4. Review of the recent international literature

In this chapter the recent (since 1995) international literature on car ownership modelling is reviewed. Also some information is added on models, especially if these are still being used as regional or national car ownership models, that have not appeared in publicly available journals, but are only available known from conference papers or project reports.


In this paper, the work model component of the Stockholm Integrated Model System (SIMS) is described. The paper describes the system as a whole, but the review focuses on the car ownership and car allocation components of the model.

In formulating the work model structure, the authors note that different travel purposes are often modelled separately. In practise, there are important cross-influences between different travel purposes, and in principle the total travel pattern should be considered simultaneously. In a similar manner, travel for each individual member of a household is often modelled separately, while in fact interactions exist between the travel patterns of individual household members. Thus if possible, the total travel pattern of the whole household should be modelled.

In model systems such as the LMS, car availability utility terms are used to account for the availability of cars to household members. This is perhaps the most important household interaction in modelling travel to work. In the Stockholm context, it was decided to explicitly model car allocation amongst workers as part of the work model structure. A high level of female workforce participation was a factor in this decision.

The overall structure of the work model adopted was complex, and incorporated a high degree of household interaction, as shown by Figure 2. All submodels are disaggregate tree logit models.
Figure 2. SIMS Work Model Structure

The models of tour frequency and car allocation are below each destination alternative. The destination alternative in this case is the workplace, which represents a long-term choice decision.

In the model of mode choice for households the modes refer to the modes available to person A in the household. Therefore:

- when no car is allocated, A can use any mode except car-driver (this option is not illustrated in Figure 2 for households with 2 cars);
- when only A is allocated a car, then A is car-driver by default (this option is not illustrated in Figure 2 for households with 2 cars);
- when only B is allocated a car, then A cannot be a car driver, so the modes available to A exclude car-passenger;
- when A and B share a car (AB) then A is car-driver by default;
- when A and B are both allocated a car (A&B), then A is car-driver by default.

Logsum accessibility measures feed back up the structure, providing a linkage between the model components.

When estimating a tree model structure, it is preferable to have the choice decisions with which more error is associated towards the top of the tree, because error is passed up the tree. The car ownership decision represents a long-term decision, and the car purchase decision may have occurred years before the date of the travel survey. Furthermore, the conditions which influenced the car purchase decision in the household may be quite different to those at the time of the travel survey. Therefore
the household car ownership decision was modelled at the top of the tree, with the alternatives 0, 1 and 2+ cars.

Below the car ownership decision is the choice is workplace for the head of the household (A) and their partner (B) conditional on the outcome of the car ownership model. So households with no cars will be predicted to choose workplaces more accessible to public transport. The choice of workplace is also a long-term decision, which cross-sectional travel diary data collected on a single day may find hard to explain.

The models of tour frequency model the combinations of household members travelling to work. Next is an explicit car allocation model. The alternatives in this model are that no household member uses the car, A uses the car, B uses the car, A and B share the same car (AB) or A and B both use separate cars (A&B). Note that the availability of these alternatives is dependent of the number of cars in the household. In the car allocation models gender variables demonstrated that, all other things equal, men had a higher probability of getting access to the car. However, women under 40 and women with a higher education had higher probabilities of ‘negotiating’ for the car than other women.

At the bottom of the model structure is a model of detours to secondary destinations during the work tour. Car and PT modes were modelled separately. The model of car detours found detours to CBD and inner city destinations were less likely, which may reflect in part difficulties in parking in these areas.

4.2 HCG and TØI (1990) A Model System to Predict Fuel Use and Emissions from Private Travel in Norway from 1985 to 2025 (also in De Jong, 1997)

The Norwegian model system was developed in 1990 in response to increasing international concern about the Greenhouse Effect. It has been updated several times since and is used now as national model system STM-4. The main objective of the project was to create a forecasting system capable of assessing the success of carbon-dioxide control measures in Norway. A secondary objective was that the forecasts of transport demand should be fully compatible with the macroeconomic forecasts produced by the Norwegian Central Bureau of Statistics (SSB). This review focuses on the car ownership and usage model components.

Due to the importance of predicting vehicle usage accurately in order to determine vehicle emissions, disaggregate models of joint car ownership and use were estimated. The joint model estimated is based on the micro-economic theory of consumer behaviour, which depicts the household decision problem as maximising utility under a given budget constraint. It is an extension of models developed for The Netherlands (De Jong, 1989), which only considered households with zero or one car. Considering the 0/1/2 car ownership decision, the approach considers two goods: automobile use in kilometres per year A, and X the volume of all other goods and services per year. The cost of usage is decomposed into fixed costs C and variable (marginal) costs v. The problem can then be formulated as:
Maximise \{ U = U(A, X) \}

subject to the budget restriction:

\begin{align*}
Y & \geq X & \text{if no car} \\
Y & \geq v_1 A_1 + C_1 + X & \text{if one car} \\
Y & \geq v_1 A_1 + C_1 + v_2 A_2 + C_2 + X & \text{if two cars}
\end{align*}

where \( Y \) represents net household income.

If a household does not own a car then it can spend all income on other goods. If the household decides upon car ownership, then to overcome the disutility associated with the fixed costs it must drive a positive number of kilometrages. Exogenous Norwegian data was used to determine the fixed and variable costs of owning a car. Comparing the costs of the first and second cars, the fixed costs were similar, whereas the variable costs (per km) of the second car tended to be lower, a reflection perhaps of smaller engine sizes.

Conditional indirect utility functions were defined for each positive car ownership outcome; for the zero cars outcome a direct utility function could be defined. The functional form for the demand function for kilometres was based upon statistical analysis of car ownership and use in the Netherlands and on research in the US. The linkage between the indirect utility functions and the demand functions was provided by Roy’s identity. It was not computationally feasible to find out which of the three conditional direct/indirect utility functions was highest for a given household. Therefore households with one licence were allowed the choice zero/one car, and households with two or more licences were allowed the choice one/two cars.

The model estimation was performed using the GAUSS package. For both cars, significant terms were estimated for the log of remaining household income, the variable cost of driving, the log of household size and percentage urbanisation. For the first car only, significant terms were identified for a female head of household. For the second car only, significant terms were estimated for age of head of household over 45 plus, and age of head of household over 65.

To validate the models estimated, simulations were undertaken in order to compare car ownership and kilometrage elasticities to 1985 Dutch values. These comparisons revealed the Norwegian predictions to be reasonable, although somewhat lower than the Dutch values.

### 4.3 Jong, G.C. de (1993) Car Ownership Forecasts for France

This memo provides an overview of how car ownership forecasts for France have been determined, based on a number of original - French - reports, mainly by INRETS. Furthermore it describes how national car ownership forecasts had been updated and translated into regional forecasts. Car use is also predicted in the form of regional fuel consumption. The car fleet is predicted using a demographic model, whereas fuel consumption is predicted using an econometric model.
The demographic car fleet model treats cars as essentially household or person attributes. The car fleet is predicted using a demographic method, looking at ownership by age cohort. Three stages were identified in the development of car ownership in France, by plotting age against cars per adult for 10-year cohorts:

1. Diffusion to all generations until the mid-sixties;
2. Movement to cruising speed until the mid-eighties;
3. A move towards saturation, shown by a shorter distance between trajectories of ownership of successive cohorts.

The model extrapolates the observed trends. The memo notes that the gaps in car ownership between cohorts will become smaller and smaller as saturation is approached. A possible problem with the approach is that it is at odds with the possible demotorisation of the elderly; however the elderly in France tend to retain their cars but drive them less. Two hypotheses are used in the demographic car fleet model: firstly that the trends in car ownership by cohort show parallelism, and secondly that car ownership by cohort approaches a saturation level.

The regional data source could not give the trajectories by cohort; instead an average ownership per cohort per region for each of the eight ZEAT regions in France was available. The lower car ownership levels for Ile de France (including Paris), particularly for younger persons, are noted. This data source was used to produce the regional car fleet forecasts, obtained by multiplying the forecast number of adults by the number of cars per adult from the cohort trend extrapolation.

In a similar fashion, car usage (kilometrage) is predicted using the same cohort trend extrapolation methods. Due to ageing of the population, the total kilometrage (‘circulation’) is forecast to grow less than the car fleet. The kilometrage is predicted by region of residence, which does not necessarily coincide with traffic by region.

The econometric fuel consumption model models fuel sales. The log of fuel samples was used as the dependent variable in a model with a constant, the log of the fleet, the log of real income per capita and the log of real fuel price as regressors. By using a double-log form, the coefficients are elasticities. The income variable was insignificant and so was dropped from the model. Regional variations in elasticities were observed. The fleet elasticity took values between 0.7 and 1.1, whereas the price elasticity was around –0.2.


This paper focuses on the development of a model of household vehicle usage behaviour by type of vehicle. Vehicle usage forecasts were needed to forecast future vehicle emissions, specifically including the potential gains from alternative fuel vehicles. The forecasts needed to be made by fuel type, body style and size, and vintage of the vehicle.
The data used household based mail-back surveys collected in California. Two SP vehicle type choice experiments were collected for each household. Vehicle usage SP questions followed the vehicle choice experiments. The usage questions asked the household to assign principal drivers to each vehicle in the new vehicle fleet, _including_ the chosen SP vehicle, and indicate how many miles per year the vehicle would be driven. Note that the chosen SP vehicle may be an alternative fuel vehicle. The survey was designed in such a way that respondents first reported principal drivers and usage patterns for their current vehicles before performing the SP task. Thus both RP and SP measures of annual vehicle miles travelled were collected.

