect science. This imperfection may result from the fact that a model is unable to capture the full complexity of the situation we are trying to represent and also from the poor quality or lack of explanatory data used to describe the system. This imprecision is further compounded when we try to forecast what is likely to happen in the future, using such a model. Changes in past trends, changes in how the situation reacts to trends and new phenomena can seriously hamper a model. With these issues in mind and knowledge of the fact that perfection is perhaps out of reach and that just good may be the most which can be expected, models can still be of use.

Modelling can be decomposed into three stages:

(1) **Model structure**. An hypothesis can be suggested as to what the elements of a model are and the

relationships between these various elements. The relationship will usually be expressed in an algebraic functional form. Trade-offs may come into play at this stage. The model can be good or mediocre in performance, complex or simple to understand/rationalise and vunerable or robust to errors. Clearly the goal is a good, simple and robust model but this may not be achievable, so then which is best - a good, complex, vunerable model or a mediocre, simple, robust model? At what level should the model be applied? Should it be disaggregated to a fine level of detail in measurement or should it be at a higher, more strategic level?

(2) **Variable selection**. Interaction between the model structure stage and this stage is necessary to ensure that all the data required for the study is available, cost effective to use or collect and of reasonable quality. The form of the data may also dictate or constrain the model structure. Common forms of data are cross-sectional, time series and longitudinal. Cross-sectional data are obtained at a single point in time and attempts to capture a snap-shot of the state of the system. Time series data are a sequence of data recorded over a period of time, usually, but not always, at regular intervals. Such a form of data can begin to show historical trends and patterns in the data. Longitudinal data takes the form of panel data where a cross-section of individuals are selected for interview, at repeated intervals.

(3) **Model calibration, validation and use**. During this stage the model is applied to the data in order to produce results. During the calibration and validation steps the true result is known therefore a measure of the model's accuracy can be obtained. The calibration and validation steps differ in that the models parameters are estimated or derived during the calibration step and tested in the validation step. It is necessary therefore to have two separate, but otherwise equivalent sets of data, one for calibration and another for validation. A reasonably calibrated and validated model can then be used to predict the effects of a change due to some new scenario of interest or to predict future values. Of course any one of these three steps could highlight deficiencies with either the model structure or the selection of variables used, in which case stages 1 and 2 have to be reconsidered.

Only when a model has produced significant and intuitive parameter values during the calibration stage, which have been validated and shown to produce reasonable answers in their use can the process be called a success.

During all the above discussion no direct reference has been made to the application area of this study, namely transport. Within transport there is a classical model which in actual fact is composed of four related models. These individual models are termed: Trip-generation; Distribution; Modal split and Assignment.

Trip generation. This model attempts to determine the demand for transportation both into (attraction) and out of (production) regions. These trips can be classified by purpose; time of day or person type. The volume of trips is usually expressed as a function of various socioeconomic characteristics associated with the region. These characteristics may be represented as totals for the zone or rates (per household for example). The demands can be derived using regression techniques which express the desire for travel as a (linear) function of socioeconomic characteristics for the region. Another approach is the use of category analysis. This approach estimates the demand as a function of household attributes. Trip rates are derived by an empirical survey which supplies the average rate for households possessing certain attributes. Clearly the larger the number of attributes the larger the volume of survey data required. Rather than presenting a traditional cross-classification of trip rates an alternative methodology suggested by Stopher and McDonald (1983) may be used which is more statistically robust, being based on ANOVA techniques. This approach is covered in more detail in appendix A.

Distribution and modal split. Here the trips generated in the preceding stage are converted into patterns of trip making, from where they start to where they finish. To some extent the determination of this information may require prior-information on the split between the different available (and competing) modes. The usual product of the process up to this point is a number of origin-destination matrices representing journeys from trip origins to trip destinations.

Assignment. This model uses information on the pattern of trips specified in the origin-destination matrices, combined with information on available infrastructure and generates routes for the trips to match the demand (traffic) with supply (infrastructure).

Once this suite of models have been individually and collectively constructed, calibrated and validated a set of tools exists for the evaluation of differing scenarios. The suite is not, however, suitable for forecasting. In order to do this suitable future estimates of all the future values of the input variables are required, along with other relevant information. Growth (or decline) rates can be applied to the trip generation process to obtain updated estimates of trip rates.

3 NATIONAL ROAD TRAFFIC FORECASTS

Periodically the UK Department of Transport (DoT, 1989) produces a set of National Road Traffic Forecasts (NRTF) for the expected volume of road traffic in each year over a 30 year span. This traffic is composed of three elements: car traffic; freight traffic and public transport. No account is taken of pedestrian, cycling or motor cycle traffic. This omission is no doubt due to the fact that the primary stated purpose to which these forecasts are put is the appraisal of improvements to the national trunk road network which has little pedestrian or cycling activity. Other uses to which these forecasts could be put are to address national issues, such as national fuel consumption, national pollutant emissions, traffic accident rates and level of economic activity. A case also exists for the production of regional forecasts, which are currently not part of the National Road Traffic Forecasts.

The NRTF do not follow the classical modelling approach detailed in section 3.

Each of the three traffic sectors in the model are considered in isolation and the total volume of travel obtained by the summation of the volumes in each sector. The car traffic sector forecasts are further split into two methods.

Most modelling effort is placed in the production of **car traffic forecasts** since this composes the largest volume of vehicle traffic. The first car traffic model attempts to forecast car ownership and the second car use, measured in kilometres per car.

Car ownership (measured in cars per thousand population {cpt}) is influenced by many factors. These factors include: income; purchase cost; running costs; location of home, work, retail outlets; demographics; parking; attractiveness of alternatives and attitudes to cars. Many of these factors will be compounded, for example income, purchase costs and running costs are all related to general wage and price inflation. The NRTF has a further division of two car ownership models. The first is the household model and the second is an extrapolatory model.

The variables used in the household model are:

Income. The reasoning behind the use of this measure as a predictor is that as incomes rise (in real terms) cars become more affordable to both purchase and run.

Saturation of ownership. This is assumed to be 90% of the driving age population, which is itself is expected to stay constant at 71-73% of the total population [Paragraph 17]. The figure used is (0.9*0.72*1000≈) 650 cpt . There is circumstantial evidence for the correctness of this figure, although P55 says "that there is no evidence anywhere yet of ownership exceeding 550cpt." (a typo?). This is a limiting value used in the forecasts.

A time trend. There is a strong, upward, time trend in car ownership figures over the period 1960 to 1987. Instead of using a straightforward time trend variable, the variable driving licences per adult (LPA) is used. In Smith (1981) the inclusion of either the time trend or LPA variable significantly reduced the complexity of the model (eliminating the need for year specific parameter estimates) whilst still retaining its explanatory power. The justification for using the LPA rather than time trend variable was that the LPA would be a more sophisticated measure when used in forecasting, compared to the monotonically increasing time variable. It should be borne in mind that LPA may not be an explanatory variable, merely a **proxy** for the true, unknown, variable which has just historically behaved in a similar manner to LPA. This may not be the case in future.

The detail of the model involves the derivation of two quantities. The probability that a given household of a given income will own one car (p_{1+}) and the probability that a car owning household of a given income will own at least two cars ($p_{2+/1+}$). The forms of these equations and estimates for the parameters derived using Family Expenditure Survey (FES) data from 1965 to 1986 are:

$$p_{1+} = \frac{s_1}{1 + e^{(a_1 + bsub1 \ln(\frac{I}{RPI}) + c_1 \ln(LPA))}} \quad (1a)$$

$$p_{1+} = \frac{1.0}{1 + e^{(-3.732 - 2.109 \ln(\frac{I}{RPI}) - 1.230 \ln(LPA))}} \quad (1b)$$

$$p_{2+/1+} = \frac{s_2}{1 + e^{(a_2 + b_2 \frac{I}{RPI} + c_2 LPA)}} \quad (2a)$$

$$p_{2+/1+} = \frac{0.70}{1 + e^{(+5.642 - 4.699 \frac{I}{RPI} - 4.616 LPA)}} \quad (2b)$$

The values of s_1 and s_2 are assumed, reasonable, values, ie that the extreme, 100% of households will own a car, and of all car owning households, 70% will have 2 or more cars.

Use is then made of conditional and joint probability results together with information on the distribution of gross household incomes, to derive the quantities p_{1+} and p_{2+}, the latter being the probability of owning two or more cars. Equation (3) uses these quantities to derive a cars per person (cpp) measure.

$$cpp = (p_{1+} + (k_{2+} - 1)\, p_{2+}) / H \quad (3a)$$

$$cpp = (p_{1+} + (2.2 - 1)\, p_{2+}) / H \quad (3b)$$

k2+ being the average number of cars owned by households owning two or more cars (here constant at 2.2) and H the average household size. The total volume of car ownership can then be obtained by the multiplication of cpp by the total population.

The past performance of the model is good in the medium term but poor for certain short historical periods. These periods have been during unusually high or low GDP growth in the economy (note that GDP is not an explicit variable in this model) when the model was predicting higher and lower car ownership growths rather than those observed.

The second model proposed for deriving car ownership is an **extrapolatory model** using regression of car ownership on income, motoring costs and a time trend. This model proved to be inappropriate for producing long term forecasts because it proved to be insensitive to differing GDP assumptions. An alternative model was suggested where "the elasticity of car ownership with respect to income was established from a single year's cross section (using 1985-6 NTS data); the time trend was established separately as the residual of growth over recent years which was not explained by this income elasticity" [P40]. This later, additional time trend figure is a 0.4% pa growth. This model was termed the separate time trend model.
Both these two methods can be used to produce **forecasts of car ownership**. With the household model, future estimates of LPA are required. These estimates are made on the assumption that LPA will follow a logistic cure:

$$LPA = \frac{S_{LPA}}{(\ 1 + A\,e^{Bt}\ )} \tag{14}$$

$$LPA = \frac{0.8}{(\ 1 + 3.572\,e^{-0.0687t}\ )} \tag{15}$$

Where S_{LPA} is a saturation level. The parameters A and B are estimated using data for the years 1953-78. The base year (t=0) is taken as 1952. This enables future values of p_{1+} and $p_{2+/1+}$ and, with income growth in line with forecast GDP, p_{2+} to be calculated.

For the separate time trend model, growth in incomes is once again expected to grow in proportion with GDP and the time trend to fall from 0.4% to zero in 2025.

Bringing these two forecasts together gives figure 2. At the lower level of GDP growth both methods are in close agreement. For high GDP growth, however, the ownership predicted by the household model is significantly less than that of the extrapolation model. Since both methods have their merits the approach adopted was to decide that no one method is correct but to average the two sets of forecasts.

This set of car ownership forecasts can then be used in the next model which attempts to predict **car use**.

Previously, car ownership forecasts were converted into car traffic forecasts through a car use model, with assumed elasticities of GDP and fuel price to kilometres per vehicle. More recently, attempts have been made to calibrate these parameters using FES data. This exercise showed that the GDP elasticity was not significant, the fuel price elasticity was low (-0.06) and the time trend strong. A separate study using fuel price increases gave a more reasonable estimate of a fuel (medium term) elasticity of -0.15. The income elasticity used previously (0.1) was thought to be too low and a higher estimate (0.2) is used. This value of income elasticity was chosen in order to calibrate the fit of the car use extrapolation model with another model which forecasts car kilometres directly (without first forecasting car ownership) using a separate time-trend method and 1985-86 NTS data.

Having dealt with car traffic at some length the NRTF turns to **freight traffic**. This sector of the transport market is split into two components, one for **heavy goods vehicles** (HGV) and another for **light vehicle traffic** (LGV). HGV traffic further divided into two categories : OGV1 (2 axles, 3 axles, rigid and articulated) and OGV2 (4 axles rigid or articulated), and is measured in tonne kilometres travelled. A 1984 prediction of a 0 to 4% growth in HGV traffic between 1982 and 1987, based on past trends and GDP elasticities, turned out to be a serious under-estimate with the actual increase being 22%. In spite of this past performance, no ready alternative approach suggests itself with the forecast from 1989 being based on GDP and modal share trends coupled with judgements of other factors. The elasticity of freight tonne km to GDP has been raised from 0.4 to 1.0. The outcome of this is a forecast almost constant growth in OGV1 and OGV2 traffic. The effect of the Channel Tunnel has been entirely neglected.

The elasticity of LGV tonne km to GDP has risen steadily from 1.08 (1964-1987), to 1.27 since 1981. Rather perversely in light of this trend, the NRTF assumes an elasticity of 1.0 for a LGV tonne km to GDP over the forecast period.

