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A comparison of car ownership models

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Abstract
In this paper, car ownership models that can be found in the literature (with a focus on the recent literature and on models developed for transport planning) are classified into a number of model types. The different model types are compared on a number of criteria: inclusion of demand and supply side of the car market, level of aggregation, dynamic or static model, long-run or short-run forecasts, theoretical background, inclusion of car use, data requirements, treatment of business cars, car type segmentation, inclusion of income, of fixed and/or variable car cost, of car quality aspects, of licence holding, of socio-demographic variables and of attitudinal variables, and treatment of scrappage.

1. Introduction

Different car ownership models are being used for a wide variety of purposes. Car manufacturers apply models on the consumer valuation of attributes of cars that are not yet on the market. Oil companies want to predict the future demand for their products and might benefit from car ownership models. International organisations, such as the World Bank, use aggreggate models for car ownership by country to assist investment decision-making. National goverments (notably the Ministries of Finance) make use of car ownership models for forecasting tax revenues and the regulatory impact of changes in the level of taxation. National, regional and local governments (particularly traffic and environment departments) use car ownership models to forecast transport demand, energy consumption and emission levels, as well as the likely impact on this of policy measures.

In this paper, we shall restrict our attention to car ownership models developed for the public sector. Some of these models could be interesting for car manufacturers or oil companies as well. However, the requirements for models (e.g. in terms of exogenous versus endogenous variables) developed for private firms are different, and such models

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[1] This paper is based on a research project that RAND Europe carried out for the Transport Research Centre of the Dutch Ministry of Transport, Public Works and Water Management. The aim of this project was to provide directions for the development of improved car ownership model in The Netherlands. The project not only reviewed the international literature, but also reviewed nine Dutch car ownership models in detail. Furthermore, government officials and other experts were interviewed about the requirements for car ownership models (see RAND Europe, 2002). The authors wish to thank two anonymous referees for their valuable comments.

are often not published in the publicly available literature. Models for national investment planning will be mentioned and discussed, but the focus will be on models that can be used for the transport planning purposes of public agencies. An evaluation of the model types found in the literature and ideas for future development will be provided, from this perspective.

Car ownership is not one of the four steps of the classical passenger transport model. Nevertheless, an external car ownership model or an internal car ownership submodel is used in many transport model systems, as an input to mode choice, and sometimes also to generation and distribution. The outcomes of this often show that car ownership is a major determinant of the number of kilometres travelled by mode, and that car ownership forecasting therefore is of crucial importance. Apart from transport modelling, forecasts of future car ownership and –use are of increasing policy relevance. Present policy questions require more detail in the output of car ownership models. This concerns the segmentation of the predicted car fleet, segmentation of the population in the model, and the need to have both short term and long term insight in the impact of policy measures. Also, car ownership and vehicle type choice models, coupled with equations for car use (uni-modal approach) and energy use and emissions, are sometimes used as stand-alone models to forecast the kilometrage, fuel consumption and emission of pollutants of the car fleet of some country or region.

The reviews of car ownership models in existing textbooks on car ownership or transport modelling in general are not very recent (e.g. Bates et al., 1981, Allanson, 1982, Button et al, 1982), brief (e.g. Ortuzar and Willumsen, 1994) or focus on a limited number of model types (e.g. Bunch, 2000), whereas many different model types can be found in the literature.

This paper provides a review covering a broad range of car ownership models for public sector planning, with some focus on models developed recently (defined here as: since 1995) or that are still in use. The models found in the literature have been classified into nine types of car ownership models. In section 2 of this paper, these nine types are discussed and worked-out examples are given for each model type. A comparison on the basis of sixteen criteria is given in section 3. Finally, section 4 presents the summary and conclusions.