The usage model variables are divided into three groups: _behavioural_ vehicle usage characteristics, _physical_ vehicle characteristics and _household_ structural characteristics. Because the models were to be used in a forecasting system, the household variables were limited to those which could be produced by the available demographic forecasting model. Separate models were developed for single-vehicle households and multi-vehicle households.

A key feature of the models is the endogenous treatment of driver allocation behaviour. However as no forecasts of principal driver characteristics are available, driver allocation behaviour is specified as a function of _exogenous_ variables, for which forecasts are available.

The two-vehicle usage model covers the usage of the _newest_ two vehicles in multi-vehicle households. Casual relationships between the endogenous variables were specified by two types of direct effects: within-vehicle effects and between-vehicles effects. The results demonstrated _driver_ age has a significant effect on vehicle usage that is uniform for the two vehicles: if either driver is younger, both the first and second vehicles are likely to be used more. Contrastingly, gender and employment status effects are consistent and reciprocal across the two vehicles: if the principal driver is female, that vehicle is driven less but the other vehicle is driven more; similarly if the principal driver is employed, that vehicle is driven more but the other vehicle is driven less.

The effects of vehicle age are stronger for the second vehicle, although consistent for both: the older the vehicle is the less it is used. Furthermore, the older the first vehicle, the less the other vehicle is used as well. The implication is reduced usage over time if no vehicle transactions occur.

The effects of operating cost were not precisely estimated, but had intuitive signs. A higher operating cost for the second vehicle implies a shift in usage from the second vehicle to the first.

Considering the impact of the SP data regarding new electric vehicle (EV) usage, the model results suggested that the EV will be driven less, _ceteris paribus_. Furthermore, if the EV is the newest vehicle in the fleet then the second vehicle (probably petrol) will be driven more than otherwise expected. Therefore the model captures a shift in usage from EV to conventional fuel vehicles, which has important implications for emissions reduction targets. Note that a range effect term also captures a reduced usage effect from alternative fuels vehicles.
The number of household members aged between 16 and 20 years old has a positive effect on usage of both the first and second vehicle. However, the number of drivers in the household has a negative effect on VMT of both vehicles, perhaps indicating a shift towards third and fourth vehicles in the household. High (three plus) vehicle ownership was accounted for via a negative dummy on usage for the first and second vehicles.

The forecasting model was applied using a dynamic microsimulation, incorporating a sociodemographic transition model and a vehicle transactions model. The usage model is used to predict before and after situations, which are applied using a pivot-point approach. This method has the advantage of preserving heterogeneity across households not captured in the usage model.


In this paper, Nobile et al. estimate a random effects multinomial probit model of car ownership level, using longitudinal (panel) data collected in the Netherlands.

The authors note that analysis of panel data enables the incorporation of both intertemporal dimensions present in car ownership choice, such as resistance to change in ownership levels due to search costs and uncertainty of financial position in the future, and intratemporal dimensions such as acquired taste for a certain lifestyle. The unobserved factors are likely to make some car ownership alternatives closer substitutes than others, which questions the validity of the IIA assumption often maintained in discrete choice models. The authors thus seek to model car ownership choice to account for both unobserved determinants using a multinomial probit (MNP) model.

The data source for the modelling was data drawn from Dutch National Mobility Panel. Ten waves were collected between March 1984 and March 1989. Data from waves 3, 5, 7, and 9 of the period was analysed, collected between 1985 and 1988. Data from wave 1 was omitted due to considerable sample attrition between waves 1 and 3. In total, the four waves comprise 2,731 households for a total of 6,882 observed choices. As less than 1% of choices corresponded to three or more cars, the car ownership alternatives modelled were 0, 1, 2+.

The approach used for model estimation was Bayesian: a prior distribution of the parameters of the longitudinal MNP model is specified and the ‘posterior’ is examined using Markov chain Monte Carlo methods. The papers details the mathematical formulae involved.

A total of 50,000 draws were used for the Markov chain, with an initial burn-in of 5,000 draws excluded to ensure that the Markov chain had stabilised. No reference is made to computation time, which may be considerable given the high number of draws.
The model results for the wave dummies were all negative (measured relative to wave 3), suggesting generic temporal effects. The authors noted the pattern of the terms was in some agreement with the Dutch business cycle during 1985-88.

Considering the cross-sectional terms, standard disaggregate household model terms were estimated for the 1 and 2+ car alternatives, with no cars as the base. Namely terms for level of urbanisation, number of licences in the household, number of full and part-time workers, number of adults, number of kids and household income.

The authors do not make forecasts with their model. Implementing such a model would necessitate a high number (thousands) of draws to be made per record, and so run times could be expected to be considerable.

The authors conclude that most of the variability in the observed choices can be attributed to between-household differences rather than to within-household random disturbances.


In this paper the authors consider two methods of modelling car (auto) ownership choice within a behavioural econometric framework. They consider ordered response choice mechanisms, and unordered response choice mechanisms. In both cases, disaggregate household based models are employed.

Ordered-response choice mechanisms are not consistent with global utility-maximisation. They are based upon the hypothesis that a single continuous variable represents the latent car owning propensity of the household. The decision process can be viewed as a series of binary choice decisions. A given household assigns utility values for each car ownership outcome, and then makes an independent utility maximisation decision for each range. Based upon the decision outcome for each range, the actual choice is determined by the range in which the household falls. Only one set of M household parameters need to be estimated in this approach, but this is also a disadvantage in that (for example) variation in sensitivity to income cannot be specified to vary between alternatives. The ordered-response mechanism employed by the authors was Ordered Response Logit (ORL).

Unordered-response mechanisms are consistent with the theory of global utility-maximisation. The choice process can be viewed as a simultaneous choice between each alternative, with the choice determined by the alternative with the highest utility. The method allows greater flexibility on the parameter effect, however substantially more parameters need to be estimated: \((K - 1) \times M\) as one base alternative is defined. This allows for variation in sensitivity to household income to vary with car ownership alternative if necessary. The unordered-response mechanism employed by the authors was Multinomial Logit (MNL).

To investigate the two approaches, four data sources were used: three regional data sets from the US and one Dutch national dataset. The US regional data sets are
obtained from the 1991 Boston Region Household Travel Survey, the 1990 Bay Area Household Travel Survey and the 1991 wave of the Puget Sound Household Travel Panel Survey. The Dutch national dataset was based on the 1987 wave of the Dutch Mobility Panel Survey. For each survey, the sample was split into an estimation sample (typically 1500 households), and a smaller validation sample (typically 500 households). Descriptive statistics of car ownership levels on the estimation sample demonstrated much higher car ownership levels in the US (up to 2.09 cars per hh, compared to 0.81 in the Dutch data). Consequently, the car ownership outcomes modelled were 0, 1, 2, 3, 4+ cars for the US data, and 0, 1, 2+ cars for the Dutch data.

For each data set, ORL and MNL models were estimated. A number of socio-economic variables were included, but only three were consistently significant across the data sets. These variables were number of working adults, number of non-working adults and household income. It should be noted that the selection of variables (no number of children terms, for example) may be significantly conditioned by the US context of three of the four data sets.

The measures of fit from the estimation sample showed a better adjusted likelihood ratio index for the MNL specification for each data set. Comparison of the aggregate elasticities demonstrated significant differences. In particular, the ORL model is constrained to have rigid and monotonic trends in elasticities, whereas MNL is more flexible in picking up the effects of variables upon specific alternatives.

The authors then applied the model results to the validation samples. Using an aggregate measure of model performance - a comparison of actual and predicted percentage shares by alternative – the MNL was superior for each of the four data sets according to the rooted mean square error measure. Using a disaggregate measure of model performance – the average probability of correct prediction – the results again demonstrated the MNL specification to be superior for each of the four data sets. The conclusion of the paper is that their comparison of the ordered (ORL) and unordered (MNL) choice mechanisms clearly indicates that the appropriate choice mechanism for modelling car ownership is the unordered-response structure, such as MNL or multinomial probit models.

4.7 Dargay, J.M. and P. Vythoulkas (1999) Estimation of a Dynamic Car Ownership Model; A pseudo panel approach

The pseudo-panel approach is a relatively new econometric approach to estimate dynamic (transport) demand models that circumvents the need for panel data and their associated problems (e.g. attrition). The purpose of the paper is to evaluate the method of pseudo-panels rather than to set up a detailed car ownership model.

A pseudo-panel is an artificial panel based on (cohort) averages of repeated cross-sections. Extra restrictions are imposed on pseudo-panel data before one can treat it as actual panel data. The most important is that the cohorts should be based on time-invariant characteristics of the households, which in this case is the age of the head of the household. By defining the cohorts one should pursue homogeneity within the cohorts and heterogeneity between the cohorts.
One important feature of pseudo-panel data is that averaging over cohorts transforms disaggregate (discrete) values of variables into cohort means, thereby losing information about the individuals.

The pseudo-panel data set is constructed from repeated cross-section data contained in the UK Family Expenditure Survey. There are on average 7,200 households per year in the survey since the 1960’s. The data is based on the years 1983-1993 resulting in a total of 165 observations.

Having defined the cohorts, a conclusion is drawn that heads of households born earlier tend to have a lower average car ownership rate over their lifetime than the ones born later.

The model in the article is a fixed effects model, but for a pseudo-panel this results in an error-in-variables estimator following Deaton (1985). A generation effect is added to the model proposed by Deaton and a lagged dependent variable is included to estimate the dynamics of the model. Three other models are estimated to compare with the fixed effect model: OLS, random effect specification and random effect with a first order autoregressive scheme.

The dependent variable is the number of cars per household. The variable now indicates the average number of cars for that particular cohort.