The problem of converting tonne kilometres into vehicle kilometres is not fully addressed in NRTF. The index of tonne kilometrage growth is applied to a base vehicle kilometrage figure.

The final sector of the road traffic market which the NRTF considers is bus and coach use. Here a constant level of usage is assumed for the forecast period, at 1988 levels, despite increasing vehicle kilometres.

Figure 3 gives the final set of traffic forecasts with high and low assumed GDP growth for the 1989 NRTF. In addition the actual recorded growth is given. The figures are taken from the NRTF and Traffic in Great Britain, 2nd Quarter 1995 (DoT). Revisions in the original NRTF, 1989, document specified in Road Traffic in Great Britain : Review of Estimates, 1989, (DoT) have also taken into account. This graph demonstrates the feature that these types of forecasts are poor in the short term but their accuracy improves in the mid to long term. The assumed GDP growth figures are long run estimates, therefore whilst in the short term the GDP figures will vary, over the longer term they are likely to stabilise at a figure in the range used for the NRTF of between 2 and 3%. Whilst year-on-year GDP increases from 1984 to 1989 were significantly large (3% to 7%), the growths from 1990 to 1993 were smaller (-2.7% to 2.1%). A features in the figure is an immediate growth in motor traffic after 1988, which far exceeds even the high GDP growth figure. This situation is then reversed with a levelling off of motor traffic for 3 years until 1994.
As new data on actual traffic becomes available, the NRTF's are re-based to take account of this new information. The re-baseing involves the ignoring of forecasts up to the latest set of information, and the application of the growth indices to this latest information to give forecasts in subsequent years. The advantage of this is that the width of the high and low forecast interval is reduced. Thus figure 2 is not an accurate representation of the DoT's current forecasts, since the forecasts in the figure are those made in 1989 and involve no re-basing.

Extensive use is made of the NRTF in the assessment and appraisal of new road schemes as outlined in the DoT's Traffic Appraisal Manual (TAM). As well as detailing the methodology and best practice to be followed in preparing a traffic appraisal the manual provides some guidance on how to forecast the traffic growth associated with a new scheme at a sub-area level. Two national sub-models are described, one for a national zonal car-ownership model and another for a national trip end model. The trip end models are not within the scope of this review and will not be covered here. The sub-areas are taken as Local Authority Districts.

The form of the zonal car-ownership model is similar to that for the national model with the estimates of household characteristics (income and licenses per adult) taken from FES data for the zone rather than national estimates. In order to ensure a consistency between these zonal forecasts and the national car-ownership forecasts, iterative adjustments were made to the zones base income values and income growth rates.

The following comments are not of immediate relevance to our study, but occurred whilst reading the NRTF document.

The methodology adopted for re-basing [P 5] may be simplistic. It may be worth considering the complete re-estimation of the parameters in the car ownership and car use models as new data become available. Hopefully this new data will not invalidate the structure of the current forecast models. Tests could, however, be carried out to establish whether there had been any significant year-on-year changes in the estimates used in the models. Whilst it is desirable from a usage and consistency bases that these year-on-year changes in parameter estimates are not significant, longer term significant changes are less of a problem since they represent a gradual evolution in the characteristics of growth in traffic.

In P 7 it is stated that "The vast majority of cars are privately owned". Figures from the NTS 88/91 vehicle fleet database suggest that 9.5% of cars were registered to an individuals employer. Questions arise as to whether this is a significant enough proportion to model in its own right, especially at the car use stage. It is likely that such company cars will run a higher kilometrage than private cars.

The comment that "The forecasts do not imply that road space will always be provided to accommodate them." [P 11] is interesting. This comment is a little weak, given that these forecasts have the potential to be self-fulfilling. New roads or improvements to existing roads may be justified on the assumption that they accommodate an *expected* growth and produce a travel time savings. If the new scheme is implemented, then it will act as both a generator and attractor for traffic, thereby fulfilling the forecasts. Indeed Tanner, 1978, in his interesting assessment of the then revised DoT methodologies for forecasting vehicle ownership, does make explicit reference to this self-fulfilling effect, although his remarks are a little dismissive of this argument.

The assumed level of saturation [P 17] is a national figure. Clearly there will be regional variations, especially in urban areas, which are caused by, amongst other things, the quality of alternative modes and pricing mechanisms (ie congestion, insurance premiums, risk of theft and parking fees).

The use of the LPA quantity provides a useful tool for estimating the effect on traffic volumes of a policy to raise the minimum driving age from 17 to 18 or 21 years or the automatic loss of a licence at 65 or 70. The forecast LPA figure is also expected to represent "future changing attitudes towards car ownership" [P 32]. Thus an increase in LPA's is expected, although at a diminishing rate of increase.

A criticism of the car use model is that it may be too aggregate. Differing individuals, with differing characteristics will use cars to differing extents. People who live in rural communities will tend to use a car more than those living in a urban area. Older car drivers will also tend to use the car less (or at different times) to other age groups. Some form of travel distribution model which takes account of this variability may be more intuitively justifiable.

The insistence on including GDP in the household model [P 35] needs to be questioned in light of the fact that during 1979-81, when GDP fell by 3.2% and the model predicts a 0.4% growth in car ownership, the observed growth was 4.1% to 4.6%. Also during 1984 to 1987, GDP grew by 6.7% with a prediction of a growth in car ownership of 7.5%, whilst the observed growth was 4.0% to 5.5%. Thus observed growth was almost immune to GDP variations. Conversely, the high GDP growths of the late 80's did generate a large increase in **car use** (and probably car ownership) and the low GDP growth in the early 90's did reduce growth in car use (see figure 3). Thus there are two instances, one where there does not appear to be a link between GDP and car ownership and another where there is. This latter case may be a false correlation, ie something else (income, wage inflation ?) is actually of importance. The doubt over GDP is re-enforced by the fact that a simple time trend explains 90% of the variation in car ownership in the extrapolatory model, with GDP and income explaining only short term variability [P 38]. There may exist a lagged effect of GDP on car use, where only longer term changes in GDP have a effect, some years hence from the initial change. Another explanation for the apparent insensitivity to GDP is the *permanent income* hypothesis, where peoples purchasing decisions are more influenced by their expectation of future income growth rather than shorter term levels of income. More recently, the greater sense of insecurity in the employment market may begin to eliminate this hypothesis, with people having reduced expectations of income growth and job security.

The simple averaging of the household and separate time trend model [P 55] is simplistic. A more sophisticated methodology may be to weight this average, based on past-performance/goodness of fit of each approach.

The assumption of a constant level of usage for buses and coaches is assumed to stay constant at 1988 levels [P 80], despite evidence of increasing bus vehicle kilometres.

4 PREVIOUS RESEARCH

A considerable body of published material exist prior to 1989 but rather than attempt to cover this I shall start with Tanner's 1978 paper. This is a very readable, open and candid account of how the DoT methodology for producing vehicle travel forecasts was in the process of changing from a rather simple model into something more complex, but not at the sophistication of the 1989 methodology. Early on in the paper, table 3 shows how accurate the various methodologies from 1958 onwards have been at predicting the 1975 levels of cars per person; number of cars and motor vehicles, and car and vehicle kilometres. The best set of estimates are the earliest (1958-1960) or in a few cases the latest (1974). The explanation for this first feature may not be that the earlier predictions use the best models, merely that these types of forecasts tend to perform better over a longer time span. The quality of the latest forecasts is down to the timeliness of their input data.

The proposed methodology replaces an S-curve formulation of the car per person model with a non-symmetric power curve. Both curves use information on base year figures, GDP per person and the cost of motoring to calibrate the model and forecast car ownership. The discussion which follows the paper centres around three points : methods of fitting growth curves; the self-fulfilling and policy issues; and the treatment of uncertainty.

Button, Pearman and Fowkes, 1982, provide a review of Tanner, and then go on to examine the issue of car ownership at a local level. The usual approach to deriving a local figure for car ownership is to calculate values for p_{1+} and $p_{2+/1+}$ using locally derived measures, coupled with local household socioeconomic data and applying the NRTF methodology. A form of category analysis is also proposed.

5 SUBSEQUENT RESEARCH

Perhaps the most recent piece of work related to the NRTF is a pair of papers by Acutt and Dodgson (1994a and 1994b). The primary aim of their study was to asses the **sensitivity of fuel consumption and greenhouse gas emissions to changes in prices of fuel and public transport**. The reactions to these price changes could be one of the following:

Reduced travel (fewer car-kilometres);
Switch to more efficient, cleaner, cars (same car-kilometres);
Switch to a different mode (fewer car-kilometres, more public transport kilometres).

Clearly all three reactions are relevant to our study.

The first section of the 1994b paper produces estimates of the total vehicle fleet split into nine vehicle types and sixteen vehicle ages. The figures are contained in a 9 by 16 matrix using NRTF figures re-based to 1991. For the production of forecasts, this car stock matrix is *moved* over time using information on survival rates. New sales of vehicles are assumed to be equal to the total forecast stock for the year, minus the survivors. The total stock forecast is the appropriate NRTF figure. Thus within each forecast year the total stock is composed of survivors from the previous year plus the appropriate number of new cars, in order for the total stock to equal the NRTF. The total vehicle stock for the appropriate year is converted into vehicle kilometerage in a similar manner to the NRTF.

The second section details equations for the prediction of passenger kilometres in various sectors of the public transport sector. These equations involve terms such as GDP, fares, motorway mileage and petrol costs. This methodology produces lower estimates for vehicle kilometerage than the NRTF in 2025.

These models were then used to produce forecasts to the year 2025 of vehicle kilometres under various **scenarios**. The scenarios were the use of the 5% real increase in petrol duty escalator announced in the November 1993 budget and reductions in real public transport fares. The effect of these scenarios were also presented on vehicle kilometres and passenger kilometres of the various public transport modes.

The Acutt and Dodgson models are able to measure the impact of differing price levels and competing modes on the total road vehicle kilometres. A number of assumed elasticities are used in their study. Alternative values for price elasticities can be found in two review papers, one by Oum et al (1992) and another by Goodwin (1992).

A further attempt at measuring the effect of fuel price increases, this time on CO_2 emissions is presented in the paper by Virley (1993). The paper starts by stating that engines emit CO_2 in proportion to the amount of fuel consumed, although this ratio is not explicitly stated in the paper. The paper presents a model of road fuel consumption, as a function of a form of real fuel price and total final expenditure. The model form is unusual in that it is given in an unrestricted error-correction form, a description of which is given in appendix B. The model predicts that CO_2 emissions can be returned to their 1990 levels by the year 2000 if a 90% increase in real fuel prices above the base case of a 20% increase is implemented.

Papers from a project studying the mechanisms for reducing the environmental impact of transport provide modelling tools to assess the effect of various policy *levers* on vehicle mileage forecasts (Fowkes, May, Nash, Rees and Siu, 1995). These levers include : real fuel prices; public transport fares; demographics and road pricing. The tools involve **arc elasticity models** which express the ratio of a quantity (road kilometrage) in a base year to its quantity in a forecast year (2006) as a function of price levels. These prices can be own price and competing mode price levels. The models use information from the 1985/6 and 1991/3 NTS to project the observed growth in this 6½ year period forward to the year 2006. The first stage is to produce forecasts of the population in 2006, then the proportion of car available persons in 2006 are made, finally forecast trip kilometrage rates are made. The NTS data is disaggregated by gender; age; area type and car availability. The car availability forecasts are assumed to follow an S-shaped curve of growth, with the average level of saturation been consistent with NRTF assumptions. The trip kilometrage growth rate incorporates some regression models to provide smoothing and adjustments to the crude figures. Type of journey: commuting; business and leisure are also modelled separately. Also an alternative set of results are possible if there is an assumption that elasticities fall as incomes rise.

The base case predicts individual mileage figures for areas; purposes and modes. The total figure is 558,998 million miles. Four policy options are presented. The first policy tested is a doubling of fuel price, this reduces the milage to 433,076 or 459,862 depending on the assumption about changes in elasticities in relation to incomes. The percentage reduction is greatest for leisure journeys. An related policy is the tripling of fuel prices, yielding forecasts of 347,471 or 386,237. The second policy is a halving in public transport fares which gives figures of 570,085 or 566,180, the increase in milage resulting from the public mode with only a small percentage drop in private mode. The third policy is a halting of the redistribution of population from urban to rural areas. The total milage falls to 556,724. The final policy is the introduction of road pricing in London. This only affects the forecasts for London. Here the national forecast falls from 558,998 to 557,713 as a result of a increase of 850 in public mode and a 2,136 fall in private mode.