2. Discussion by model type

2.1 Aggregate time series models

These models usually contain a sigmoid-shape function for the development of car ownership over time (as a function of income or gross domestic product, GDP) that increases slowly in the beginning (at low GDP per capita), then rises steeply, and ends up approaching a saturation level. Examples are the work done during a long period spanning the late fifties to the early eighties in the UK by Tanner (e.g. Tanner, 1983) and in the early nineties by Button et al. (Button et al., 1993), mainly using the logistic function. More recent applications are Ingram and Liu (1998), the aggregate model in the

National Road Traffic Forecasts (NRTF) in the UK (Whelan et al., 2000, Whelan, 2001) and Dargay and Gately (1999). Ingram and Liu (1997) use a double logarithmic specification to explain car and vehicle ownership in many countries and cities across the world. The NRTF aggregate model builds on the earlier UK work in applying a logistic curve for saturation, and extends this by including the saturation levels (by household type) to the overall disaggregate tree logit calibration. Dargay and Gately used the more flexible Gompertz function to predict the motorisation rate (the number of cars per 1,000 persons) on the basis of GDP per capita for a large number of countries, including developed and developing countries. This function gives the long-run equilibrium prediction. For the time path towards this new equilibrium they use a partial adjustment mechanism. Besides GDP per capita, the aggregate time series may include fuel price levels, population density, road network density , rail network density and time trends as explanatory variables.

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. Ingram and Liu (1999) observe that the estimated saturation levels tend to increase over time and question the validity of this concept.

These models are attractive for application to developing countries, because they have the lowest data requirements (motorisation and GDP per capita for some country over time, or for several countries), while income is generally considered to be the main driving force behind car ownership growth. Gakenheimer (1999) makes two remarks on this. First, for low-income developing countries, the income of the top 20% of the population might be a better explanatory variable than overall income. Secondly, in a thesis project at the Massachusetts Institute of Technology, Talukdar recently found that a quadratic function outperformed the sigmoidal curve.

Romilly et al (1998) differ from the above saturation curve approach, by estimating a time series model (using the co-integration method) without assuming saturation levels.

2.2 Aggregate cohort models

Examples are the models of Van den Broecke (1987) for the Netherlands and cohort-based car ownership models in France (Madre and Pirotte, 1991) and Sweden. These models segment the current population into groups with the same birth year (often five-year cohorts), and then shift these cohorts into the future, describing how the cohorts as they become older, acquire, keep and lose cars. One of the major reasons for expecting a further substantial increase in car ownership in most Western European countries lies in the demographics: the 'cohort effect'. The older generations of today were born before the second world war, grew up when a car-owning lifestyle had not yet become firmly established, and now still have a relatively low motorisation rate. The older generation of tomorrow grew up during the 'Car Era', it has more cars now and can be expected to keep owning cars as long as possible. This demographic force behind car ownership growth can be expected to remain important in Western Europe for another couple of decades.

The Van den Broecke car ownership model (1987) can be characterised as a combination of a cohort survival model and an econometric model. The econometric component is used for producing the impact of changes in income on car ownership. This model starts by relating car ownership to the number of owners of a driving licence in a population cohort. The saturation level of licence holding and the income growth per cohort are determining factors for the future growth of car ownership. Predictions of future licence holding (these come from cohort models for licence holding also developed by Van den Broecke) and the income elasticities used in the model are therefore crucial factors in the model for forecasting car ownership. Both in predicting licence holding and car ownership, Van den Broecke assumes that the preferences of persons with regards to owning licences and cars remain unchanged. Only the numbers in the cohorts and the incomes that can be spent will change in the model. The model gives total car ownership per cohort, without distinguishing between private and business cars. It also does not produce the distinction between first and second cars in the household (it is a model at the person not the household level) or car types by vintage, engine size or weight. Car costs or other policy levers are not included. The model is most suited for predicting the impact on car ownership of changes in the size and composition of the population.