The explanatory variables are socio-economic characteristics of the household: income, the number of adults, the number of children, metropolitan and rural areas and a generation effect for the head of the household. Price indices for car purchase costs, car running costs and public transport fares are added to the set of explanatory variables.

The four models are estimated and the lagged dependent variable is significant in all, indicating that the number of cars of an average household depends on the number of cars in the previous year. Almost all other variables are significant in the four models and have the expected sign. Only the number of children and the public transport fares are insignificant at a 95% confidence level.

The random effects model with a first order autoregressive scheme is the favoured model. The long term elasticities in this model are almost 3 times as large as the short term elasticities, which indicates a lot of dynamics in car ownership.


In this paper, the authors estimate an econometric model to the relationship between per-capita income and car ownership, defined throughout as total cars divided by total population. The model is estimated on annual national data from 26 countries over the period 1960-1992, using both high and low income country data. The authors then go on to make projections of car ownership up to 2015.
The authors first consider patterns in the growth of car ownership at the national level, relative to growth in per-capita income, during the period 1970-1992. Relative to growth in per-capita income, the increase in car ownership has been greatest in the fastest growing economies, South Korea and Japan. Vector plots of per-capita GDP against car ownership for a range of countries show a clear positive relationship between the two variables.

The ratio of the average annual percentage growth in ownership to the average annual growth in per-capita income is a rough measure of the income elasticity of car ownership. Historical plots show that for low-income countries, car ownership has grown at least twice as fast as income, i.e. the income elasticity has been much higher than 2.0. A further pattern apparent is that the higher a country's per capita income the lower its ratio of ownership growth to income growth. From the plots produced, a saturation level of ownership would be reached at income levels of around $30,000 (all figures quoted are 1985 US $).

To fit a model to the relationship between vehicle ownership and per capita income, the authors considered a range of functional forms to describe the S-shaped curve observed. The functional form selected was the Gompertz function, which is more flexible than the logistic model, as it allows the specification of different curvatures at the low and high income levels of the ownership curve. Their ownership model took the following specification:

\[
V_{it} = \gamma \theta e^{\alpha \exp(\beta GDP_{it})} + (1 - \theta) V_{t-1}
\]

where: i denotes country, t denotes time (at yearly intervals)
- \(\alpha, \beta\) are low and high income shape parameters respectively
- \(\gamma\) is saturation level
- \(\theta\) is a speed of adjustment affect (0 ≤ \(\theta\) ≤ 1)

The authors choose to estimate a single value for parameters \(\alpha, \gamma\) and \(\theta\) but country-specific values for \(\beta\). Thus they estimate a family of long-run Gompertz functions from pooled time-series cross-sectional data, allowing the high-income shape parameter to vary between countries, but assuming changes with income at the bottom of the curve, and final saturation levels, are constant between countries. It is noted that in order to estimate the curve properly, data from both low and high income countries is required.

In estimation, each country’s data was weighted by its total population. The estimated model gave a global saturation level of 0.62 cars per-capita. The value for \(\theta\) was 0.09, suggesting only 9% of the total response to income changes occurs within one year, a slow response.

The Gompertz form allows plots of income elasticity against per-capita GDP to be determined. These plots show an asymmetric curve, with rapid rise to a peak income elasticity around 2.4 for per-capita GDP around $4,000, dropping down again fairly rapidly, and then trailing off to around zero income elasticity for per-capita GDP of $30,000.
Projections of car and vehicle ownership up to 2015 are made using population and GDP predictions; these predictions are more relevant to lower income countries were the predicted increases in ownership are more significant.

In conclusion, the authors believe that for most OECD counties car ownership levels will converge to levels close to saturation in the two few decades. The most rapid increases on car ownership within the OECD will occur in countries with relatively low incomes but high rates of income growth, such as Portugal. The fundamental point of the paper is the strong historical relationship between the growth of per-capita income and the growth of car ownership.

4.9 Hanly, M and J. Dargay (2000) Car Ownership in Great Britain – A Panel Data Analysis

A car ownership model is set up to examine whether owning in car in the previous year(s) has a significant effect on the current state. The main purpose is to test the dynamics within the model by applying advanced econometric estimation methods.

A panel analysis is carried out using data from the British Household Panel Survey. Data of four years (1993-1996) are used to estimate the model.

The dependent variable is the number of cars owned by the households in each of the four years. This is a discrete variable, which can take the values 0, 1, 2, and 3 or more. The dependence on past experience is incorporated by introducing lagged endogenous variables. The model specification is an ordered probit model. With four choices this results in a quaternary, ordered choice latent regression model.

Three types of models are estimated: a model without a lagged dependent variable, a model with a lagged dependent variable and a model with dummies for the number of cars in the last year (0,1,2,3 or more cars). For each of the three models an additional model is estimated with a household specific, time invariant error-component to compensate for household heterogeneity.

The explanatory variables are household income and household socio-demographic variables, such as number of adults of driving age, number of children, number of adults in employment and a dummy variable indicating whether the head of the household is of pension age. Five location dummies are included reflecting urbanisation and the population density.

The results of the model focus on the issue of state dependence, meaning the state of car ownership a household was in last year compared with the state it is in this year. The results support the hypothesis that last years car ownership influences the current car ownership significantly at a 95% confidence level.

Almost all the estimated coefficients for the exogenous variables are significant at a 95% confidence level, like the number of adults of driving age and in employment. The head of the household who has a pension status negatively influences the car
ownership. More rural areas will generate higher car ownership, because there are less alternatives.


Introduction

TREMOVE is a behavioural model designed to analyse cost and emission effects of a wide range of technical and non-technical measures to reduce emission from road transport. The model was developed to support the policy assessment process within the framework of AOII, the second European Auto-Oil Programme.

TREMOVE can be seen as consisting of three key, interlinked, blocks. The first describes transport flows and the users' decision making process when it comes to choosing which mode they will use. The second is the stock module: it describes how changes in demand for transport across modes or changes in price structure influence the number of vehicles of each type in the stock. The third block calculates emissions, based on the number of kilometres driven by each type of vehicle. See figure 3 and 4.

TREMOVE is a simulation model, not a forecasting model. It's more a scenario explorer; the equations in TREMOVE are specifically designed to analyse changes in behaviour as a result of changes in economic conditions.

What does TREMOVE compute?

TREMOVE computes the effects of various types of policy measures on the key drivers of transport emissions, such as the size and composition of the vehicle stock and vehicle usage. It simulates consumer behaviour with regard to the choice of transport mode and vehicle type, assesses how these choices are affected by introduction of policy measures, and what effect this has on emissions. The model takes into account a large number of transport modes, and determines the demand for each mode and emissions from road transport by taking into account the many interactions between the various transport modes.

TREMOVE computes the difference in costs between alternative transport scenarios, and can decompose these by category of costs (cost of transport, cost to government and cost to transport producers).

What's the output of TREMOVE?

The output of TREMOVE includes annual forecasts of transport flows (vehicle usage), vehicle stock size and composition, costs to society from transportation, and emissions from transport both in the base case and in any variant thereof.

The model describes for example transport flows, vehicle stocks and vehicle usage across three modelling domains per country: a target city, other urban areas, and non-urban areas. In these three domains a distinction is made between daily peak and off-
peak periods. In the urban modules, a further distinction is made between commuters and inhabitants. There is no distinction between different purposes of trips, and the model does not provide information on seasonal variations in traffic or emission.

**Modelling vehicle stock and usage**

The module on the vehicle stock calculates the size and structure of the vehicle stock. It gives a full description of the vehicle stock every year, by vehicle type and by age of the vehicle. The age structure of the vehicle stock is an essential variable to assess the impact of emission reduction policies. The key input variables of this module are road transport demand by mode, vehicle costs, fuel prices and policy measures that affect vehicle choice. This module also calculates the usage for each category of vehicles from which the usage cost can be derived. *See figure 5.*

The vehicle stock consists of annual vintages that are handed over from period to period. The vehicle stock size in a given year t is a function of:

- The vehicle stock in the previous year (given value)
- New vehicle sales (endogenous variable)
- Retirements, or scrapping of vehicles (endogenous and exogenous variable)

\[
\text{Stock } i(t) = \text{Stock } i(t-1) - \text{Scrap } i(t) + \text{Sale } i(t)
\]

\(i=\) vehicle type

The module takes into account traffic demand by mode that leads to desired stock. New sales is the outcome of the difference between the desired stock and the surviving stock (the surviving stock is the stock that remains when the scrapping stock is subtracted).

Scrapping of vehicles is both an endogenous and an exogenous variable. The endogenous scrapping is based on the idea that there is an age dependant probability of breakdown. Following breakdown, repair expenditures are needed to restore vehicles to operation conditions. Exogenous scrapping representing the cars that can no longer be repaired.

**Figure 3. TREMOVE structure**
Figure 4. Overview of TREMOVE

- **Demand of Passenger Transport**
  - Exogenous Factors and Base Case Assumptions
  - Equilibrium Price Module
  - Generalised Consumer Price
  - Supply of Passenger Transport
  - Supply of Freight Transport
  - Policy
  - Cost Module

- **Demand of Freight Transport**
  - Exogenous Factors and Base Case Assumptions
  - Equilibrium Price Module
  - Generalised Consumer Price
  - Supply of Passenger Transport
  - Supply of Freight Transport
  - Policy
  - Cost Module

- **Equilibrium Price Module**
  - Generalised Consumer Price
  - Producer Price
  - Time Cost

- **Supply of Passenger Transport**
  - Producer Prices
  - Fuel

- **Supply of Freight Transport**
  - Producer Prices
  - Fuel

- **Policy**
  - Vehicle, Fuel Standards
  - Fiscal Policy Variables
  - Public Transport Subsidies

- **Cost Module**
  - Road Infrastructure, Speed Limits

This paper describes the submodel developed to model the car fleet in the ALTRANS (ALternative TRANsport systems) model complex. ALTRANS is a model developed for analysing the environmental impact of different policy proposals on car and PT usage in Denmark. The model of the car fleet submodel described in the paper gives as outputs energy consumption and emissions stemming from car use.