A final study by Terzis, Dix, Bates and Dawe (1995) presents a disaggregate study into the effects of higher fuel prices. The methodology hypothesised three fuel price scenarios, 50%, 100% and 200% increases in (real) fuel prices. Respondents could react in any number of 10 ways. Separate surveys were conduction in the household and business sectors. The study yielded disaggregate elasticity values for mileage with respect to fuel price in both sectors. For the business sector percentage reductions in key variables are also presented.

In a paper by de Jong, 1988, a joint forecasting model is proposed, where car ownership and usage are **jointly** predicted (see appendix C for a more detailed explanation of the methodology). The main influential factors on these measures are fixed and variable car costs. The first section of the paper outlines a theoretical model for an individual. A utility function is suggested, which individuals attempt to maximise subject to a budgetary constraint. The next section derives an expression for the maximum variable cost of motoring a household will *tolerate*, which if it is below the actual variable cost, a household will not own a car. Estimates are then made of the parameters in the utility model and maximum cost values are calculated from a survey of 2,344 households. If an individual household is predicted to own a car, their usage can then be calculated. The paper finishes by presenting the individual results of a 10% increase in incomes; fixed costs and variable costs on car ownership and use.

Another modelling approach which uses utility maximising techniques is presented by Berkovec (1985). The paper models a simulation of the American automobile market, disaggregate by vehicle stock. The simulation combines a disaggregate model of household car ownership numbers and type choice with econometric models of vehicle scrappage and new car supply. Three sectors operate during each time period:

(1) Manufacturers produce new cars for sale to consumers;
(2) Scrappers purchase used vehicles from consumers;
(3) Consumers purchase cars from produces, sell used cars to scrappers and trade used vehicles amongst themselves;

Three functions forms are described for each of these sectors (vehicle production model, vehicle scrappage model and consumer demand model). The model allows cars to be differentiated and consumers to be heterogeneous. Short-run equilibrium is defined as supply equal to demand for every vehicle type during each period. The car stock then evolves as new vehicles are added and old vehicles are scrapped.

The example in the paper uses 12 consumer groups and 131 vehicle types. Data from the US National Travel Survey, registration and car characteristic databases are used to calibrate the equations. The results of this exercise are presented in the paper, but the models appear to contain a large number of insignificant terms (mainly 0/1 dummy variables) which have, for no given reason, not been removed. A scenario is run for 1978-1984 and compared with observed behaviour. The performance can only be described as poor. A level of agreement between modelled and actual growth rates in car stock (the demand model) can be said to exist. Prediction of new vehicle sales is poor both in aggregate (errors for the 7 year period ≈ 0, 10, 0, 20, 25, 25 and 0%) and split into market segments (domestic sales, imported car sales and light truck sales). The explanation for this is the lack of socio-economic variables in the model formulation which made the effects of the early 80's recession absent. The performance of the scrappage model is also poor. Other simulations are run to investigate the effect of a real petrol price changes (5% per year decline, 5% per year increase, and an once and for all increase to 1981 prices followed by a 5% per year increase). The stock is predicted to increase for each scenario. Given the poor performance of the base scenario, I shan't go into any detail on the performance of these alternative scenarios.

Another paper which attempts to model the **disaggregate composition** of the vehicle fleet rather than an aggregate approach is by Hensher and le Plastrier (1985). The basic component of their model is an expression for the probability that a household will choose a car fleet of size s and composition c, given that it held a particular fleet previously, $Pr[c_t s_t | c_{t-1} s_{t-1}]$. The structure of the stock is evolved from a series of vehicles holdings, to which adjustments are made, to give updated vehicle stock holdings. Since the methodology is disaggregate in nature it will not be considered in any further detail here.

Another attempt at producing a model of the car stock is reported in Dodgson et al, (1995). The purpose of this study is to predict the total **fuel consumption** of the vehicle stock. This vehicle market is split into cars, HGV, LGV and PSV's.

Taking the car fleet first. Given that differing car types of differing vintages will possess differing fuel consumption characteristics the market is modelled as nine engine sizes by sixteen vintages. Travel on each of three differing road types, fuel type and ownership are also disaggregated. This structure is represented by a set of time dependant matrices. Each stock matrix is *moved* through time, the new stock matrix given by the survivors from one year to the next plus new vehicles. Scrappage rates are primarily determined by prices, both for new and second hand vehicles, and fuel efficiency. New car purchases (which are the difference between NRTF and survivors) are split into engine sizes, fuel type and ownership type. Once a vehicle stock matrix has been obtained for the year of interest, the national annual kilometrage is obtained by a multiplication of number of cars by the annual kilometrage for that type of car.

Forecasts of kilometres in the other vehicle sectors (HGV, LGV and PSV) are obtained in a similar manner to those for the car market although the vintage and road type dimensions are not included.
At the time of writing no results from this study are available.

Williams and Yamashita, 1991, presented some work on travel demand forecasts under congested conditions. This paper attempts to address the issue of **self-fulfilment** in the production of travel forecasts, particularly in the car sector. Their main concern is the implicit assumption that the **elasticity of demand** with respect to travel time is zero. Reference to the NRTF is made in the introduction.

The paper is rather bogged down in notation and algebraic re-arrangements but a number of points emerge. The paper starts by hypothesising a scheme and deriving before and after traffic volumes and before and after generalised costs over a 30 year time span. These are described under **inelastic** demand and **elastic** demand assumptions. In inelastic demand the traffic growth is specified using a uniform, cumulative growth factor over time. For elastic demand this growth factor is modified by a demand function which is either in difference (negative exponential) or ratio (constant elasticity) form. The user benefits from the scheme (discounted over time) under the two elasticity assumptions are derived from a function of the appropriate volumes and costs. These benefits are combined to produce an overall measure of the **error in deploying inelastic demand**. Figure 7 (reproduced here as figure 4) shows the relationship between the elasticity of demand, E^S_D and the error, Δ, for various demand to capacity ratios, κ, with the growth rate in traffic assumed to be 4% per annum. This clearly shows that as the elasticity of demand increases, especially in near capacity conditions, the error becomes significant. Figure 9 in the paper (reproduced here as figure 5) re-enforces this effect by showing how larger growth assumptions (r) also cause greater errors when inelastic demand is assumed.

The effect of the application of the discounting of future benefits is also presented. With undiscounted benefit and inelastic demand the benefit is predicted to grow in an almost exponential form to 30,000 in year 30. If elastic demand is used then the benefit rises in an almost linear manner to 4,000 or 6,000 in year 30 depending on the form of the demand elasticity model (*). Inelastic demand gives an exponential growth in benefits whilst elastic demand gives a linear growth.

With a discounted benefit of 8% per annum and inelastic demand the benefit grows exponentially until year 11 and there after is constant at 2,750. If inelastic demand is used the benefits peak in year 12 at 1,200 and then falls-off to a level of 500 or 1,000, once again depending on the form of the demand model.

As an aside mention is also made of the application of 'growth cut-offs' which are applied with inelastic demand assumptions to prevent a rapid increase in travel costs. The authors recommend these as a practical expedient. To demonstrate the effect of cut-offs, four situations of discounted benefit are applied in inelastic and elastic demand conditions (The authors do, however, say in the paper that "[cut-offs] will be applied only in conjunction with the inelastic demand assumption").

The base situation of no cut-off is the same as discounted benefit mentioned above (*). With a cut-off of 2,400 vehicles per hour, inelastic demand peaks at 2,750 in year 11, falling to 1,000 in year 30, elastic demand peaks at 1,150 in year 11 to 600 in year 30. With a 2,200 vehicles per hour cut-off, the inelastic demand peaks at 1,600 in year 8 to 500 in year 30 and the elastic demand peaks at 1,100 in year 12, falling to 500 in year 30.

The final graph shows the effects of two cut-offs, one before the scheme and another after the scheme. Inelastic demand peaks at 1,600 in year 8 and falls to 400. With elastic demand the level of discounted benefit is constant at 1,050 until year 12 before falling to 600 in year 30. Only in this later situation is the final (year 30) benefit greater with elastic demand.

Thus the deployment of either elastic demand or growth cut-offs can moderate against the exponential growth in car use which is predicted by many models.

This study and earlier ones (Thomson, 1970 and Williams, 1990) are primarily concerned with the assessment of individual schemes under various demand elasticity assumptions. We may need to take this approach into a regional and national context.

A disaggregate study into the effects of congestion on drivers' behaviour is given by Christie (1995). They hypothesis that traffic growth in the past has been restricted by road congestion and that it is reasonable to assume that increasing congestion will affect the amount of travel by road. Since this is essentially a disaggregate study only a brief reference is given here. Interviews were used to establish respondents reactions to calculated increases in journey times for specific journeys, under three levels of assumed traffic growth. Ten behavioural reactions to this increase in journey times are presented. Results measured trip adaption; trip suppression and mileage suppression in terms of percentages. The response to congestion varied with journey purpose, the greatest trip adaptation occurred with to work journeys (25.5% of trips); greatest trip suppression for travel for non-home based non-work trips (7.2%) and greatest milage suppression for employers business (19.1%).

6 BUS TRAFFIC FORECASTING

Less material is present in the literature on traffic forecasts for bus travel. One paper by Oldfield et. al, in 1981, is rather dated now. Rather than attempt to paraphrase the paper I shall reproduce an abridged copy of their summary here, losing some of their less relevant conclusions.

"Two bus travel prediction models have been constructed to investigate how the total number of stage service bus journeys in Great Britain is likely to be affected by different levels of bus subsidy, different fuel prices and different rates of growth of the national economy and of car ownership levels over the next two decades.

Both models use Tanner's car ownership predictions, usually for two different growth rates of the economy (Low growth and High growth) corresponding to increases in GDP per head of 1 and 2 per cent per year (this study uses real earnings as a proxy for GDP per head).

Households were divided into those owning no cars, one car, and two or more cars. The first model, the **traveller-type** model, considered the country as a whole and categorised trips by a combination of purpose and type of individual, ie work, school, trips by old age pensioners (OAP), and the remainder. Forecasts of future numbers of bus trips were made by assuming that the propensity to travel by bus was a function of the generalised costs of both bus and walk for households which owned no car, and bus and car for car-owning households. The second model, the **area-type model**, did not distinguish between different journey purposes, but divided the country into four types of area which are broadly comparable with the operating areas of London Transport, the Passenger Transport Executives, the Municipal Operators, and the National Bus Company plus the Scottish Bus Group. For a given amount of subsidy in any one year. ('subsidy' here refers to general revenue support, payment for unremunerative services, fuel duty and new bus grant: moneys paid to cover concessions for OAPs and school children are considered separately), both models adjusted the fare paid and the number of bus-kilometres run in a way which maximised the patronage attracted. The concession for OAPs was usually assumed to remain at one-half the average fare, while all children travelling more than 5 km to school could receive free bus travel.

Bus patronage was found to be highly sensitive to the way the level of car ownership and the economy were assumed to grow. Naturally, growth in car ownership is very dependent on growth in the general economy, but in addition bus costs, and therefore fares and service quality, are also strongly related to the level of average earnings.
The difficulty of calibrating the second model, which dealt with travel in different types of urban and rural areas separately, made it less amenable to detailed analysis than the traveller-type model, and it was not used extensively in the predictions. Predictions made by this model were slightly more sensitive to changes in the subsidy provided than were the forecasts of the traveller-type model, but it predicted very similar amounts of bus travel with constant subsidy. There were no marked differences in the rates of decline in bus patronage between one area and another."

Another factor which is thought to be important in determining bus patronage is **demographics**. This aspect is considered in Hill and Link, 1988. Information is taken from the National Travel Survey, Expenditure Survey and General Household Survey to give a detailed breakdown of frequency, purpose and mode of travel by age, sex, location and household composition. Bus travel appears to be an urban phenomenon, no doubt due to concentration of potential users in such areas. Other contributory factors for an increase in bus patronage are the size of the urban area (more populous areas tend to have higher patronage) and the distribution of population within that area (more concentrated populous in the inner city gives a higher patronage). Other information shows a higher bus trip rate for girls and women (approximately +0.2 to +2.0 trips per person, per week) and for girls and boys (+2.0). Membership of a car owning household reduces bus travel by typically 10.7 miles per person per week. A section considers the demographic factors which influence rail travel. The paper suggests that increased income increases rail patronage but decreases bus patronage (via increase car ownership). In conclusion the paper suggest that demographic trends are moving in the *wrong* direction for increased bus use. Useful information that emerges from this study are that factors which are important in determining bus trip rates are: location; age; sex; income and possibly employment status (although this effect may be captured to some extent by income data).