2.3 Aggregate car market models

Early examples of such a model are Mogridge (1983) and the Cramer car ownership model (Cramer and Vos, 1985). Mogridge distinguishes between demand for cars and supply of cars in the car market, which sets the car market models apart from the aggregate time series models. In the Cramer model, which is based on time-series data, car ownership depends on car prices, income, the variation of income and the development over time in the utility of using a car. The second hand car price is endogenous. Manski (1983) developed an aggregate car demand and supply model in which the prices on the used car market are determined endogenously. This model was estimated on car registration and price data in Israel. In most car market models, supply of new cars is not modelled explicitly, the assumption is that this supply is perfectly elastic and follows demand. An exception is Berry et al (1995), which is a model of the market for new cars only, with consumer demand, oligopolistic manufacturers and endogenous prices.

The main structure of the recent TREMOVE model (KU Leuven and Standard & Poor’s DRI, 1999) and of the equally recent ALTRANS model (Kveiborg, 1999) is also that of an aggregate model (with the possibility of some disaggregate submodels).

TREMOVE is a model designed to analyse cost and emission effects of a wide range of technical and non-technical measures in the European Union to reduce emission from road transport. The model was developed to support the policy assessment process within the framework of the European Commission’s second 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. TREMOVE is a simulation model, not a forecasting model; it is specifically designed to analyse changes in behaviour as a result of changes in economic conditions.

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. The model describes transport flows, vehicle stocks and vehicle usage across three modelling domains per country: a target city, other urban areas, and non-urban areas.

The module for the vehicle stock (see Figure 1) calculates the size and structure of the vehicle fleet. 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.
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)

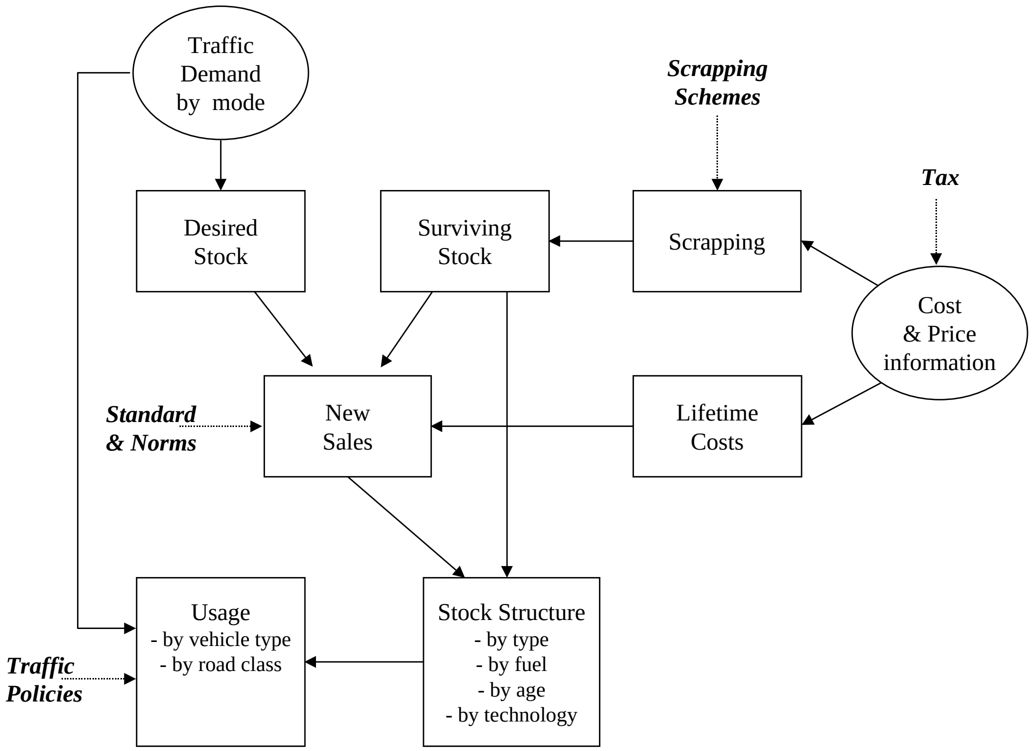
$\text{Stock i}\,(t) = \text{Stock}_i\,(t\text{-}1) - \text{Scrap}_i\,(t) + \text{Sale}_i\,(t)$

i= vehicle type

The module takes into account traffic demand by mode that leads to the desired stock. New sales are 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-dependent 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 1. Flow chart of vehicle stock and usage module in TREMOVE