The car fleet is modelled as being composed of three parts – the existing fleet, the purchase of new cars and the scrappage of old cars. Different exogenous variables have been used to model new car purchase (acquisition) and scrappage. The acquisition model was developed by the Danish consultancy firm Cowi, and is not described in detail in the paper.

The paper describes the historical developments of the Danish car fleet, demonstrating the impact of changes in economic conditions, the effect of high new car purchase taxes and the impact of a scrappage policy.

Focussing on the car-fleet model, the model system is basically an accounting type model. Acquisitions are forecast using Cowi’s model, which takes as inputs prices, incomes etc. The historical stock of cars in different categories is used to determine the existing fleet. The scrappage model is calibrated to historical scrappage rates in different categories. Once the car fleet model has been run, the total car emissions for the forecast year can be determined through application of the emissions model.
The scrappage model predicts the number of cars scrapped by two fuel type, three weight of vehicle, and 20 age of vehicle categories. The model was estimated of detailed vehicle registration data from 1991 to 1997, augmented by more aggregate data from between 1977 and 1990. The final scrappage model contained terms for stock, income and fuel costs. The stock term was necessary because the model was estimated on *levels* of scrappage, as opposed to scrappage rates.

In the emissions calculations component of the model, a degradation factor is determined dependent the kilometrage driven. The kilometrage is determined from a formulae from the Road Directorate, dependent upon age of the vehicle. The emissions per vehicle are then determined using a formulae based upon the kilometrage of the vehicle. Cars fitted with a catalytic converter have higher emissions levels when cold. This has been accounted for in the emissions model by defining a cold engine component for the first 4 km of a trip (applied to catalytic cars only).


In this paper, Brownstone et al. compare multinomial logit (MNL) and mixed logit models for data on Californian households’ revealed and stated preferences for automobiles. In the vehicle choice modelling context, they found RP data was critical for obtaining realistic body-type choices and scaling information, and SP data was critical for obtaining information about attributes not available in the marketplace, but pure SP models gave implausible forecasts, hence the use of joint models.

The SP and RP choice data were collected as part of a multi-wave panel survey carried out in California, commencing in June 1993. In Wave 1, 4,747 households completed a mail-back SP survey after recruitment via a telephone interview. The SP models in the paper were estimated from this Wave 1 data. Approximately 15 months after the Wave 1 survey, a geographically stratified sample of the households telephoned in Wave 1 was used for a second wave (Wave 2) of interviewing. In this survey 874 out of 2,857 households surveyed reported at least one vehicle purchased. An RP data set was constructed using these new purchases.

To deal with the large number of make-model-year combinations in the market, for each year model year usually beginning in 1974, the authors categorised vehicles into 13 body type/size categories, in turn sub-divided into a high and low purchase price group, and a domestic and import group. This gave 689 possible RP vehicle categories. Attribute data (current used prices, fuel economy, top speed etc.) was determined for each of these categories.

Before estimating joint SP/RP models, separate SP and RP models were estimated. However, a particular feature of the problem is that some preferences are only identified in the SP, and some preferences are only identified in the RP.
The SP models were estimated using both MNL and mixed logit model forms. To identify the normally distributed random coefficients in the mixed logit form, the Lagrange multiplier test from McFadden and Train (1997) was used. Five random coefficients were identified. Four were applied to the different vehicle fuel types modelled, demonstrating large heterogeneity in taste for alternative fuel vehicles. The authors also note unpublished work with the SP data which found significant nesting for the different fuel types. Hence the variance components of the mixed logit models may model substitution patterns similar to those from nested logit models. The fifth random coefficient was for fuel cost, with a large variance indicating a wide range of cost sensitivity. An issue in estimating mixed logit models is the higher computation time required, resulting from the need to draw repeated numbers from in this case a normal distribution to estimate the random coefficients. In this work, it was found 1,000 draws were needed per observation to obtain numerically reliable estimates.

The RP models were also estimated separately. No significant random coefficients could be estimated in these models. A key issue with the RP models was the large number of vehicle type alternatives available. Initially random sampling was used, but the problem was that new vehicles only comprised 52 of the 689 alternatives, and so a random sample of 30 would only contain one or two new vehicles. The solution was to use importance sampling, where a stratified sampling according to vehicle vintage, including seven new vehicles, and modelling 28 choices in total. In terms of model results, only terms for price and operating cost could be determined with any accuracy due to high co-linearity between range, speed and acceleration.

Joint SP/RP models were then estimated. A scale factor was used to scale the SP data relative to the RP data. For the MNL model, this factor was less than one, indicating the stochastic error term is the SP data has a larger variance than the RP data set. Interestingly, in the mixed logit model specification (using the same random error terms as the SP model), where preference heterogeneity is captured by fuel-type error components, the scale factor greater than one. Note that both the MNL and mixed logit models assumed that unobserved error terms are independent across RP and SP choices made by the same households.

The authors proceeded to make new vehicle forecasts for California, using both the pure SP models, and the joint RP/SP models. An interesting result was that the SP models predicted unrealistically high sports car markets shares compared to the RP/SP model, demonstration of the benefits of combining RP and SP data. The mixed logit models tended to result in higher market shares for the alternative fuel vehicles. A key point here is that the IIA properties of MNL means a proportionate share of each new vehicle’s market share must come from all other vehicles, whereas the mixed logit specification results in the more plausible result that the market share for electric fuel vehicles comes disproportionately from other mini and subcompact vehicles.

The authors conclude that mixed logit models are a general and feasible class of models for joint RP/SP choice data. However, modelling RP vehicle choices with a discrete choice model presents difficulties due to the large number of alternatives in the marketplace, and procedures that rely on sampled choice sets for non-IIA models require more investigation. The alternative fuel models highlight the advantage of using joint RP/SP data in the vehicle choice context. Although plagued by
multicollinearity, RP data appears critical for obtaining realistic body-type choice information, and for scaling information. SP data is critical for obtaining information about attributes not readily identifiable from the marketplace.


In this report HCG describe the car ownership models estimated as part of their recent work to extensively update the Sydney Strategic Transport Model (STM). Disaggregate models of company and total car ownership at the household level were estimated.

The disaggregate models were estimated from two data-sources, one collected during 1991/92, and one collected during 1997/98. However, prior to model estimation longer term trends in car ownership between 1971 and 1997/98 were investigated. These investigations revealed that a large part of the long-term trends could be explained by income changes and changes in licence holding. However, it could not be concluded that these effects accounted for all of the changes, and consequently the models included trend terms.

Model tests were undertaken to determine the most appropriate way of modelling company and total car ownership. Three approaches were tested:

1. Modelling private and company car ownership behaviour independently;
2. Modelling private car ownership conditional on company car ownership;
3. Modelling company car ownership conditional on private car ownership.

The model tests revealed the second approach gave the best structure, i.e. households choose the number of private cars dependent on company car ownership. The model structure adopted is shown in Figure 6.
A logsum variable was tested to try to determine a significant linkage between the models. A significant logsum term could not be estimated however, this may be due to the similarity between the specification of the explanatory variables in the two models. As a result of the similar model specifications, the inter-household variation in utility is similar (accounting for scale differences) between the two models. This pattern makes identifying a significant logsum term difficult.

Both models predict car ownership dependent on the logarithm of net household income. The total car model accounted for impact on net household income of car ownership costs, with the effect dependent on the number of cars owned.

The number of licence holders in the household was an important term in both models. In both models, significant negative parking cost terms were estimated, accounting for lower car ownership in zones where parking is more expensive.

Both models identify the head of the household is identified as the individual with the highest income, and terms are estimated to reflect car ownership differences according to the age and gender of the head of the household.

The total car ownership model included an accessibility term from the home-work mode-destination model. This term accounts for higher car ownership in zones which are accessible to work places. No such term could be estimated in the company car model, consistent with the belief that company car ownership is dependent on job position and type, not accessibility to the workplace.

In this paper Hensher and Greene estimate both multinomial logit (MNL) and mixed logit models to a combined SP/RP data, modelling vehicle choice in single vehicle households.

The data source for the analysis was a stated preference survey undertaken in late 1994 in six capital cities in Australia (Sydney, Melbourne, Brisbane, Adelaide, Perth, Canberra). The SP survey had two aims: the determination of respondents’ preferences with regard to conventional vehicles for a given range of price and running cost attributes, and to assess whether respondents are willing to consider alternative fuel or electric vehicles as substitutes for conventional vehicles given a price, running cost and some physical differences.

In the SP survey vehicles were categorised according to the following attributes: three size categories based upon engine size (within a given engine size, respondents were asked to indicate a preferred body type), price of vehicle, registration fee (e.g. on conventional vehicles), fuel cost to travel 500km (variable described as approximate cost of filling a tank so respondents understood levels), fully fuelled range (only for non-conventional vehicles, as envisaged conventional vehicle ranges will remain stable, and expressed as percentage of conventional vehicle range), acceleration (frequently lower for non-conventional vehicles) and boot size.