A study of the relationship between the level of public transport subsidy and fares, service costs and productivity in an international context is presented by Bly and Oldfield, 1985. This study suggests that an increase in subsidy to cover an additional 1% of operating costs is split into _ for fare reductions or service increases, a ¼ for increases in wages, and a $^1/_5$ each for productivity reductions and other cost increases. For town (urban) data the fraction of the increase going to reduced fares or service increases was higher at near to ½, at the expense of wages and productivity losses. Thus if changes to subsidy levels are one of the mechanisms under consideration as a policy lever, account needs to be taken of this effect. With the subsequent advent of competitive tendering in the bus operation market, this leakage may be less of a effect.

More recent research on the forecasting of public transport patronage both at a national level (Aleem 1995) and a regional level (Doti and Adibi, 1991 and Preston et al, 1994) uses **regression** type equations **on historical time series** data. Typically this methodology attempts to measure bus demand (ridership, passenger trips, passenger miles) as a function of time, fare, bus miles, seasonality and various socio-economic variables. All the models address the statistical problems which can be inherent in such modelling. These models produce elasticities and together with forecasts of the independent variables in the relationship, can produce short time horizon forecasts. In both the regional studies these models have been validated on subsequent data. Goodwin and Williams (1985) present a review of the relative merits of various public transport demand models and elasticity measures. As an aside, Doti and Adibi quote the comment by Harvey (1985), that there is an increasing trend towards technically sophisticated travel demand models which "has inhibited the flow of knowledge from the research community to transport organisations".

Some studies on the interaction between car ownership and public transport use exist. One is the Acutt and Dodgson paper (1994b) mentioned above, others are by Toner et al (1995), Goodwin (1993), Selvanathan and Selvanathan (1994) and a series by Peirson et al (1994). The Toner study uses revealed preference data to estimate a disaggregate mode choice model and so will not be considered here, although a second piece of work in the paper on the aggregate modelling of rail and air competition is discussed in section 10.

The Goodwin (1993) study does not attempt to forecast either car ownership or bus patronage, and neither does it try to model or quantify the degree of interaction between these two transport modes. What it does do is suggest that the various accepted wisdoms within the transport planning community may not be as firm as suspected. A consensus was emerging in the early 1980's that bus service levels, fares and quality of service had a small but possibly **important effect** on car-ownership, but these findings have been neglected. Much of the evidence of this effect is taken from Jones and Tanner (1979), Fairhurst (1975) and Bates & Roberts (1979,1981). Jones and Tanner investigated the effect of public transport on car-ownership rather than the more usual reverse relationship of car-ownership on public transport. Fairhurst found that public transport access gave a satisfactory explanation for observed variations in car ownership. Bates & Roberts state that "there is compelling evidence that both density and bus frequency influence car ownership" (1979) and "there can be no doubt that the level of car ownership is linked to the supply of public transport services" (1981). These result will have relevance to any regional models developed in this study, which will have differing levels of public transport provision.

After this review Goodwin goes on to use transport data from a South Yorkshire panel survey, collected at regular intervals from 1981 to 1991, to explore the interaction between car-ownership and public transport patronage. Of particular interest in this data is the use of three policies: constant cash fares (1975 to 1985); a sharp fare increase of 225% in fares (1985/6) and full de-regulation (1986 to 1991). The impacts measured were bus use and car-ownership and occasional comparisons with the neighbouring conurbation of West Yorkshire are made. During the constant fares period an increase in the bus trip rates occurred for the (5-14)/(15-24)/(25-34) age groups, thereafter the change became consistently negative across all age groups. Car ownership (measured as cars per household) was also **lower** during the constant fares period, in comparison to West Yorkshire. Tables on bus trip rates for differing car owning individuals shows that those with one car actually **increased** their bus trip rate during the constant fares period. A final table shows how households whose car ownership has changed over a period modified their bus trip rate. Those who have *lost* a car showed an increase of 0.43 bus trips per person per day over the constant fare period compared to an increase of only 0.13 in the later part of the survey. The figure for those with *stable* car ownership is a drop from +0.09 to -0.10, and for those *gaining* a car is -0.18 to -0.49. Goodwin also showed that car ownership can be quite volatile, with a third of people living in households with two cars having fewer cars in two or three years time. The main cause of this would be a two car household (parents and older child perhaps) splitting into two one car households. Goodwin states in his conclusion that "The balance of evidence is that public transport policy does influence both the incidence of car ownership changes, and the effects of these changes on public transport use."

An interesting study by Golob (1990) covers some of the same ground as the Goodwin (1993). Here use is made of a Dutch panel travel survey from 1985/86, 1986/87 and 1987/88 to examine travel time expenditures and car ownership decisions across car, public and non-motorised modes. The first section of the paper provides evidence that as households change their car ownership decisions, path **dependency** and **asymmetry** occurs. Measured in hours per week, those households who are increasing their car ownership are those who already have a high usage figure, whilst those who are decreasing their car ownership are those with a low usage. Also the increase in usage by those gaining cars is greater than that of those losing cars. Thus even though the car fleet market may remain stable, the car use will not. The second section of the paper then develops a longitudinal structured equation model to explain the dynamics in the travel market. The paper gives eight reasons for the choice of this model form. The two main justifications are that it allows **multiple** endogenous variables that may be interrelated and that alternative **directions** of causality can be tested. The model has four endogenous variables: travel time by car; travel time by public transport; travel by nonmotorised modes (all measured in hours per week) and number of cars. Exogenous, *background*, variables are either dynamic over time (eg. income; household composition; number of drivers) or static (location). The four main conclusions from this study are:

(1) The three household travel demand variables are mutually interdependent. A demand model which specifies one variable as a function of others (eg car usage as a function of car ownership) without "feedback" will be subject to bias. the error term will be correlated with an explanatory variable;

(2) The interrelationships amongst car ownership and travel time by mode and the relationship between exogenous household characteristics and car ownership are not all contemporaneous but lagged. For instance, high income implies higher public transport use at the same point in time but the same variable implies lower public transport use one year later due to adjustments in car ownership and use.

(3) What is termed *panel conditioning bias* can be controlled. Since the panel date came from three time periods, variations of panel tenure over time will exist. Panel conditioning allows the separation of panel conditions and period effects (eg fuel price).

(4) Similarities and differences in the explanations of car ownership and mode use by household

characteristics are apparent. Thus some household characteristics will affect car use but not car ownership.

Another approach to estimating the demand for transport across differing modes is presented by Selvanathan and Selvanathan, 1994. In the paper they model the demand for transport and communication in the UK and Australia using a system wide approach. The paper disaggragates this market into three modes, private transport, public transport and communications. The paper touches on whether all three modes are in competition with each other. The system wide approach does not take a single-equation perspective, instead it considers simultaneously all three demand equations. The basic form of the equation is:

$$w_{it}\, D\, q_{it} = \alpha_i + \theta_i\, DQ_t + \sum_{j=1}^{n} \pi_{ij}\, D\, p_{jt} + \varepsilon_{it} \qquad i = 1,..5$$

Where w_{it} is the budget share of i in arithmetic average form;
Dq_{it} is ($\ln q_{it} - \ln q_{i(t-1)}$) the quantity log-change;
θ_i is the marginal share of good i, $\partial(p_i q_i)/\partial M$;
DQ_i is the change in consumers' real income;
π_{ij} is the $(i,j)^{th}$ Slutsky coefficient;
Dp_{jt} is ($\ln p_{jt} - \ln p_{j(t-1)}$) the price log change;
n is the number of commodities;
and M is fixed income.

The marginal share, θ_i, measures the change in expenditure on good i resulting from a one-dollar increase in income. The Slutsky coefficient, π_{ij}, measures the effect of a change in the price of good j on the demand for i, when real income is held constant. If goods i and j are substitutes, then π_{ij} will be positive. The income elasticity, η_i is given by (θ_i/w_{it}) and the price elasticity of good i with respect to the price of j, η_{ij}, is (π_{ij}/w_{it}).

The data used to estimate (5) is taken from Annual Abstracts of Statistics and International Statistics Year Books. The results, at the sample mean, for the UK are presented in table 1.

	Income elasticity	Price elasticities		
	η_i	η_{i1}	η_{i2}	η_{i3}
Private Transport	2.11 (3.36)	-0.53 (2.24)	**0.07** (23.25)	0.08 (30.67)
Public Transport	0.98 (0.11)	0.19 (8.10)	-0.41 (5.90)	**0.03** (24.25)
Communication	1.19 (0.61)	0.57 (2.53)	0.09 (9.10)	**-0.12** (11.00)

Table 1 : Elasticity values

The figures in brackets are the t-ratios for the null hypothesis of unitary elasticity. Figures in bold are those obtained from insignificant parameter estimates. All the cross elasticities are positive which indicates that all modes are pair-wise substitutes.

The series of papers by Peirson et al (1994a, 1994b, 1994c) address the issue of how the failure to take account of the marginal pricing of internal and external costs (congestion, accidents, air pollution, noise and disruption to local communities) and economies of scale can distort the transport market. The suggested mechanism for internalising the external costs is taxation. This effect is addressed in two markets, London passenger travel and inter-city travel.
The London modelling methodology follows three steps: estimating and calibrating the demand function; estimation of internal costs and the estimation of external costs. The model is formed for four modes (car, bus, rail and underground) and two time periods (peak and off-peak). The form of the demand function

is:

$$D_i = \alpha_i \prod_{j=1}^{n} P_i^{\beta_{ij}} Y^{\gamma_i} \qquad (6)$$

where D_i is the demand for transport mode i (passenger kilometres);
P_i is the price of transport mode (per passenger kilometre);
Y is income;
β_{ij} is the price elasticity of mode i with respect to mode j;
γ_i is the income elasticity.

Information on internal costs were obtained from the operators and the DoT. The information on external cost were taken from a variety of sources, both published papers and official documents (for example, DoT, OECD, CEC, CSO). These two price assumption (internal only and internal plus external) can be used in (6) to estimate the effect of including external costs via taxation. The paper concludes that efficient pricing and taxation of externalities does not produce a significant mode shift towards modes with lower external costs. Reasons for this are suggested in the paper. In the long term (10 years) income tends to dominate mode choice.

The companion paper on the inter-city passenger travel market adopts a similar methodology to that described above. This approach suggests that small to moderate shifts to modes with lower external costs can be achieved.

7 FREIGHT TRAFFIC FORECASTING

Although the main emphasis in this study will be on the passenger transport market, some account needs to be taken of freight transport, since this occupies the same infrastructure (road or rail) as passenger vehicles. The freight market is split into six sectors : road haulage; rail freight; inland waterways; coastal shipping; air and pipelines. Only road haulage is to be considered in this section. A discussion of rail freight can be found in the next section on rail traffic forecasting. The remaining sectors are not considered in their own rights as part of this study although a shift in mode to or from the first two, to these sectors is of importance.

The methodology employed by the DoT is given in section 4. A study into the **plausibility** of the DoT's forecasts for the road freight sector is given by Hallett (1990). Hallett contrast the predicted 66% to 141% rise in vehicle kilometres by 2025 with the observed 9% rise over the 80's. This 9% increase is said to have arisen from longer hauls, whilst the total HGV fleet has shrunk. A forecast rise of 66% to 141% could mean a doubling or trebling in the demand for products, or that industry would be much more concentrated geographically. In conclusion Hallett states that "...the freight traffic forecasts are implausible because they appear to have been substantially overestimated." McKinnon and Woodburn (1993) suggest that "The main shortcoming of the DoT's freight traffic forecasting is that it is **not rooted in a detailed understanding** of the causes of freight traffic growth". Whilst historically, the relationship between GDP and road tonne-km's has been good and consistent amongst most industrial countries, there is no guarantee that this relationship will continue. They suggest that the real cause of the growth in freight traffic include : the spatial concentration of production and distribution operations; choice of suppliers and distributors (degree of subcontracting in the production process); scheduling of product flow (a move to Just-In-Time processes which require frequent small deliveries) and more efficient utilisation of transport resources. They do not suggest an alternative to the DoT's modelling methodology.