Kveiborg (1999) describes the submodel developed to give 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 public transport 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, as in TREMOVE. Different exogenous variables (prices, income, etc) have been used to model new car purchase (acquisition) and scrappage. The historical stock of cars in different categories is used to determine the existing fleet. The scrappage model is calibrated to historical scrappage rates, from the vehicle registration data, 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 software package TRESIS (Hensher and Ton, 2002) has been developed for integrated stategic planning of transport, land use and the environment. It includes disaggregate models for household fleet size, vehicle type choice and car use. The aggregate car demand of the households by vintage in each year is then compared to aggregate supply (taking account of endogenous scrappage) and the used vehicle prices (new vehicle prices are exogenous) are used to reach equilibrium. TRESIS was developed for the six capital cities in Australia (Sydney, Melbourne, Brisbane, Adelaide, Perth and Canberra).

2.4. Heuristic simulation methods

The FACTS model (NEI, 1989; AGV, 1999) belongs to this category, but another example would be the UMOT model of Zahavi (1979). Both of these models use as starting point the assumption of stability of household money budget for transport (as a fraction of the household's net income) over time. Zahavi also uses the assumption of stable time budgets for transport. A discussion of international evidence on these assumptions can be found in Schafer (2000).

The FACTS model is used in The Netherlands for forecasting energy use and emissions and to give the total number of cars for a future year, to be used as control total in the LMS. It (and its predecessor the GEBAK-model, NEI, 1987) distinguishes 18 categories of passenger cars (three fuel types times three weight classes times two age of car classes). First for each household, annual income and annual car kilometrage are drawn at random from household-type-specific distributions. Business car ownership (this contains both cars of self-employed persons who registered the car in the name of their firm and cars provided by employers to their employees, either owned by the company or leased) is dependent on sectoral employment. These business cars are allocated to the households. For each household, the budget share of the income drawn is calculated for each category of passenger cars (using the car-category-specific cost and the kilometrage drawn) and for pairs of cars, also taking into account that the household may already have a business car at its disposal. The household then chooses the car category or categories of which the costs are closest to the budget. Households with low incomes may not be able to afford any car and will not own one. This mechanism is based on the hypothesis that households will be striving for maintaining their (car) mobility: they are unwilling to give up kilometrage. Why households would choose for the most expensive car category they can afford at the given annual kilometrage is not explained. Within some range this is cost maximising behaviour, which is at odds with economic theory. Nevertheless, FACTS has been used successfully for many policy simulations in the Netherlands. A drawback of the mechanisms used is that car type choice can only be influenced by the fixed and variable car cost per car category (including a variable called 'psychological' car cost, which mainly has to do with preferences against diesel cars). FACTS also has a function for the supply side of the market, distinguishing between 'old' cars (more than five years old) and 'new' cars (five years old or less), and a demand-supply equilibrium mechanism for the 'old' cars.

2.5 *Static disaggregate car ownership models*

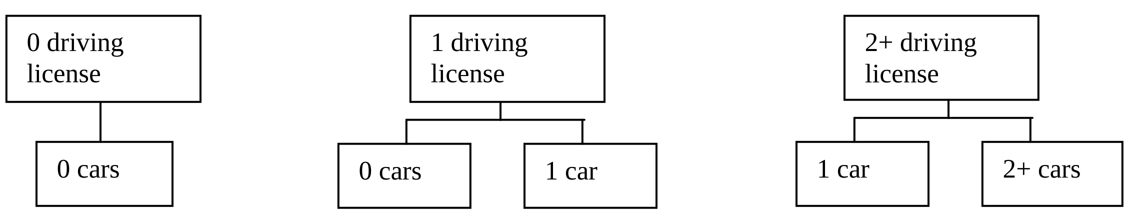
This category contains discrete choice models that deal with the number of cars owned by a household. There are many older publications on static and (pseudo)-dynamic vehicle ownership models, most of which only deal with the demand side of the car market, such as Gunn et al. (1978/1979).