The SP experiment was a two stage process. The first stage of the SP required a household member to consider three conventionally fuelled vehicles (one from each size class) and choose one. In the second stage, three electric vehicles and three alternative fuel vehicles were added to the choice set, and the household member asked to choose one vehicle from the nine. This experiment was repeated three times.

A total of 36 alternatives are possible in the SP vehicle type choice model (three size classes, three fuels, four vehicle ages). Tests of a reduced choice set demonstrated a choice set of 12 alternatives would give statistically indistinguishable parameter estimates. To select the choice set, four alternatives were selected from each fuel class. The age profile was randomised within each size class.

The RP model is defined by a 10-alternative choice set, using a random sampling procedure within each size class to assign vehicles of each vintage to the 10 alternatives given their size class. The advantage of using a ranked model was that it is possible to introduce class-specific constants and apply choice-based weights to the RP choice set to reproduce the base market shares for the 10 size classes.

To estimate the joint SP/RP models, one nested logit and three mixed logit specifications were estimated. In addition to the choice-based weights in the RP data set, exogenous weights were used for each observation to correct for differences in sample and population income distribution. For attributes common to both the SP and RP, separate parameter estimates were considered, but it was found that generic parameters were statistically preferable.
In the mixed-logit models, random parameters were estimated for the electric and alternative fuel vehicle constants (normally distributed), and for the vehicle price (log-normally distributed to ensure parameter is always negative). The heterogeneity in consumer preference for non-conventional fuel vehicles is consistent with the findings in California, reported in the review of Brownstone et al (2000).

The three mixed logit formulations considered were:
1. No correlation assumed;
2. Correlated attributes;
3. Correlated attributes and SP choice sets.

The results for the three mixed-logit model were compared to those obtained from the comparable nested MNL model by examining variations in the willingness to pay (WTP) for a marginal improvement in vehicle range for non-conventional fuel vehicles. The WTP figures were similar for nested logit and the first two mixed logit models. However, when correlation between the two SP choice sets was allowed for, the impact on the WTP figures was large, with the WTP values almost halving in magnitude.

Switching propensities were also compared for the nested MNL and the third mixed logit formulation. This comparison demonstrated consistent patterns of over and under-prediction under a range of scenario options. The tendency was for MNL to over allocate to new fuels and hence under-estimate shares on conventionally fuelled classes, relative to mixed-logit.


In this paper, Page et al. describe the development of a model of new car sales for incorporation within the Vehicle Market Model (VMM) of the then UK Department of the Environment, Transport and the Regions (DETR). The objectives of the project were to improve knowledge of the factors which influence people’s decisions when they buy new cars, and to develop a computer model to forecast the future distribution of new car sales.

The data collected for this study comprised four elements:

1. Existing revealed preference (RP) data – National Travel Survey (NTS) data from 1985-97 was used;
2. Focus groups – to discover what factors are important to potential and actual buyers;
3. Interview data – a survey of 500 respondents who answered a stated preference (SP) questionnaire;
4. Fleet managers’ survey – the buying decisions of fleet managers were probed, and this included an SP survey to assess the behaviour of this important section of the market.
An important requirement of the model was the ability to discriminate between private (retail) and company (fleet) purchases, and therefore the relevant decision maker in each case had to be identified and approached.

The outcome of the focus groups provided input into the final SP surveys. The focus groups revealed that aspects of performance, engine size and image are more important to company car buyers than to private buyers. Purchase price and to an extent running costs were important factors as they provided a constraint on the range of vehicles considered.

The RP data used UK NTS a household survey data. For each vehicle less than one year old, information was extracted on population density and area type where the household was located, the socio-economic characteristics of the household and the attributes of the household’s vehicle fleet. The sample generated gave 3,090 observations, 1,070 company owned, 2,020 privately owned.

The SP interview data collected information from households who were either planning to acquire a new car, or had just acquired a new car. The questionnaire was administered on laptop computers, and thus allowed customisation of the levels of the attributes. Background information was collected on the respondents’ socio-economic characteristics, details of the household’s existing fleet, company policy on company cars (where applicable), details of the preferred specification of the new vehicle and details governing future purchase decisions. The information provided a check on the representativeness of the sample, and was used to set the SP levels to ensure meaningful choices were presented.

The household SP experiments presented the following vehicle attributes to respondents: additional income tax (comp), monthly supplement due to loss of salary arising from company car ownership (comp), fuel costs, purchase prices, running costs, standing charges (road tax and insurance, private only), resale value, engine size, vehicle emissions, safety measures, fuel type (petrol, diesel or hybrid petrol-LPG) and fuel economy. Two SP questionnaires were presented to assess the likelihood of respondents opting in or out of the company car market, the aim being to elicit a ‘value’ associated with company car ownership.

The background questions in the SP revealed that after cost, the greatest concern for private buyers was reliability, whereas for company car users it was comfort, perhaps a reflection of greater mileages.

The fleet managers survey revealed that after necessity for work, the key reason for providing a company car was ‘to aid staff retention/recruitment’. Clearly company car ownership is seen as an important benefit. Cost, both in terms of purchase and running costs, dominated the decision making process for fleet buyers. Fleet buyers were willing to consider alternative fuel vehicles, but only if they were cost effective and practical drawbacks could be overcome. SP models derived from fleet managers were generally very good; given the knowledge the respondents have of the market this was expected. However, the fleet managers model was not incorporated in the final structure.
The SP and RP data-sources were combined to form two nested household based models. The first model predicts the binary choice between a private and company car (ownership status model). The final model variables were the number of children in the household (seen as a proxy for stage in life cycle), male head of household dummy, age of head of household, the log of vehicle tax, the log of ownership cost and an alternative specific constant.

The second model predicted a multinomial choice between different vehicle types. Separate models were used for company and private cars. In the private car model terms were estimated for population density, log of annual household income, log of purchase price, number of children, running costs, variations in emissions, safety features, resale value, fuel economy, standing charges, hybrid engine type and diesel engine type. In the company car ownership model, the terms were population density, log of annual household income, log of monthly cost, number of children, fuel cost, engine size, variations in emissions, safety features, hybrid engine type. In both models, a scale factor was used to scale the SP data relative to the RP data. Some of the factors of importance in the choice of private vehicle were similar to those for company vehicles – an interesting feature of both models is that in areas with high population densities, where parking is likely to be more difficult, there is a higher probability of acquiring a smaller vehicle.

The model system was implemented using a pivot point or incremental logit model. The implementation was undertaken in Visual Basic 5. The model system predicts the proportions of different types of new cars over the period 2000-2031 inclusive. The new car sales are disaggregated by:

- Engine size (9 bands for petrol, 7 bands for diesel);
- Fuel type (petrol / diesel);
- Ownership type (private / company).

Note that individual make – model combinations, such as Ford Escort 1.6 L, are not disaggregated. The model can assess the impact of a range of policy measures through their effects on the impacts of the model which include:

- Engine size;
- Purchase price of the new vehicle;
- Standing charge (tax plus insurance);
- Running costs – pence per mile;
- Fuel economy;
- Fuel cost;
- Tax – tax liability for company car ownership;
- Ownership costs – for private car ownership.


This paper is not about car ownership, but was included because it included an international review of the constant budget assumption that is crucial for FACTS.
In this paper, Schafer compared major mobility variables from around 30 travel surveys in more than 10 different countries. He analysed both longitudinal and cross-sectional data, and his research broadly confirmed the theory that time and money travel budgets are stable at an aggregate level. He found that the two travel budgets showed strong regularities across space and time for all countries examined.

The papers begins by reviewing other literature in this area, and highlights previous findings that while travel budgets tend to be stable at high aggregation levels, such as national levels, variability exists at more disaggregate levels. Some research has emphasised the aggregate stability, other work seeks to explain the disaggregate variability. Zahavi, using cross-section data from cities inside and outside the US, suggests a time budget of 1.1 hours per day, and an income budget of 10-15 %, for individuals in car owning households.

The travel survey data sources were collected between 1975 and 1995, and as a first step in his analysis Schafer considers their comparability. He emphasises that more recent travel survey diary methods are more successful at recording all travel, and when compared to earlier surveys may imply growth in travel which is in fact due to better reporting. Another comparability problem is the inherent sample bias in any survey, which will vary between surveys, and problems of nonresponse. Non-respondents may have atypical travel patterns which bias the results. Other possible inconsistencies result from different survey designs, objectives, and definitions. For example some surveys were carried out on a single day, others represent a working day average. Schafer notes these problems should be borne in mind when analysing the results of his inter-survey comparisons.

Schafer used 26 travel surveys at different time periods (cross-sectional data) to calculate a mean travel budget of 1.22 hours per capita per day (h/cap/d) with a standard deviation 16 % of the mean. At the same time, the mean daily distance travelled showed considerable variation between surveys, from under 5 km in African villages to over 60 km in a 1995 US survey. Using the same data sources Schafer calculated a mean travel money budget of 10.73 % of disposable income with a standard deviation 31 % of the mean. Therefore the money budget showed more variation than the time budget. While both travel budgets demonstrated a horizontal response when plotted against daily distance travelled, plotting mean trip rates and trip distances against daily distance travelled demonstrated both increased with increasing daily distance travelled. The pattern in the data suggested as incomes increase, people make more trips (more personal business and leisure), and are able to afford to travel using faster modes, and so make longer trips. The next step of his project is to try to combine the data-sources in a more formal statistical manner, correcting for major inconsistencies in the surveys.