Hallett mentioned that prior to 1989, the DoT freight forecasts used past trends in tonnages and tonne-kilometres of various commodities and vehicle stock to produce forecasts. These forecasts were further constrained to the influence of GDP growth on road kilometres. Fowkes et al (1993) suggest almost a return to a **disaggregated sector** approach method of producing freight forecasts. Instead of using past trends however, they recommend using information on forecast sectoral output to predict tonnes lifted or tonne-kms moved within the sector. The paper also discusses the availability and consistency of the historical data required by the modelling philosophy.

The freight market is divided into 16 sectors, each modelled by two model types (Sectoral output and GDP) in two functional forms (linear and double-log {either form can have lagged dependant variable}) to predict both tonnes and tonne-kilometres. This represented a considerable modelling exercise.

The forecasting quality of three modelling approaches were applied to try and predict 1990 tonnes lifted and tonne-kilometres. The first is a series of disaggregate models based on the forecast output from individual market sectors. The second is also a series of disaggregate models, but based on the forecast of GDP. The third approach is an aggregate GDP model. The results are presented in table 2.

	Actual 1990	Sectoral output model	Sectoral GDP model	Aggregate GDP model
Tonnes lifted (m)	1645	1639± 111	1730 ± 113	1719 ± 141
Tonne-kms (bn)	131	130 ± 7	133 ± 7	129 ± 13

Table 2 : Aggregate predictions of the disaggregate linear models with 95% CI.

Clearly for this one period, short time horizon, prediction the sectoral model has performed best. The width of the CI is also less for the sectoral model. The drawback for the sectoral model is the requirement for predictions of the future output in each sector, whilst the sectoral GDP model only requires the prediction of future GDP. Also for the purposes of our study the prediction units are inappropriate. Information on the weight composition and utilisation of the freight fleet would enable an approximate conversion from tonne-kms to vehicle-kms to take place.

The Fowkes et al paper also considers the forecasts for the use of small goods vehicles. This exercise was hampered by the lack of historical data. Models to predict vehicle stock; tonnes lifted and vehicle kilometres are presented.

The **vehicle stock models** were: a time trend model in exponential form (the best predictor of the three presented here); a log-linear GDP model (suffered from autocorrelation) and the time trend model with a deviations in GDP from a trend term. Four models are presented for the **tonnes lifted** data: a log-linear GDP model; a time trend exponential model with deviation in GDP; a linear model with output from the *miscellaneous* sector and a time trend exponential model with deviations in miscellaneous output from a trend. Each model gave plausible elasticities of tonnes lifted of somewhere between 1.86 and 3.15. The **vehicle kilometres model** is perhaps the one most relevant to this study. The same model forms as described for tonnes lifted were applied here, except for the linear model with miscellaneous sector output which was replaced with a log-linear model. All these models suffered from autocorrelation.

A paper by Soliman et al (1991) presents an aggregate "Abstract Mode" model for the transport of end products (inedible) for the Canadian market. The primary purpose of the model is to assess the effect of new national vehicle weight and dimension regulations for trucks. In essence the model predicts volume by truck as a product of the socio-economic characteristics of the origin and destination province, trucking travel time, trucking costs and rail travel times and cost, all individually raised to some power. Notice that some account is taken of the competing effect from rail transport. The final model used cross-sectional data from 1983 to 1986 to estimate the power parameters. This model produced significant and intuitively correct signs for the (power) estimates and hence elasticities.

8 RAIL TRAFFIC FORECASTING

Rail traffic has two components, the movement of people and freight. Most emphasis in this section will be placed on studies which have attempted to forecast rail passenger demand.

British Rail's demand forecasting procedure is described in the Passenger Demand Forecasting Handbook which is, however, commercially confidential and not in the public domain. The broad approach adopted, however, can be ascertained from a number of published sources. BR's general approach is described first, followed by consideration of these sources.

The overall framework for demand forecasting in the rail market is composed of three elements:
Those who's effect on demand can be calculated directly via an elasticity (GDP, fare and time trends); those which can be converted into monetary terms before applying a fares elasticity (stock and facilities); and those which can be converted into journey time terms before applying a journey time elasticity (frequency and interchange).

The predicted growth in volume of travel from a base year is a multiple of an index which is itself composed of three indices, one for each of the above mentioned three elements. Expressions and recommended parameter values are provide for each of these indices. The recommended parameter values are rail sector specific (for elasticities and time trends), service specific (penalties), mode specific (weightings) and type specific (valuations).

The book on "Analysing Demand for Rail Travel" by Fowkes and Nash (1991) contains a introduction to the topic and a collection of studies into the rail demand market, some of which (Owen and Phillips, 1987, Rickard, 1988 and Preston,1991) are covered below. The introductory chapters on data sources, methodology, aggregate and disaggregate methods provide a useful summary of the research in this area up to 1991.

The paper by Shilton, 1982 presents an explanation of the methodology used to model demand for High Speed Train services. This paper will form the bases of the review of forecasting service level changes here, but the paper does cover some material from previous papers (Tyler and Hassard, 1973 and Whitehead, 1981). The paper starts by defining a quantity Q which is a **measure of service quality**, and in essence is a measure of perceived journey time over distance (ie a speed measure). This perceived journey time is a composition of actual journey time plus time change from ideal arrival time (either at the origin station or the ultimate destination station) necessary to catch a specific train plus interchange time penalties. A rooftop model is used to derive an average Q value over a day. The paper then suggests relationships between the number of journeys and Q using elasticity forms. The preferred form is a non-constant elasticity model which was thought be more intuitively correct than a constant elasticity model (see appendix D).

The first of two approaches to estimating the effect of a service change is using cross-sectional data. The estimated value of the service elasticity constant, α, was on the high side at 87mph. A suggested problem with this formulation involves the transference of rail business from one railhead to another. For example residents of Bolton may chose to re-book at Manchester, resulting in lower predictions for Bolton, relative to Manchester.

An alternative approach to assessing the effect of a service change is the use of historical time series data. This involves the comparison of affected flows with a set of control flows. These control flows are a set of flows which closely match the service of interest prior to any changes and are unlikely to change in the near future. The change in journeys which results from the implementation of the service change is derived from the difference between the control flows and the affected flows in subsequent time periods. This approach estimates a value for α of between 50-60mph due to the introduction of HST between London and Bristol and the South West.

A re-calibration of a slightly different model form to that given in equation (D4) was carried out in 1980. The main modification was to introduce an image variable to account for some of the increase in patronage. Previously it was suspected that the high α value was as a result of compounding actual service improvements with the enhanced image of the HST's. This suggestion is borne out since the revised value for α is much lower at 26mph.

The use of these types of model for forecasting purposes would require future predictions of the dependant variables and some notion of future service levels.

A paper by Wardman (1994) explores the relative merits of various functional forms in order to estimate time, frequency and interchange elasticities, all of which are similar to service elasticities. Another paper by the same author (1996) presents results from a study into the inter-urban rail demand market. The noteworthy feature in this paper is the form of the direct demand model which includes a dampening factor to be applied to constant elasticity model.
Another major study into the passenger demand market was undertaken by Owen and Phillips (1987). In their study they used historic, four-weekly, time series data from 1973 to 1984 to estimate various **elasticity** measures for London in and out bound rail passenger traffic. Various explanatory variables were selected to try and account for the variation in single passenger journeys. An overall problem was a matching of the high resolution of the passenger journey data (4-weekly) with other lower resolution data (quarterly or annual). Their models included the following significant terms:

Rail Fares: This was a weighted sum of differing fare types, the weight being the number of journeys made on this route of the fare type.

GDP: Various measures of macro-economic activity were considered for inclusion in the study. From a list of: real personal disposable income; consumer expenditure; and gross domestic product, GDP emerged as the best measure of this activity.

Time Trend: A simple time trend was thought to act as a potential proxy for other measures which also show monotonic behaviour over the period of the data. These other measures were: car usage; local levels of economic activity; changes in population. A better quality model would probably emerge if these data could be obtained on a regional basis. The car use figure (vehicle kilometres travelled by car) possessed little explanatory power. The best candidate for local economic activity was unemployment. This measure was rejected because of substantial underlying changes in the operation of the labour market.(?) Changes in regional population were thought to be so gradual as to provide little information.

Dummy variables:
A number of 0-1 dummy variables were used to account for intervention events. The events included the introduction of High Speed Trains on a route and significant competition from other modes (coach or air).

Seasonality: Twelve intervention variables were used to account for the seasonality in the 13 four-week periods.

Three demand equations were formed for each of the 20 London based flows, one for total journeys, one for first class journeys and the last for second class journeys. These equations were of the double-log form. Generally a set of consistent and significant demand elasticities were formed, both in the short and long run. Once again, given future forecasts of the independent variables mentioned above forecasts of passenger journeys may be made. Clearly it would not be suitable to forecast 30 years into the future using such a small time step of four-week periods. This is due to the fact that confidence intervals associated with forecasts, which are themselves based on other forecasts, tend to widen since the variance involves a feed-back of the variance of the forecast. A quarterly or annual time step would be more suitable.

The various elasticities derived from this study are reported, along with those from other studies, in Oum et al., 1992 and Goodwin, 1992.

Two further papers examine the market for rail travel, one on long distance travel (Rickard, 1988) and the other on local services (Preston, 1991). Rickard attempted to predict the **trip rate** of long distance journeys (trips per person per two week period) in the business and non-business sectors of the rail market. The data used in the analysis was Long Distance Travel Survey data from 1974 to 1984. The stated objective of the paper is to bridge a perceived gap between the market research data collected by on-mode surveys and statistical models of inter-urban demand from ticket sales data. To model trip rates, a **regression** exercise was performed under the assumption that the dependent variable, trip rate, followed a negative exponential distribution. Explanatory terms in this regression included the size of the subgroup and various dummy variables which represented the characteristics of the subgroup. The characteristics were, for example, gender, household size and composition, age and access to rail network.

For the business trip model the significant dummies were associated with : employers and managers, self-employed, non-manual, armed forced and students; professional employees; aged 18-54 and those with a district of origin of urban areas. For the non-business trip model the significant dummies were : professional employees, armed forces and students; aged 18-24 and over 65; resident in a district with a main line station; household type and an interaction term of membership of the first two groups listed here. These models were validated with predictions for trip rates in selected counties. Although the sample sizes at the level of trips per person per 2 week period is low, there does appear to be good agreement between the predicted and observed number of trips. This validation exercise begins to show that the derived national model can be applied at a regional level, a result which is of interest to this study. Issues related to the temporal stability of this model are not discussed in the paper. The paper concludes that there are **enormous differences** in the propensity of various sub groups to make rail journeys.

The paper by Preston, 1991, is primarily concerned with the prediction of demand for new, local, rail stations and services. This demand is thought to come from other modes or through generated demand. Two types of model are considered, **revealed preference** and **stated intention/preference**. Since disaggregate mode choice is not a prime concern in this paper, only a summary of that element of the paper is given here.

Three forms of revealed preference model are discussed: Trip Rate Models; Aggregate Simultaneous Models and Dissagregate Mode Choice Models. All three type of model were calibrated using various data sets from the West Yorkshire conurbation. The trip rate model was thought to be poor since it failed to take into account the socio-economic characteristics of the catchment population and was thus not spatially transferable. The aggregate simultaneous models developed were shown not to be temporally transferable and questions arose as to the spatial transferability of the models. Attempts were made to fit separate work and non-work models. The type of model for the dissagregate mode choice model was the hierarchical logit. Once again this model was shown to be not spatially transferable. The dissagregate models were aggregated using the extended incremental logit model which is appropriate for the aggregation of non-linear functions.

The use of stated intention surveys was not recommended since these types of survey tend to overestimate the demand for new services. The advantages of stated preference techniques are listed and the application of these techniques described in a study conducted in Leicester. The paper produces some case study comparisons of differing revealed preference methods and revealed preference and stated preference methods.

Rail freight in the UK is characterised by bulk commodities such as coal, petroleum and chemicals. These products are typically of low value and transport costs form a large proportion of their end-user costs. Thus cheap modes of transport are attractive. The main competing modes for these commodities are coastal shipping and inland waterways. Fowkes et al (1987) present a paper on freight mode forecasting. They suggest that the traditional commodities transported by rail are those in the declining industrial sector (iron ore and coal for steel works for instance) and as a result the rail freight market is declining, both in absolute terms and relative to the road mode. In the paper they cover some of the historical and current issues which affect mode choice in the freight market. The include: freight rates; service quality; depot rationalisation and new manufacturing techniques. The paper proposes a stated preference survey to gain an understanding of freight mode choice, which was undertaken and published in Transportation Research (REF ?).