An early example of an operational model in this category is the car ownership submodel within the Dutch national model system (LMS) for transport (Hague Consulting Group, 1989), but there were many models developed in the late eighties and in the nineties that use a similar approach (Italian, Swedish and Danish national model systems, the Antonin-model for the Paris region and the model for the Stockholm region). Recent applications are Bhat and Pulugurta (1998), the car ownership model for Sydney (Hague Consulting Group, 2000), the disaggregate model within the NRTF (Whelan, 2001) and Rich and Nielsen (2001). The LMS car ownership model and the most recent models are discussed below.

Within the LMS there is a car ownership model, which operates at the household level. This model is still in use. The LMS car ownership model reproduces the car ownership model developed in an earlier project, the 'Zuidvleugel Study' (Daly and van Zwam, 1981). The car ownership choices of the household are conditioned on household licence holding (which is also explained in the LMS by using disaggregate models; also see Figure 2):

- A household without licences will have zero cars;
- A household with one licence can choose between two options: zero cars or one car;
- A household with two or more licences can choose between two options: one car or two more cars.

Figure 2. Structure of LMS: Household car ownership conditional on the number of driving licences in the household



These choices are modelled as binary logit models, estimated on disaggregate data from the Dutch National Mobility Survey (LVO). These models are based on random utility theory and can be interpreted within this behavioural framework.

An important explanatory variable in both the 0 or 1 cars choice-model and the 1 or 2+ cars choice-model is the monthly income that a household can freely spend; the monthly expenditures on food, clothing and housing have already been subtracted. If the household would chose to own a car it incurs fixed car cost; if there would be two cars, the household would have to pay fixed car cost for two cars.

So if the monthly incomes in the Netherlands rise, the probability of car ownership will rise as well. If the fixed car costs rise the car ownership probability will decrease. Other explanatory variables are age, gender, household size, number of workers in the household and region-specific variables.

The total number of cars in a future year in the Netherlands in the LMS is usually imported from an external model (initially the van den Broecke model, later FACTS). This has been done to be able to compare different policy variants (e.g. changes to the networks) on the same basis. The role of the disaggregate model then is to subdivide the national total supplied by an external model over zones and households. Household car ownership, in combination with personal and household licence holding, then influences tour frequencies and mode/destination in the model system.

Bhat and Pulugurta (1998) 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: $(K - 1) * M$ 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. 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. 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 Bhat and Pulugurta 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. All other models reviewed in this section use unordered mechanisms.