Considering the travel time budgets for the US in more detail, Schafer notes that the travel time spent by individuals has a skewed distribution and consequently the mean and median differ strongly, so that while the average per capita travel time is 1.18 h/cap/d, the typical resident travels only 50 minutes. Similarly the mean transportation expenditure represents 19.3 % of total expenditure, but the typical (median) household dedicates only 13 % of expenditures to travel.
Examining trends in the time budgets between journey purposes, Schafer looks first at commuting, which he notes tends to be well reported in travel surveys. For commuting, it seems travel time budgets have been increasing slightly at a country level, suggesting commuters have been unable to compensate longer distances with higher mean speeds. A similar pattern was observed for work related business. However, these patterns varied between countries, with no such increase being detected in Norway for example. Personal business and leisure do not show this pattern, i.e. follow a time budget pattern with increasing trip distances. Overall however, Schafer concludes that the per person travel time budget can still be considered roughly constant at high aggregation levels.

Considering travel money budgets, Schafer looked at six Western countries: France, Italy, the Netherlands, UK, US and (former) West Germany between 1970 and 1995. He observed that in general travel budgets have remained stable above motorisation rates of 0.30 cars per capita, where on average nearly all households own a vehicle. Only in West Germany have travel budgets risen (slowly) after this point in time.

Schafer goes on to examine the implications on travel patterns of travel budget stability. In terms of mode-choice, increasing incomes imply rising travel demand from the money budget, and the constant travel time budget requires travel at higher speeds and hence shifts towards faster modes. In terms of land use, as people travel further population tends to disperse, and mean distances to work are increasing, even in high density countries with good public transportation such as the Netherlands. In the US the distances to work are much higher than the European context, with a mean trip distance to work of c 60 km in a 1995 survey.

In conclusion, Schafer states that aggregate travel behaviour is determined largely by the two travel budgets. However, he believes neither budget is unique or completely stable. He believes that while most of the variation between travel budgets can be attributed to inconsistent survey methods, part of the variation may represent behavioural change. Given that the two budgets vary across different countries, Schafer suggests it may be most suitable to consider them as approximately constant on only very high aggregation levels (world-regional, global). Despite the very rough nature of the budgets, Schafer believes them to offer an elegant framework for explaining aggregate travel behaviour characteristics, and notes that so far no large alterations in either travel budget have been observed.


Tam and Lam describe an aggregate zonal model for determining the maximum number of cars by zone in view of the capacity of the road network and the number of parking spaces available. Their model seeks to examine whether the existing road network is capable of accommodating future zonal car ownership growth. In their model, vehicle trip production and attraction are dependent on car ownership, available parking spaces and the accessibility measures of traffic zones.

The authors use a bi-level programming problem. The lower level problem is an equilibrium trip distribution/assignment problem, whereas the upper-level problem is
to maximise zonal car ownership by considering travellers route and destination choice behaviour while satisfying network capacity and parking space constraints.

A number of assumptions are made in the model developed. Parking is modelled as a fixed supply of public and private spaces by zone, and illegal parking is ignored. It is assumed that each car must occupy one parking space at its destination zone during the study period. Trip attraction is modelled as parking demand, and zonal trip production is assumed to be a function of the number of cars owned by the residents in the households in a zone, which reflects the number of households in the zone. The relationship between trip production and the number of cars is established by an elastic trip production rate. The accessibility measure for trip production is affected by the number of trips attracted and the generalised travel time between origin and destination.

Therefore while the authors have sought to account for the impacts of congestion and parking constraints on car ownership, they have modelled car ownership within a short-term aggregate network based framework. Car ownership is not modelled within a behavioural framework.

The authors proceed to present the formulae involved in their optimisation problem.

In conclusion, the authors propose their model can be used to determine the maximum number of cars by zone subject to network capacity and parking constraints. The output from the model in terms of number of cars by zone indicates to what extent zonal car ownership growth could be accommodated by the existing transportation facilities. At this stage, however, zonal car ownership growth projections would be best provided from an external model.


In this paper Whelan et. al. describe two approaches which have been used to estimate car ownership saturation levels explicitly, one disaggregate and one aggregate.

The paper begins by noting that a common theme of many car ownership models is the S-shape growth curve. The economic rationale behind the use of the S-curve is provided by product life cycle and diffusion theories, whereby the take-up rate for new products is initially slow, then increases as the product becomes more established, and finally diminishes as the market comes closer to saturation.

Examining trends in per capita and per household car ownership in the UK over the last 50 years, no S-shaped plot is apparent, suggesting overall saturation levels have yet to be reached. However, looking at variations in ownership across different household income groups, more clear S-shaped patterns are apparent, with higher income groups approaching saturation. If car ownership models were specified with an S-shaped functional form and a saturation level (either implicit or explicit), then forecasts of vehicle ownership will be curtailed as saturation is approached. This is a highly significant feature in mature markets such as Great Britain or the Netherlands.
Describing the background to the disaggregate model approach, the authors note the 1997 NRTF forecasts use information on household income, household type (number of persons and age structure), car-type and area type. Two separate models were estimated, a model predicting the probability that the household owns at least one car \( (P_{1+}) \), and a model predicting the conditional probability that the household owns two or more vehicles \( P_{2+|1+} \). The saturation level \( S \) formed an input to the model, determined by plotting cars per household against income within each household category, and examining levels of car ownership amongst the highest income households. The disaggregate approach developed by the authors aimed to explicitly estimate these saturation levels.

Describing the background to the disaggregate model approach, the development of long-term extrapolation techniques by Tanner and others is noted. The initial preference for logistical time-series extrapolation is noted. This approach avoided the need for forecasting the future levels of explanatory variables, and Tanner believed the rate of growth in ownership in the forecast time period was closely related to the rate of growth in proceeding periods. Tanner believed a saturation point exists for car ownership, and that a logistic curve was compatible with this theory of car ownership. To estimate the saturation point \( S \), Tanner fitted linear regressions from the US and the UK based on the relationship between the rate of growth in car ownership levels and the actual levels of car ownership. There was debate at the time as to whether the saturation point should be determined from time-series of cross-sectional data, with a general conclusion that time-series data was best.

To estimate saturation levels using disaggregate models, a partially constrained binary choice model was estimated, using the tree-logit structure. In this context the constrained group are the fraction \( 1 - S \) who are constrained not to own a car. Within the alternative ‘no-car’, a nest structure was set up to represent the constrained choice. Exploiting the binary choice situation, one of the attractiveness functions \( V_{\text{no car}} \) was set to zero, and so \( V_{\text{car}} \) contained all the utility terms.

The model results are not described in the paper, but the review of Whelan (2001) outlines some of the findings. The outcome was that plausible saturation levels could be estimated from the data, with different saturation levels estimated for different household type and region combinations.

To estimate aggregate saturation levels, the authors used Tanner’s power growth model. They calibrated the model to the proportions of \( P_{1+} \) and \( P_{2+|1+} \) households using data from Transport Statistics Great Britain for the 47 years between 1951 and 1997. Other official publications provided figures on GDP indices of car purchase cost and car running cost. The estimation procedure used was non-linear least squares to estimate a model which is non-linear in parameters. The estimation was undertaken using the SAS statistical package. The separate estimation of \( P_{1+} \) and \( P_{2+|1+} \) cases represents a development of previous approaches considering overall saturation levels only.

The aggregate models estimated also allowed for explicit estimation of saturation levels, for which significant estimates were obtained. The two models \( (P_{1+} \) and \( P_{2+|1+} \)) contained significant terms for trend effects, household income, purchase cost,
saturation level $S$ and the power optimal power term. Operating cost was not found to be significant. For owning at least one car, a value for $S$ of 0.85 was estimated with a confidence interval of ± 14%. For owning two plus cars, the saturation level is much lower at 0.49 ± 63%. Both figures were lower than were expected and were at odds with the disaggregate findings, and on this basis the authors concluded that there were problems with the aggregate approach.

In conclusion, the authors note that with a few exceptions car-ownership models incorporate the notion of saturation, and so direct estimation of saturation within the car-ownership model framework represents an advance on the use of externally derived saturation levels. This can be achieved through the use of a disaggregate model framework.

Comparing the results of the disaggregate and aggregate approaches, they believe the former to be more credible. The authors believe the problem with the aggregate approach is related to the use of time-series data, which has resulted in the estimation of time trend effects and both income and purchase price elasticities. To overcome these deficiencies the authors recommend the use of cross-sectional data, such as that used by Dargay and Gately (1999).


Birkeland and Jørgensen developed a car type choice model for car buyers’ choice of new cars, and then used this model to analyse which policy measures could be used to obtain a more efficient car fleet. The main focus therefore was on studying consumer behaviour in order to achieve a tool to analyse the possibilities of improving fuel efficiency for new passenger cars through changes in the tax structure. It is noted that energy efficiency changes are only modelled by modelling the purchase of new cars – changes in taxation structures impacting upon older vehicles and or vehicle scrappage are not considered.

The new car choice model was based upon three data sets. The first dataset describes the supply of new cars, and contained detailed information on approximately 1,500 different types of car available on the Danish market in 1997. The cars were described by a wide range in characteristics including price, performance, size and fuel consumption. The second data set described the demand for new cars, and described the 150,000 individuals and companies who purchased a new car in Denmark in 1997. Private and company car purchases were then modelled separately. For confidentiality reasons, the consultant never received the detailed database, instead they received data detailing the numbers of cars sold for each combination of car type and two background variables. The third dataset was a stated preference survey of 200 car buyers. This survey posed hypothetical questions such as changing fuel prices and the owner tax, and aimed to clarify buyers’ preferences for different types of taxes.