9 AIR TRAFFIC FORECASTING

The UK Civil Aviation Authority's (CAA) method for modelling UK regional airport traffic is summarised, with a critique, in Caves (1992). The CAA's derivation of an airports modal share is based on a **multi-nomial logit model**, using individual's travel pattern information from CAA's own surveys. The model's general form is:

$$P_{ij} = \frac{A_j\, e^{-\lambda C_{ij}}}{\sum_{k=1}^{n} A_k\, e^{-\lambda C_{ik}}} \qquad (6)$$

Where P_{ij} is the probability of a passenger in zone i choosing airport j out of n;
A_j is the attraction factor of airport j;
C_{ij} is the passenger utilities from zone i using airport j;
λ is a calibration constant.

The air travel market was segregated into four markets: short haul; long haul; charter and domestic. The attraction factor and utilities vary depending on the sector. The model was calibrated exactly for 1987 data.

Caves' comments concentrate on three aspects of this model: relevance to regional airports; form of the model; model calibration and zonal trip generation, each of which is taken in turn. The main purpose to which the model has been used is to predict air travel demand in the south east of England, the forecast of regional airport demand is only considered in so far as it impacts on the relief of congestion in the SE of England. The model uses relative frequency as part of the attraction factor, whilst absolute frequency or frequency differences may be intuitively better. Also it may be better to include frequency as part of the utility measure. Only 164 zones were used for calibration, compared with 131 administrative districts in the SE of England and 238 in the rest of England. Thus with full coverage of the SE of England, 31 zones remain to cover the rest of England, and one individually for each of Wales and Scotland. Overall UK traffic forecasts are used for the annual estimate of new trip generation per zone, regardless of differences in population or economic activity.

Toner et al (1995) present a paper on **competitive inter-urban travel** in the UK. The two mode pairs considered are (rail and air) and (rail and car). Two methodologies are presented, aggragate demand models and disaggregate mode choice. Only the former will be discussed here.

The volume of trips on route i at time t, V_{it}, is given by the general form:

$$\ln\left(\frac{V_{it}}{V_{i0}}\right) = sumfromi\, \alpha_i + \sum_{t=2} \beta_t + \sum_j \gamma_j \left(X^{air}_{ijt} - X^{air}_{ij0} \right) + \sum_k \delta_k \left(X^{rail}_{ikt} - X^{rail}_{ik0} \right) + \sum_l , \tag{7}$$

The air and rail X variables include cost, time and headway whilst the other variables are natural logarithm of GDP and the lagged dependent variable. Variants on this model form were also explored but rejected. The paper then reports air demand elasticities with respect to these variables. Policy options are then tested with both this and the disaggregate model.

Another paper on air passenger traffic forecasting considered here which takes into account competing modes is a paper by Fridström and Thune-Larsen, 1989. The paper develops a **direct demand gravity model** for forecasting air traffic volumes on the domestic Norwegian network. The model was calibrated using cross-sectional and time series data. Factors taken into account include traffic-flows, fares, travel-time, income, population and surface mode competition.

The very general form of the model is:

$$Y_{ijt} = \psi(B_{it} B_{jt})^{\beta} (Rsubit\, R_{jy})^{\rho} \left[\frac{P_{ijt} / Q_{ijt}}{P_{ij0} / Q_{ij0}}\right]^{\pi_1} \left[\frac{P_{ij0}}{Q_{ij0}}\right]^{\pi_2} \left[\frac{Q_{ijt}}{Q_{ij0}}\right]^{\pi_3} [Q_{ij}$$

$$\left[\frac{T_{ijt} / S_{ijt}}{T_{ij0} / S_{ij0}}\right]^{\tau_1} \left[\frac{T_{ij0}}{S_{ij0}}\right]^{\tau_2} \left[\frac{S_{ijt}}{S_{ij0}}\right]^{\tau_3} [S_{ij0}]^{\tau_4} \tag{8}$$

$$[R_{it} R_{it}]^{\lambda_1 \ln P_{ijt} + \lambda_2 \ln T_{ijt}} \varepsilon^{U_{ijt}}$$

Where Y_{ijt} is the number of passenger travelling from airport i to j in year t;

- B_{it} is the number of inhabitants in airport i's zone of influence;
- R_{it} is the income of airport i's zone;
- P_{ijt} is the average air fare paid by passengers between i and j;
- Q_{ijt} is the fare payable on the competing surface mode (rail, ship, bus);
- T_{ijt} is the air travel time between zones i and j;
- S_{ijt} is the surface travel time by fastest means between i and j;

U_{ijt} is a white noise disturbance term;
$_{ij0}$ is the base year value.

This model yields the following information. If $\lambda_1 = \lambda_2 = 0$ then 2β and 2ρ denote population and income elasticities. π_1 is the short and medium term direct fare elasticity, π_2 is the long term direct fare elasticity, π_3 is the short and medium term demand elasticity with respect to travel fares in general, π_4 is the long run equivalent of π_3. $(\pi_3 - \pi_1)$ is the cross demand elasticity of air travel with respect to surface fares and $(\pi_4 - \pi_2)$ is the long term equivalent. τ_1, τ_2, τ_3 and τ_4 are analogous travel time elasticities.

Relaxing the $\lambda_1 = \lambda_2 = 0$ assumption yields different information. λ_1 measures the interaction between air fare and income. If λ_1 is positive then the income elasticity increases with higher fares, whilst the price elasticity decreases with increased income. λ_2 is the interaction effect between income and air travel time. The various short, medium and long term population, income, fare and travel time elasticity expressions are now more complex. These new forms and prior expectations about the signs of these elasticities are listed in table 1 of the paper.

The air traffic volume data (Y) is based on link flows, converted to OD information when airport transfers are taken into account. An airports zone of influence (B) was derived from inflight passenger surveys which enabled various municipalities to be allocated to an airport. A zone's income (R) is both personal and corporate. The air fare (P) is an *average* air fare calculated from a basket of such fares. Air travel time (T) was the fastest journey time plus check-in, check-out, transfer and access times. Information on competing modes (cost, Q and travel time, S) were taken from a comprehensive bi-monthly publication of transport schedules. In total 1,140 observations were used to estimate the parameters in the equation.

Various variants of the general model are presented in the paper.

(a) $\pi_1 = \pi_2 = \pi_3 = \pi_4$; $\tau_1 = \tau_2 = \tau_3 = \tau_4$; $\lambda_1 = \lambda_2 = 0$;
(b) $\pi_1 = \pi_2$; $\pi_3 = \pi_4$; $\tau_1 = \tau_2$; $\tau_3 = \tau_4$; $\lambda_1 = \lambda_2 = 0$;
(c) $\beta = \rho$; $\pi_1 = \pi_2$; $\pi_3 = \pi_4$; $\tau_1 = \tau_2$; $\tau_3 = \tau_4$; $\lambda_1 = \lambda_2 = 0$;
(d) $\lambda_1 = \lambda_2 = 0$;
(e) $\beta = \rho$; $\tau_3 = 0$; $\lambda_1 = \lambda_2 = 0$;
(f) $\beta = \rho$; $\tau_3 = 0$;

The τ_3 term was set to zero since its estimate was statistically insignificant and β was set equal to ρ since β was almost the same as ρ in variant (d). The paper then goes on to interpret the economic meaning of the estimated values. The R^2_{adj} figures are around the 69%-75% level which is described as "not too impressive"! The paper attempts to improve this figure by the introduction of airport specific dummy variables. The paper suspects that there may be problems with autocorrelation in the models' residuals and heteroscedasticity.

Not withstanding these issues the authors then move on to a description of what the final model form and parameter estimates disclose about the operation of the Norwegian air passenger transport market.

10 WATER BORNE TRANSPORT

The water borne transport market is composed of mainly freight, although there have been attempts in the past at a passenger service on the river Thames in London. Freight is transported by inland waterways such as canals and navigable rivers or around the coastline of the UK. The greatest extent of water freight transport is in the Yorkshire and Humberside region, which is composed of bulk commodities, both dry and in liquid form (Tweddle and Nash, 1993). Of the first nine NST chapters, just under 7% of the tonnes lifted in Yorkshire and Humberside are transported by waterway. A movement from road to rail and waterborne modes has, since 1981, attracted a grant based on the switch in lorry miles, although the effect has been limited in the waterborne mode.

11 DISCUSSION

The case for support commits the project to consider certain model forms. The first of these is a **trip rate** model, where the classification and trip rates are derived from an ANOVA with MCA tests. Thus a set of **mode specific** trip matrices need to be defined and created. Obviously the most up-to-date NTS data should be used in this process but it may also be worthwhile deriving the same matrices from previous years' NTS data. This may identify any trends and also allow the accuracy of any forecasts to be assessed against subsequent observations (ie 1985/86 NTS data used to calibrate a model to forecast 1987-1995). It may emerge from this research that the sophistication of MCA may not be appropriate.

The second is a direct demand model based on time series data. This model uses the information from the trip rate model along with income and own and competitor's price series. The case for support suggests a number of data sources which need to be pursued. Price information is required, which should include the cost of in-vehicle and access time. External costs, as covered in the Peirson papers may also be worth including, inspite of the result that there is little effect from their inclusion.

A concern is an assumed elasticity of demand with respect to travel time of zero in the NRTF. In a world were the supply keeps pace with demand then this should not be an issue, however, it is unlikely (or undesirable ?) for this to happen in the case of road transport. Thus as congestion increases then the growth needs to take this effect into account, choking off (sic) exponential growth.

Minor changes to previous research may be to attempt to predict new car sales in the Acutt and Dodgson model, rather than assuming that this is the difference between the NRTF and the survivors. The volume of new car purchases could be derived from econometric models of varying degrees of sophistication, calibrated with historical data on, amongst other things, car prices, fuel prices and incomes.

Given the poor modelling of **bus traffic** in the NRTF, an improvement should be possible. At the least, some form of within market econometric modelling could be attempted along the lines of Preston et al for Merseytravel. These model forms could include error-corrective, co-integration models once we work out how to fit them. A system wide model along the lines of Selvanathan, is suggested in the case for support. The drawback with these models is that a consistent, in time and form, set of data is required across all considered modes. This model may be possible for the private, bus and rail passenger markets. Selvanathan did not consider bus and rail separately.

Rail passenger demand is, after car travel, perhaps the most modelled market. Simple econometric models could be attempted (a la Owen and Phillips), depending on the data availability. Forecasts will, however, emerge from modelling approaches suggested above which include the rail mode. As in the NRTF car ownership model, more than one set of travel forecasts can be combined, but not in a simplistic, averaging, form.

The approach adopted by Fowkes et al to forecast freight traffic as a function of sectoral output appears to be attractive, especially if future forecasts of sectoral output can be obtained. Whilst their models of HGV traffic appeared robust, this can not be said for the LGV traffic. Alternative data models may be necessary to produce a robust (set of) model(s). The approach in Soliman will not help here since it is geared towards long distance HGV traffic.

The various sectors of the freight market tend to be captive to their existing mode. This means that there is likely to be little movement between modes, thereby simplifying the modelling task to within the sector's mode only, ie coal transport forecasts should assume rail transport whilst white goods transport should assume HGV's.

The Fridström air demand model appears to be a powerful and informative model form, which may be worth employing outside the air demand market. The authors do say that they suspect their model suffered from autocorrelation in the residuals but make no attempts to correct for this. We should.

Once a set of models have been produced some mechanism needs to be put in place to ensure that as newer, up-to-date information becomes available, then the model's parameters are re-estimated.

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APPENDIX A: Multiple Classification Analysis

Multiple classification analysis (MCA) possesses a number of features which recommend itself over traditional trip-generation and cross-classification methodologies. Nearly all these advantages stem from the fact that the method is rooted in the sound statistical technique of Analysis of Variance (ANOVA). Much of the explanation and the examples given in this appendix are taken from Stopher and McDonald's 1983 paper.

The traditional approach to forming a trip-generation matrix is to firstly decide on the basic unit of trip generation, usually a person or household. The second stage is to decide on those characteristics which are important in determining trip rate (household size; car ownership; household type; income; area type etc). The next stage is to form some kind of grouping within these characteristics (ie household size may be grouped into 1 person, 2 and 3 persons; 4 persons and 5 or more persons). Once these characteristics and groupings have been established then the trip rate per characteristic group (A0) can be made using observed data.

$$t_m^p = \frac{T_m^p}{H_m} \qquad \text{A0}$$

Where t^p_m is the trip rate for the p^{th} purpose for characteristic m;
T^p_m is the observed trips by characteristic m for purpose p;
H_m is the observed number of characteristic m.