The private car choice model was estimated as a household choice decision using standard utility maximisation theory. To deal with the large choice set available (1,500 vehicles), 49 vehicles were randomly selected, so that including the chosen
vehicle each household had 50 alternatives available to them. Note that detailed make and mark combinations, such as Ford Escort 1.6 L, were considered in the model. Separate models were estimated for eight household types, described by the type of family (single/couple), the gender of the car owner, and the presence of children.

A total of 60 parameters were estimated in the private car choice model. The parameters represent car expenses for prices and fuel consumption, size of the car by cabin space, luggage space and exterior dimensions, engine capacity and acceleration. Variation in price sensitivity with household incomes was accounted for in the model specification.

The key estimation results are outlined in the paper. As expected, lower income households were more price sensitive than higher income households. Significant fuel cost parameters were estimated. A positive effect for petrol engine size was discovered, and regional variations in the utility of a large engine were also determined. No such effect could be determined for diesel engines, which tend to have a smaller range of engine sizes. Acceleration was also an important effect, and the model found it was most important to young buyers, and least important to old buyers.

The private car choice model has been used to forecast 1997 car sales in Denmark, and compared to actual sales figures. Overall, the model matches actual car sales well. A revised version of the model is being used at present to analyse the impact of tax changes on the energy efficiency of new cars, and to validate the model a series of tests have been made to assess its use in EU member states, comparing actual and forecast measures. The validation process considered three key outputs: CO$_2$ emission levels, new car registrations and estimates of parameter elasticities.

The model forecasts of CO$_2$ emission levels of new cars (CO$_2$/km) for Germany and Denmark revealed a good match to observed data, with private emissions lower than the overall observed mean, and company car emissions higher than the overall observed mean, for both countries. In Germany, company cars represent 41% of new car purchases, which is substantially higher than in Denmark. Consequently observed CO$_2$ emissions are closer to the predicted company car emissions in Germany.

The models forecasts of new petrol car registrations for Germany showed a good correlation with the observed data, with the small discrepancies attributed to country specific preferences that the model (calibrated to Danish data) cannot capture. The model forecasts was validated for number of registrations by CO$_2$ emissions, number by engine size and number by nine engine size classes.

The model was compared to parameter estimates from a similar model based on data from 11 European countries, and against observed data from these countries. These tests confirmed the overall accuracy of the model. There were some discrepancies which result from the application of a Danish model to different countries.

The conclusion of model runs made suggests controlling choice of car through taxation may lead to a reduction in average fuel consumption of the new car fleet, hence reducing CO$_2$ emissions. However, differentiations in registration tax alone cannot achieve the aims of substantial reductions in CO$_2$ emissions.

De Jong et al describe the results of work to improve the scrappage forecasting component of the UK Vehicle Market Model (VMM). This work recognises that the emission of pollutants and energy use is strongly affected by the age composition of the fleet, since catalytic converter technology and fuel efficiency have been developing rapidly. Consequently in order to forecast emissions and fuel consumption accurately, forecasting vehicle scrappage is important. Prior to this work, the VMM contained a scrappage model which was calibrated to observed data, but was not formulated within a behavioural framework. In particular, the effect of policy measures such as differential taxation levels by engine size could not be assessed. The work also aimed to determine the relative importance of the different reasons for scrappage.

The first phase of the work was a literature review of scrappage literature over the last 25 years. More detail on the papers reviewed can be found in the paper. The key paper in the area is identified as Parks (1977), who considers vehicle scrappage as an economic decision. Parks considered the decisions ‘keep’ and ‘scrap’, and suggested that each year individuals considered the repair costs associated with the vehicle. If the repair costs for the vehicle exceeded its market value minus its scrap value, then the individual would scrap the vehicle. To explain the logit of the scrapping rate, Parks used make-specific age dummies, make-vintage dummies which capture durability effects, make-specific used prices expressed relative to the price of repair, and make-specific scrapping prices relative to the price of repair. Parks was worried about a strong correlation between used car price and durability, so he used new car price index as an instrument for used car price.

Much of the subsequent scrappage literature built upon Parks’ economic treatment of scrappage. Research in the US into the use of scrappage bounties to encourage scrappage of older polluting vehicles has suggested that the policy can work in selected urban areas, where pollution problems tend to be most acute. However the policy is best viewed as a transitional strategy, as once the dirtiest vehicles are scrappage the gains are significantly reduced.

The literature review provided a framework for the design of the stated preference (SP) survey. The aim of the stated preference survey was to elicit preferences from owners who are about to scrap, or have recently scrapped, a vehicle. Both car and HGV owners were considered. Owners were defined as ‘in scope’ according to the following conditions:

- Owners of vehicles aged seven years or older: analysis of the Vehicle Information Database (VID) had suggested this is the age when vehicles may be scrapped due to final deterioration;
- Owners who had scrapped a vehicle in the last two years.

Respondents were recruited by telephone. No cash incentive was offered for questionnaire completion, but the potential environmental benefits of the research
were emphasised. The choice decisions presented to vehicle owners were either ‘keep vs scrap’ or ‘keep vs sell’ their existing car.

The SP model for car owners had the following findings:
- The older the existing vehicle, the more likely it is to be scrapped;
- The older the suggested replacement vehicle, the more likely it is that the existing one is kept;
- The greater the value of the new vehicle, the more likely it is that the existing one is kept;
- The greater the running costs of the existing vehicle, the more likely it is to be scrapped;
- The greater the running costs of the new vehicle, the more likely the existing one is kept;
- The lower the tax on the existing vehicle, or the higher the tax on the newer vehicle, the more likely the existing vehicle is kept;
- The higher the scrap value of the car and/or the associated scrappage bounty, the more likely it is to be scrapped;
- Larger engined cars are more durable and so less likely to be scrapped for a given age.

The model results suggested different disutilities associated with different types of cost. For example, road tax was perceived as having a higher disutility than weekly running costs.

The SP scrappage models have been combined with RP data of the UK Vehicle Information Database (VID) which provides observed revealed preference data (RP) on scrappage rates to form a forecasting model. This forecasting model has been developed using Visual Basic within an Excel spreadsheet package, and predicts scrappage rates by age of vehicle, engine size and fuel type, for each year up to 2031. The model uses the results of the SP survey to allow the assessment of the impact of the following policy measures: replacement price (new and second hand prices), scrappage schemes, tax incentives (road tax rates) and fuel prices. The model assumes vehicles up to seven years of age are only scrapped due to accident damage, which in turn is influenced by policy on speed restrictions.


As the Schafer paper, this paper is not about car ownership models, but we included it because it is related to the basic assumptions of FACTS.

In this paper, Mokhtarian et al question the assumption that travel is a derived demand, instead suggesting travel has an intrinsic positive utility. They suggest that demand for travel arises from a fundamental human need for mobility and other subjective characteristics, as well as from the external causes typically measured.

The paper begins by reviewing literature, both academic and popular, covering the concept of a positive utility of travel. The common themes of the work quoted are that travel has both positive and negative features, and that travel may be performed
as a desired activity in itself, and not just as a means of accessing activities. Rather than considering the dichotomy between undirected (e.g. leisure) and directed travel (e.g. mandatory and maintenance), the authors suggest all travel falls somewhere along a continuum, with totally undirected travel at one extreme (travel is primary, destination auxiliary) and totally directed travel at the other (e.g. a trip to the dentist).

The authors suggest three components in the utility for travel can be identified:
1. The utility of arriving at the destination;
2. The utility of activities that can be conducted while travelling;
3. The utility of travel itself.

The utility of activities of activities while travelling, e.g. working on a laptop or listening to music, contribute positive utility, and the authors suggest at a maximum make the utility for the whole trip positive. The theory that these activities may represent a way of minimising the negative utility conditional on the trip being made is not discussed by the authors.

Considering the travel time budget debate, a modified version of the travel time budget is suggested, which is that individuals have a desired travel time that is a function of their personality, lifestyle and attitudes (particularly attitudes towards travel itself and activities which can be conducted whilst travelling). Individuals whose utility of travel contains more of the second and third components are likely to have a larger travel time budget, all other things equal, are will be more resistant to policies intended to promote travel reduction.

To improve the understanding of the positive utility of travel, a 14 page questionnaire was designed and administered for 8,000 residents in San Francisco. A randomly selected adult in each household was asked to complete the survey. A total of 1,900 fully completed questionnaire were returned for analysis. Some sample bias towards persons with higher incomes and higher levels of education, and two-person households, was reported.

The questionnaire measured variables grouped into 11 categories: objective mobility, perceived mobility, relative desired mobility, travel liking, attitudes, personality, lifestyle, excess travel, mobility constraints, travel modifiers and demographics. Objective mobility questions recorded information about trip distance and frequency of travel, by mode and purpose. Trip frequency was recorded on a five point semantic scale. Total mileage per week was also recorded. It is emphasised that typical travel was recorded, as opposed to cross-sectional travel diary data. Perceived mobility was also measured on a five point semantic scale. The other variables were generally measured using five point semantic scales.

Examining descriptive statistics of some key indicators, nearly half of respondents disagreed that travel time is wasted time, and more than a third saw their commute trip as a useful transition and used that time productively. For ‘travel liking’, the results suggested a majority (55 %) of respondents were neutral about short-distance travel, and an even larger majority (63 %) were positive about long-distance travel (> 100 miles).
Considering ideal commute time, the authors report an average ideal one-way commute time of just over 16 minutes, suggesting this implies a non-zero optimum commute time. The reviewer suggests this may a context effect, reflecting people with higher commute times reporting a commute time they would consider short on the basis of their experience, but not necessarily implying they prefer 16 minutes to 10.