A noted drawback to this approach is that it has the potential to induce a large degree of variability in trip-rates, which is due to unequal or small sample sizes.

An alternative approach to deriving trip rates which uses group averages (which tend to be based on larger, pooled sample sizes) is traditional ANOVA with MCA techniques (available in SPSS for Windows, v6.1). This technique also allows the use of statistical tests to establish the superiority of one arrangement of attributes over another. These tests include the F-test and an R^2 test to assess the entire cross-classification and ε^2 tests to test the contribution of each classification variable to explaining the variability in the data.

One way ANOVAs can be used is to establish the important individual characteristics in determining trip rates and to suggest groupings. Multi-way ANOVAs can suggest combinations of characteristics. Once an ANOVA table is formed F tests can be conducted to examine main and interaction effects. An overall F statistic is available which indicates the extent of covariance between trip rates and the set of characteristics. A highly significant F statistic for the main effects suggests that the variable is **strongly** associated with trip-rate variations. A highly significant F statistic for the interaction effects suggests that the classification characteristics may be too highly correlated to be useful and that it may be worthwhile choosing alternative variables to try and **reduce** the interaction effects.

The only disadvantage of the MCA approach over cross-classification mentioned is that the shape of the relationship between trip rates can not differ from class to class.

Example 1

A case study is taken from a household survey of 2,446 individuals who described their trip-making activity for a number of differing purposes. These purposes were work; shopping; recreation; other and non-home based trips. Candidate variables to use in classification were:

Household size; Car ownership or availability; Housing type; Household life cycle or structure; Number of workers; Number of licensed drivers; Income and Area type.

The initial stage in forming an MCA is to conduct one-way ANOVAs to establish which characteristics have the strongest relationship to trip-making and to suggest the best grouping. The results of the analysis were:

(a) Vehicle ownership or availability should be grouped as 0, 1 or 2 or more;
(b) Household size should be grouped as 1, 2 or 3, 4 and 5 or more;
(c) Income should be grouped as low or high;
(d) Household structure should be grouped into five categories;
(e) Number of workers should be grouped as 0, 1, 2, 3 and 4 or more;
(f) Number of licensed drivers should be grouped as 0, 1, 2, 3 and 4 or more.

All of which are intuitive.

To determine the best multi-way ANOVA based on these results a number of alternatives were tried for each of the five purposes. The F statistic was used to establish which alternative was the better at explaining the variability in the data:

(1) Car ownership; Housing type and Household size;
(2) Car availability; Housing type and Household size (superior to (1) and fewer interactions);
(3) Car availability; Employment and Household size (inferior to (2));
(4) Car availability; Housing type and Income (inferior to (2));

Thus classification (2) was selected as the best (but not necessarily optimal) scheme.

Example 2

By way of another example the two following tables present the traditional approach to deriving trip generation (table A1) and the MCA, without interactions, approach (table A2).

Notice that in some of the cells of table A1 there is no trip information since none of the surveyed households fall into these category combinations.

CROSS CLASSICATION		Persons							
Area Type	Vehicles	1		2,3		4		5+	
Rural	0	0.00	17	0.48	60	1.35	17	1.39	28
	1	1.50	4	1.46	88	1.88	48	1.65	69
	2+	-	0	2.10	48	2.23	40	2.36	70
Urban	0	0.10	40	0.62	110	1.00	34	0.70	40
	1	0.80	20	1.29	133	1.58	55	1.69	93
	2+	-	0	2.19	58	2.70	43	2.59	63

Table A1: Cross-classification table (trip rate and sample size)

MCA		Persons			
Area Type	Vehicles	1	2,3	4	5+
Rural	0	0.00	0.52	1.12	1.00
	1	0.45	1.38	1.98	1.96
	2+	1.30	2.23	2.83	2.81
Urban	0	0.00	0.33	0.93	0.91
	1	0.26	1.19	1.79	1.77
	2+	1.11	2.04	2.64	2.62

Table A2: MCA derived trip rate table (without interactions)

The information needed to calculate the value in each MCA cell is the grand mean and the deviations of the appropriate group mean from this grand mean. These means and deviations are given below:

```
Grand mean :         1.49
Group means :        Area type 1 :  1.60    (+0.11) Area type 2 :  1.41    (-0.08)

                     0 Vehicle :    0.65    (-0.84) 1 Vehicle :    1.51    (+0.02)
(with deviations     2+ Vehicles :  2.36    (+0.87)
from grand mean
in brackets)         1 Person :     0.33    (-1.16) 2,3 Persons :  1.26    (-0.23)
                     4 Persons :    1.85    (+0.36) 5+ persons :   1.84    (+0.35)
```

Thus in order to calculate the trip rate for a 4 person household with 1 vehicle living in area 1 the expression is: Area type 1; 1 Vehicle; 4 persons = 1.49 + 0.11 + 0.02 + 0.36 = 1.98.

This approach means that the trip rate means are calculated not just from the observations in each cell but from all available, relevant data.

Table A3 presents the fully interactive MCA for this same data.

MCA		Persons			
Area Type	Vehicles	1	2,3	4	5+
Rural	0	0.12	0.62	1.01	0.96
	1	0.86	1.36	1.75	1.70
	2+	1.63	2.13	2.52	2.47
Urban	0	0.10	0.60	0.99	0.94
	1	0.84	1.34	1.73	1.67
	2+	1.61	2.11	2.50	2.45

Table A3: MCA derived trip rate table (with interactions)

The differences between tables A2 and A3 clearly show that there are significant interactions in this classification. The effect of the interactions has been to decrease the range of rates in the table. The root mean square errors comparison between tables A1 and A2; tables A1 and A3 and A2 and A3 are 0.47, 0.51 and 0.24. Thus A1 is most different to A3; and A2 are A3 the closest, perhaps an unsurprising result.

There is no test as to whether table 1 or table 3 is the *correct* table. All that MCA provides is that if the ANOVA approach to classifying the data is to be adopted, then better use will be made of the observed data and a statistically better classification may be derived over other MCA's.

A similar approach, which uses weighted regression techniques to re-estimate the cell means for trip rates is given by Rengaraju et al, 1994. They suggest a model form of:

True cell mean = overall mean + row interaction + column interaction + row . column interaction

In the case of a two variable classification, the statistical expression of this model is:

$$Y_{ij} = \mu + \beta_1 x_{1j} + \beta_2 x_{2i} + \beta_3 x_{1j} x_{2i} + \varepsilon_{ij} \tag{A1}$$

Where Y_{ij} is the mean trip rate for cell ij;
x_{1j} is the level of characteristic one (eg household size);
x_{2i} is the level of characteristic two (eg vehicle ownership);
μ, β_1, β_2, β_3 are calibration constants.

The estimates in (A1) are derived using weighted least squares where the weight is the number of observation in cell ij, n_{ij}. This approach allows us to express the trip-rate for any combination of characteristics. Also alternative classifications and groupings can be assessed using the standard statistical goodness of fit measures for regression type models.

The paper presents an example of the application of this approach and concludes that the model produced reasonable fits and that cells with insufficient data showed significant discrepancies between observed and predicted trip rates.

APPENDIX B: Error Corrective and Co-integration Models

This section attempts to explain the general form of both error corrective and co-integration models. Discussions on why they are to be recommended over more traditional models and how to estimate them will be given. Much of the material will be taken from Harvey (1990).

Some basic definitions:

The Difference operator, Δ, takes differences in a series of data ie:

$$\Delta x_t = (x_t - x_{t-1})$$

The lag operator, L, shifts back a time series of observations ie:

$$L(x_t) = x_{t-1}$$

$$L^2(x_t) = L(L(x_t)) = L(x_{t-1}) = x_{t-2}$$

A polynomial in L can be defined such that:

$$A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \ldots - \alpha_n L^n$$

after which

$$A(L)\, x_t = x_t - \alpha_1 L(x_t) - \alpha_2 L^2(x_t) - \ldots - \alpha_n L^n(x_t)$$

Starting point

The starting point for the construction of an error corrective model is a standard *distributed lag* model of the form:

$$y_t = \delta_0 x_t + \delta_1 x_{t-1} + \ldots + \delta_n x_{t-n} + u_t$$

$$y_t = D(L)\, x_t + u_t$$

$$\text{where } D(L) = \delta_0 + \delta_1 L + \ldots + \delta_n L^n$$

If the disturbance term, u_t, is an autoregressive, moving average process, ARMA(p, q), then equation (B8) can be generalised into the following form, known as a *transfer function*:

$$y_t = \frac{B(L)}{A(L)} x_{t-v} + \frac{\theta(L)}{\phi(L)} \varepsilon_t \qquad \text{B}$$

where :

$$B(L) = \beta_0 + \beta_1 L + ... + \beta_s L^s$$

$$A(L) = 1 - \alpha_1 L - ... - \alpha_r L^r$$

If there is a delay before x has an effect on y then the value of v is positive.

The building of a transfer function model usually involves a cycle of identification, estimation and diagnostic checking. The identification and estimation procedures necessary when more than one explanatory variable, x_{ti}, i=1...k, is involved in the model form (B9), become cumbersome. The function is highly non-linear and contains k(s+r)+q+p unknown parameters. The transfer function can be simplified into a *stochastic difference* model if certain assumptions are applied, ie if A(L) is set equal to φ(L), to give:

$$A(L)\, y_t = \sum_{t=1}^{k} B_i(L)\ xsubti + \theta(L)\, \varepsilon_t \qquad \text{B}$$

This is termed an ARMAX (r, s_1, s_2, ..., s_k, q).

Estimation of stochastic difference models

In the discussion on how to best estimate the parameters in a stochastic difference model, the following simple instance of such an ARMAX (1,0,?) model is used (notice that the form of the disturbance term is not specified):

$$y_t = \alpha\ y_{t-1} + \beta\ x_t + u_t \qquad \text{B}$$

If the disturbance term, u_t is white noise ie q=0, then α and β can be estimated by OLS regression of y_t on y_{t-1} and x_t. If, however, the disturbance term follows an AR(q) process then the values of α, β and **θ** are estimated by those which minimise the sum of ε_t^2 where, if q=1,

$$\varepsilon_t = y_t - \alpha\ y_{t-1} - \beta\ xsubt - \theta\ \varepsilon_{t-1} \qquad \text{B}$$

The issue still remains of how to obtain starting values of α, β and θ. This is generally a two stage process. Firstly initial estimates are made of the α and β terms using instrumental variables (these are variables which are uncorrelated with the disturbance term u_t but highly correlated with the explanatory variables). The residuals from (B11) can then be used to estimate θ.

The previous discussion is based on the assumption that the desired functional form is given, ie

(B11), and all that remains is estimation and diagnostic checking. The omitted stage of model selection is now addressed. The general approach suggested is to start with a general model specification and test-down to a more specific model. Since econometric time series typically change rather slowly, including a large number of lags in a model may lead to numeric instability because of multicollinearity. If for simplicity θ(L) is set to 1 and k=1, ie white noise error terms and one explanatory variable (ie ARMAX(r,s,0)), then (B10) can be re-written as (I am assured):

$$y_t = \sum_{k=1}^{r} \alpha_k \ y_{t-1} + \sum_{j=1}^{r-1} \Big(- \sum_{k=j+1}^{r} \alpha_k \Delta \ y_{t-j}\Big) + \sum_{k=0}^{s} \beta_k \ x_t + \sum_{j=0}^{s-1} \Big(- \sum_{k=j+1}^{s} \beta_k \Delta \ x_{t-j}\Big) + \varepsilon_t$$

(B13)

What has been achieved here is a recasting of equation (B10) in terms of levels (x and y) and differences (Δx and Δy), which separates out **long-run** and **short-run** effects. Subtracting y_{t-1} from both sides leads to the dependant variable being Δy_t and if x_t is replaced by x_{t-1}, the form of (B13) is now:

$$\Delta y_t = \Big(\sum_{k=1}^{r} \alpha_k - 1\Big) y_{t-1} + \sum_{j=1}^{r-1} \Big(- \sum_{k=j+1}^{r} \alpha_k \Delta \ y_{t-j}\Big) + \beta_0 \Delta \ x_t + \sum_{k=0}^{s} \beta_k \ x_{t-1} + \sum_{j=0}^{s-1} \Big(- \sum_{k=j+1}^{s} \beta$$

(B14)

Observe that the lag on the dependent variable corresponds with the lag on the explanatory variable. Also the dynamics are captured by the differenced variables. Their higher order lags will often have the smallest coefficients, thus it is natural to begin by testing them for significance, gradually moving to lower order lags. Notice also that the usual attempt at parsimony has been abandoned.