The paper concludes by suggesting that the same positive characteristics of travel which encourage people to engage in transport as a recreational activity are likely to motivate people to engage in apparently excess travel in the context of their mandatory and maintenance activities as well. The positive affinity for travel is believed to be universal to some extent, but distributed unevenly across the population dependent on personality, lifestyle, travel related attitudes, mobility constraints, demographic characteristics, and the mode and purpose of a given trip.

It is suggested that travel is not modelled as a disutility, but as a literal good having both positive and negative characteristics, and that some of the subjective factors giving rise to positive utility should be incorporated in modelling. To achieve this, the authors suggest the population should be segmented according to how they rate the three components of utility identified, and different travel models should be developed by segment on the premise that people who weight the different components of utility differently are likely to also weight typical explanatory variables differently.


In this paper Rich and Nielsen present the results of a long-term travel demand model for households with up to two active workers. This model is formulated within a microeconomic framework. Car ownership is explicitly treated within their model structure, but does not form the main focus of the paper.

The paper notes that there is not much literature on modelling the behaviour of two worker households, and in particular co-operation between workers in the household is often not considered in model structures. Co-operation between workers in the household was investigated in Rich and Nielsen’s research.

The model was specified as a nested logit model comprising two main components: a work model (W-model) modelling the choice of work location and car ownership, and a residential location model (R-model) modelling the zone and type (house/apartment) of residence. The work model was at the bottom of the structure, i.e. they assume that individuals choose their work location dependent on where they live. The paper does not discuss investigation of a different structure, for example workers choosing residence location dependent on work location.

The W-model considers A as the main worker (highest income), and B as the second worker. The W-model is itself is nested, with choice of work location for A at the top of the tree, followed by work location for B, and finally car ownership at the bottom of the structure. Hence car ownership is modelled as a decision made after both
residential and work location choice. The car ownership alternatives considered in the model are 0, 1, 2 cars. No explicit treatment of company cars is mentioned.

To model choice of work location, Rich and Nielsen defined an interesting measure of co-operation between the workers which they termed $\omega$:

$$\omega = \frac{[1 - \min(GTC_A, GTC_B) + GTC_{AB}]}{\max(GTC_A, GTC_B)}$$

where:  
- $GTC_A$ is the generalised cost of travel from home to A  
- $GTC_B$ is the generalised cost of travel from home to B  
- $GTC_{AB}$ is the generalised cost of travel from A to B

Thus $\omega$ measures the detour involved by the worker most distant from home picking up the worker closer to home on the way home from work. As $\omega \to 0$, the location bundle approaches optimal workplace choice, as no detour is required. Strictly speaking from a car-pooling perspective the term is most applicable to one car households of two workers, as here the need to pool if both workers travel by car is absolute. However, it remains a general measure of workplace choice process for other household types, for whom having workplaces located ‘cleverly’ remains advantageous.

The observed values of $\omega$ demonstrated households in more rural areas tended to locate more cleverly, as might be expected. However, it should be noted that if there is a single large centre of employment distant from a rural areas, we would expect a lower value of $\omega$ than for a household located in the middle of a centre of employment. The observed data also showed variation in $\omega$ with household type.

The best estimated models of work location were segmented by commute accessibility (four segments), and this segmentation proved significant, i.e. choice of work location varies according to commuting accessibility. The best models used a Box-Cox form for time and cost, as opposed to linear forms, and this finding was a key conclusion of the paper. The Box-Cox cost form was net travel costs (travel cost – allowance) divided by average net wage in the household. The inclusion of the $\omega$ term improved the models significantly. The model results also demonstrated workers from less accessible residence zones were more likely to locate cleverly. Higher values of time for the main worker were implied by the model results.

The R-model of residential choice uses housing supply, commute accessibility and consider surplus as variables. The consumer surplus varies between houses and apartments. A highly significant accessibility term from the W-model was estimated, which pleased the authors. They suggest this term reflects the successful description of work-location and car ownership lower down in the model.
4.23 Whelan, G (2001) Methodological Advances in Modelling and Forecasting Car Ownership in the UK

In this paper Whelan describes the result of recent work to update the car ownership forecasting methodology employed by the UK Department of Transport, Local Government and the Regions. The work forms part of a process of incremental improvement to the UK National Transport Model. Furthermore, the resulting model is intended to become the new standard for the UK (at least, after the new car purchase and vehicle scrappage components, described in other papers reviewed in this memorandum, will have their full effect).

The 1997 National Road Traffic Forecasts (NTRF) represented the previous major change in forecasting methodology. These models were calibrated on pool cross-sectional Family Expenditure Survey (FES) data from 1971 and 1997. The model used household income, household-type (eight types, defined by number and age structure of residents), and area type (five types: Greater London, Metropolitan Districts, and three other area types defined by population density) to define probabilities of household car ownership. Two binary models were calibrated for each household type – a $P_{1+}$ model to predict the probability of the household owning at least one car, and a $P_{2+|1+}$ model, defining the conditional probability of the household owning two or more cars, given that they own at least one car. The ownership models used a saturation level (S) of maximum car ownership, and a linear predictor (LP) which comprised a linear combination of explanatory variables. The model variables were licences-per-adult (LPA), household income and area type.

In 1999 the Department decided to improve the scope of the NTRF forecasts to include the economic, environmental and social impacts of traffic growth so that the forecasts could be used as a tool for policy analysis. Consequently Whelan undertook an audit of the 1997 NTRF models, and identified a number of possible improvements that could be made to the models:

- To account for the increase in multi-vehicle households;
- To assess the impact of company cars on ownership levels;
- To re-examine ownership saturation levels;
- To seek to explain why London has experienced minimal growth in ownership since 1991;
- To assess the impact of employment levels on car ownership;
- To introduce sensitivity to ownership and use costs within the model.

The new ownership model, provisionally named NTRF-2001, is similar to the 1997 NTRF but incorporates the improvements listed above. To account for the increasing numbers of multi-car households, an additional sub-model was introduced, modelling the conditional probability of a household owning three or more vehicles ($P_{3+|2+|1+}$). Unlike the 1997 NTRF, multiple car ownership by single person households was allowed. Multiple car ownership by a single household would not be expected to impact upon traffic forecasts, as only one person can drive the car. However to enable accurate forecasts of total vehicle stock, modelling such households is necessary.
To account for the impact of company car ownership on total household car ownership, company car dummies were introduced into the ownership models. In the $P_{2+|1+}$ model, a new term was estimated to account for the higher probability of owning at least two cars if the first vehicle is a company car. Similarly, in the $P_{3+|2+}$ model, a term was introduced if both of the first two vehicles are company cars. Thus total household car ownership is predicted as a function of company car ownership. This is consistent with the findings of HCG’s work in Sydney, described above.

Saturation levels have an important impact upon the results of ownership models. The 1997 NTRF models had allowed variation by household type, but not area type. In the 2001 NTRF, variation in saturation levels by both household type and area type was allowed. Saturation levels were estimated from Family Expenditure Survey (FES) data (see Whelan, Wardman and Daly, 2000). A general pattern of higher saturation levels in more sparsely populated areas was observed for each model type ($P_{1+}$, $P_{2+|1+}$, $P_{3+|2+}$). Furthermore, a distinct ‘London’ effect was found, whereby saturation levels in the Greater London area were lower than in other area types, including Metropolitan districts. This pattern is likely to reflect restrictions upon parking (particularly in Central London), high levels of congestion, and the high density of PT provision relative to other areas.

The Department has raised concerns of a correlation between employment and income in the base data for the 1997 NTRF. The improved model dealt with this issue by explicitly including an employment term within the household utility function.

When attempting to model sensitivity to ownership and use costs, it was found that there has been little variation in real costs over the period (1971-1996), and the variation that did exist was strongly correlated with time. To overcome this problem, car ownership and cost indices did enter the household utility function, but the coefficients were constrained to use cost elasticities determined from external sources. Ownership cost elasticities were determined from an aggregate power growth model, giving an elasticity value of $-0.34$ for 1991. A use cost elasticity of $-0.1$ was supplied directly from the Department.

The models are applied using a prototypical sample enumeration procedure, whereby an artificial sample is generated and the models applied to this sample. The sample combines the detailed information between model variables in the base year, together with aggregate characteristics of the forecast area. In this application, weights are defined for 24 different household categories, as opposed to each individual household. A problem found in application was poor predictive performance in zones with low or high average incomes. This problem was overcome by adjusting income levels in the base sample by a common factor so that they on average they match the true income levels in each zone.

4.24 Other models used in practice

The recently completed Swedish national model for passenger transport (SAMPERS) uses car ownership totals from an external model, which is aggregate, cohort-based.
The Italian national transport model contains a disaggregate model for the number of cars on the household, similar to the LMS car ownership model. The Danish national model system also uses a discrete choice model for household car ownership.

The Antonin-model for passenger transport in the Paris region, is quite similar to the LMS, also with regards to car ownership: it uses control totals on licence holding from a cohort-based approach and discrete choice models for the number of cars in the household. This model includes parking cost variables.

There are many older publications on static and (pseudo)-dynamic vehicle ownership models, most of which only deal with the demand side of the car market (number of cars per household and/or vehicle type choice), such as : Berkovec (1985), Chandrasekharan et al (1991), Gilbert (1992), Gunn et al. (1978/1979), Hensher et al. (1992), Hocherman et al. (1983), Mannering and Winston (1985), Manski and Sherman (1980), Manski (1983) Kitamura and Bunch (1990), Smith et al. (1989) and Train (1986). Especially the studies by Hensher et al., Manski and Sherman and Train have been very influential; all three include disaggregate vehicle type choice models with detailed vehicle types. The models of Hensher et al. and Train also include the number of vehicles in the household and car use.