If the contribution of the two level variables in (B14) are brought together as

$$\Big(\sum_{k=1}^{r} \alpha_k - 1\Big) y_{t-1} + \sum_{k=0}^{s} \beta_k x_{t-1} = \Big(\sum_{k=1}^{r} \alpha_k - 1\Big)\big(y_{t-1} - D(1)\, x_{t-1} \big)$$

$$Where\ D(1) = \frac{B(1)}{A(1)} = \sum_{j=0}^{infinity} \delta_j$$

this leads to the general form of an *error corrective model* as being:

$$\Delta y_t = \delta + \sum_{j=1}^{r-1} \Big(- \sum_{k=j+1}^{r} \alpha_k \Delta \ y_{t-j}\Big) + \beta_0 \Delta \ x_t + \sum_{j=0}^{s-1} \Big(- \sum_{k=j+1}^{s} \beta_k \Delta \ y_{t-j}\Big) + \Big(\sum_{k=1}^{r} \alpha_k - 1\Big)\big(y_{t-}$$

(B16)

Examples

This general specification can be intimidating, so a specific application can be seen if r = s = 1, ie an ARMAX(1,1,0) model in (B10) :

$$y_t = \delta + \alpha\, y_{t-1} + \beta_0 xsubt + \beta_1 x_{t-1} + \varepsilon_t\,,\ \ |\alpha| < 1 \qquad \text{B}$$

the equivalent error corrective form is:

$$\Delta\, y_t = \delta + \beta_0 \Delta xsubt + (\,\alpha - 1)(\,y_{t-1} - v\, x_{t-1}\,) + \varepsilon_t$$

B

$$where\ v = \frac{\beta_0 + \beta_1}{1 - \alpha} : (the\ long\ run\ elasticity)$$

$$Since :$$

$$\Delta\, y_t = \delta + \beta_0 \Delta\, x_t + (\,\alpha - 1)(\,y_{t-1} - v\, x_{t-1}\,) + \varepsilon_t$$

$$\Delta\, y_t = \delta + \beta_0 \Delta\, x_t + (\,\alpha - 1)\, y_{t-1} + \beta_0 x_{t-1} + \beta_1 x_{t-1} + \varepsilon_t$$

$$y_t - y_{t-1} = \delta + \beta_0(\,x_t - x_{t-1}\,) + (\,\alpha - 1)\, y_{t-1} + \beta_0 x_{t-1} + \beta_1 x_{t-1} + \varepsilon_t$$

Virley, 1993, gives an unrestrictive (since no co-integration factor, v in B18, is required) error corrective formulation for the modelling of CO_2 emissions. His formulations are:

$$D_t = \alpha + \beta\, P_t + \lambda\, Y_t \qquad \text{B}$$

Where D_t is total road transport fuel consumption (thousand tonnes);
P_t is consumption-weighted real price of fuel (pence/therm);
Y_t is total final expenditure (in £m).

The dynamic adjustments to (B19) are incorporated by using the unrestricted error correction form:

$$\Delta\, D_t = \alpha_0 + \alpha_1 \sum_{i=0}^{n} \Delta\, P_{t-i} + \alpha_2 \sum_{i=0}^{n} \Delta\, Y_{t-i} + \alpha_3 \sum_{i=1}^{n} P_{t-i} + \alpha_4 \sum_{i=1}^{n} Y_{t-i} + \alpha_5 \sum_{i=1}^{n} D_{t-i} + \varepsilon_t$$

(B20)

An initial overparameterised form of (B20) with four lags was tested, the removal of insignificant lag terms one by one using t-ratios gave the following final equation:

$$\Delta\, D_t = 4.606 - 0.092\, \Delta\, P_{t-i} + 0.537\, \Delta\, Y_{t-i} - 0.046\, P_{t-1} + 0.119\, Y_{t-1} - 0.098\, D_{t-1} - 2.509\, I_{57} +$$

$$(2.55)\quad (-5.76)\quad (6.23)\quad (-4.08)\quad (2.01)\quad (-2.06)\quad (-3.38)$$

(B21)

With I_{57} a dummy intervention for the Suez crises. From this equation the short run (one-year) price and income elasticities are $\eta_p = -0.09$ and $\eta_i = +0.54$. Using 1990 data the long-run elasticities are $\eta_p = -0.46$ and $\eta_i = +1.22$. This suggest that the first year adjustment to a price change is only 20% of the long-term adjustment.

Co-integration

A time series $\{x_t\}$ is weakly stationary if both its mean, $E[x_t]$, and variance, $VAR[x_t]$, are independent of t and the autocovariance, $E[x_t, x_s]$ depends only on the difference between t and s. Strong stationarity requires that $E[x_t, x_s]$ is constant for all combinations of t and s.

Most econometric series are not stationary, they may exhibit a trend (increasing mean) or seasonality (non-constant mean). Many can, however, can be approximated by stationary processes if they are differenced. If a series must be differened d times to make it stationary then it is said to be integrated of order d, and expressed as $\{x_t\} \sim I(d)$.

The primary problem when attempting to model an I(d) series is that the usual statistical properties of first and second sample moments do not hold and neither of the usual t and F tests are valid. Consider, however, two series, $\{x_t\}$ and $\{y_t\}$ both of which are I(1). It is possible that at linear combination of these two variables, $\{z_t\}=\{y_t - \lambda x_t\}$, is I(0) in which case $\{x_t\}$ and $\{y_t\}$ are said to be **co-integrated** and λ is unique. This suggest that the general trends in the two series are similar, drifting apart only in the short-run or according to seasonal factors.

A straight-forward way of assessing whether two series are co-integrated is to regress one series on the other. A necessary but not sufficient condition is that the R^2 value is high. Other tests for co-integration involve the Durban Watson statistic; regression of differened residuals on various lagged residual levels; test of the error-correction component after co-integration (see below).

Co-integration and error corrective models

In equation (B16) there is a term, $(y_{t-1} - D(1)\, x_{t-1})$, which is similar in structure to a co-integration between the y_{t-1} and x_{t-1} terms. These two components work together. The co-integration component represents the **long-term** equilibrium in the relationship between the two variables whilst the error corrective component accounts for **short-term** equilibrium error.

The fitting of an equation such as (B16) is a two stage process. The first stage is to estimate the parameters of the co-integrated component. These are then used in the second stage to estimate the error correction component. Engle and Granger 1987 contain a discussion on how to carry out each stage but their explanation is difficult to follow. From what can be gathered, stage one involves performing a *co-integration regression* by regressing the variable $\{x_t$ or $y_t?\}$ normalised to have a unit coefficient on the other variables $\{x_t$ or $y_t?\}$. The estimate from step one is substituted into the full error corrective model which is then estimated.

Clearly some more study into the fitting of these types of model is required. The best approach to gaining an understanding may be to attempt to re-produce one of the models from a paper or text *book.*

APPENDIX C: Joint Car Ownership and Use Models

The individual household model starts by forming a relationship between car usage, disposable income (ie total income minus the fixed costs of owning a car), the fixed cost of owning a car, the variable cost of running a car and an *other effects* term (C1). An indirect utility function is derived (C2) and if this utility exceeds the direct utility expression for not owning a car (C3) then the household will own a car and the usage is given by (C1).

Demand function:

$$\ln A = \alpha \ln(Y - C) - \beta v + \delta \qquad (C1)$$

Indirect utility function: (C2)

$$\frac{1}{\beta} e^{(\delta - \beta v)} + \frac{1}{(1-\alpha)} Y - C^{(1-\alpha)}$$

(C3)

Direct utility function:

$$\frac{1}{(1-\alpha)} Y^{(1-\alpha)}$$

Where A is automobile use;
Y is household income;
C is fixed cost of owning a car;
v is the running cost of a car.
δ is the other effects;
α, β are parameters to be estimated.

by setting (C2) equal to (C3), and solving for v_{max}, the maximum variable cost at which the household will choose to own a car can be established.

$$v_{\max} = \frac{-1}{\beta} \ln \beta + \delta overbeta + \frac{1}{\beta} \ln(1-\alpha) - \frac{1}{\beta} \ln[Y^{(1-\alpha)} - (Y - C)^{(1-\alpha)} \qquad (C4)$$

$$\ln A_{\min} = \alpha \ln(Y - C) + \ln \beta - \ln(1-\alpha) + \ln[Y^{(1-\alpha)} - (Y - C)^{(1-\alpha)}] \qquad (C5)$$

This model can be generalised from a particular household to a collection of households, and the other effects term decomposed into a *genuine* other effects term and an error component which reflects natural household to household variability. This enables the probability of household i not owning a car to be given as (C6) and re-arranged as (C7):

$$Pr\left[\left(\frac{1}{(1-\alpha)} Y_i - C_i^{(1-\alpha)} + \frac{1}{\beta} e^{(\gamma S_i + \varepsilon_i - \beta v_i)} \right) \leq \left(\frac{1}{(1-\alpha)} Y_i^{(1-\alpha)} \right) \right] \qquad (C6)$$

$$Pr[\varepsilon_i \leq \ln[Y_i^{(1-\alpha)} - (Y_i - C_i)^{(1-\alpha)}] - \ln(1-\alpha) + \ln \beta - \gamma S_i + \beta v_i] \qquad (C7)$$

Where S_i are a vector of observed socioeconomic characteristics;
γ is a parameter to be estimated;
ε_i is an error term.

the ε_i term follows an idd N(0, σ_e^2) distribution, so dividing both sides by σ_e^2 enables the use of standardised Normal probabilities to establish the probability of not owning a car. Using this result an expression in the paper is given for a Likelihood function, which can be maximised by numeric estimation.

The paper then moves onto the data necessary to maximise the above Likelihood and obtain parameter estimates. Use is made of a Dutch panel survey, similar in nature to the UK FES data. The fixed costs were estimated as C=2,536 guilders per year and the variable costs at 21.09 guilders per 100 kilometres. The socioeconomic variables are log of household size, age of head of household by 13 classes and two dummies, one for a farmer and one for a female as head of household. How these variables were selected is not mentioned in the paper.

Once the parameter estimates have been made the values of v_{max} and A_{min} in (C4) and (C5) can then be calculated for each household in the Dutch survey. The sample mean values are 24.48 and 8,900 guilders. Car ownership is thereby given as those households whose individual variable costs exceeds the actual variable cost (here 21.09). If the variable and fixed costs are known for a particular car owning household then (C1) gives usage.

The model predicts 1,771 car owning households in the sample of 2,344, close to the observed number of 1,792. The predicted kilometrage is 12,765 against the observed value of 12,553.

APPENDIX D: Rail Service Elasticities

Given a measure of service quality, Q, then an assumed relationship between it and its elasticity is given by

$$\eta_Q = \frac{\alpha}{Q} \qquad (D1)$$

Where η_Q is the elasticity of journey with Q (mph);
α is a constant to be estimated (mph).

The full relationship between volume and Q may then given by:

$$V = A\, e^{\left(-\frac{\alpha}{Q}\right)} \qquad (D2)$$

Where A is a flow specific constant.

At its simplest the expected number of rail journeys between two centres may be a function of the population of each town. A trip distribution gravity model form which may describe this relationship is given in (D3).

$$V_{ij} \propto \frac{P_i^x\, P_j^y}{d_{ij}^z} \qquad (D3)$$

Where V_{ij} is the volume of traffic from town i to town j;
P_i is the population of town i;
P_j is the population of town j;
d_{ij} is the distance between towns i and j;
x, y, z are constants to be calibrated.

Tyler and Hassard, 1973 describe an enhanced version of this model which is given the name MONICA (Model for Optimising the Network of Inter-City Activities) and calibrated to 1969/70 journeys between London and provincial centres. The form of the equation is given in (D4) which is a combination of (D2) and (D3) and can be estimated using cross-sectional data.

$$J = K\ p^{\beta}\, d^{\lambda}\, c^{\gamma}\ PIfromi\ e_i^{\varepsilon_i} \left(1 - \frac{1}{Q}\right)^{\alpha} \qquad (D4)$$

Where J is journeys by rail;
p is population of catchment area;
d is distance;
c is competing modes;
e_i are various socio-economic factors;
Q is the Quality of rail serves (in a slightly different form to that in 6);
K, α, β, λ, γ, ε_i
are constants to be calibrated.

Notice that the formula only contains one population variable since one of the origin/destinations, London, is constant for all flows.