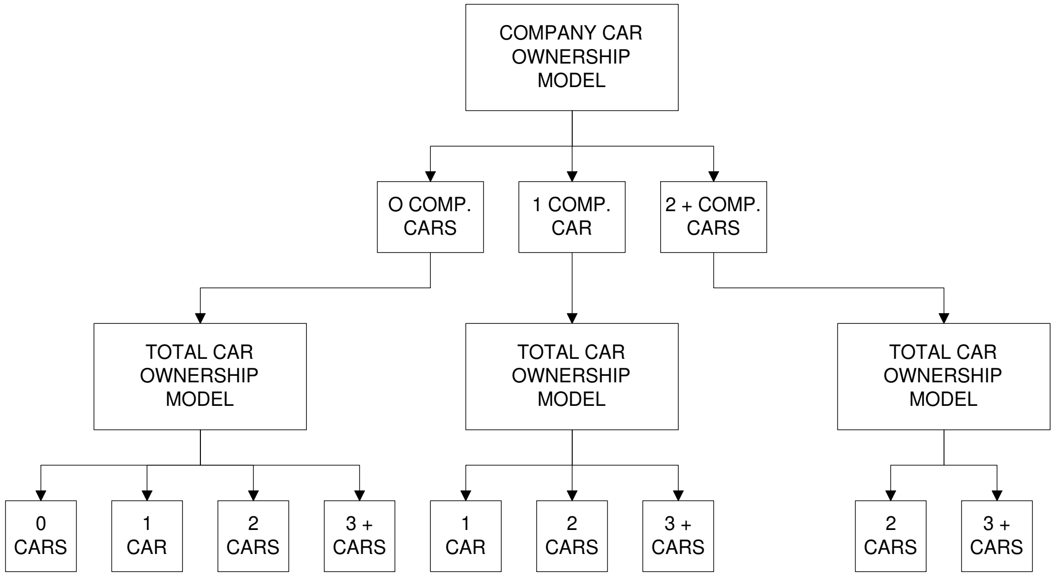
In the Sydney Strategic Transport Model (STM, Hague Consulting Group, 2000), disaggregate models of company and total car ownership at the household level were estimated. The disaggregate models were estimated from two data-sources, one collected during 1991/92, and one collected during 1997/98.

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 3.

Figure 3. Sydney Strategic Transport Model Car Ownership Structure



Both the company and total cars 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 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 1999 the UK Department of Transport 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, identified a number of possible improvements, and a new ownership model with the improvements, provisionally named NTRF-2001 (see Whelan, 2001) was developed.

The 1997 NRTF included two binary models 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

that they own at least one car. The ownership models used a saturation level of maximum car ownership, and a linear predictor which comprised a linear combination of explanatory variables. The model variables were licences-per-adult, household income and area type. To account for the increasing numbers of multi-car households, an additional sub-model was introduced in NRTF-2001, 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. As in the FACTS model, company cars contain both cars of self-employed persons and cars provided to employees by their employers. 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 Hague Consulting Group's work in Sydney, described above.

Saturation levels by both household type and area type was allowed in NRTF-2001. 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.

Rich and Nielsen (2001) 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 their paper. 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 W-model considers A as the main worker (highest income), and B as the second worker. The W-model is itself 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 conditional on both residential and work location choice. The car ownership alternatives considered in the model are 0, 1, 2 cars per household. No explicit treatment of company cars is mentioned.

Several of these models (e.g. Zuidvleugel, Stockholm, Sydney, Rich and Nielsen's model for Denmark) link car ownership via a logsum variable to a range of other travel choices, allowing impacts on car ownership of variable car costs, public transport cost and quality etc. to be represented.

2.6. Indirect utility car ownership and use models (joint discrete-continuous models)

Parts of the models of Train (1986) for California and Hensher et al. (1992) for Sydney and the models of De Jong (1989a,b and 1991) for The Netherlands belong to this category, as does the extension of the latter model as part of the original Norwegian national model. These models explain household car ownership and car use in an integrated micro-economic framework

De Jong developed two different disaggregate models (De Jong, 1989a) each of which simultaneously explains:

- Whether a household will own a private car or not
- Conditional on car ownership: the number of kilometres driven per year (private car use).

The basic idea for both models is that decisions of households on car ownership and car use are strongly interrelated and should be studied together. Both models are joint discrete-continuous models (variants of the tobit model), and were estimated on data from the Dutch Budget Survey.

The first model can be used for demand predictions in a situation without major policy changes. It is not directly based on economic theory and was called the 'statistical model'. It assumes that a household has a structural desired annual kilometrage, which depends on attributes of the household. Only if this desired kilometrage exceeds a threshold, the household will own a car. The observed kilometrage can deviate from the desired kilometrage through a random disturbance term. Explanatory variables for car ownership and use in this model are household income, household size, age, gender and occupation of the head of the household.

The statistical model has not attracted much attention, unlike the second model, the 'indirect utility model', which can also be found in De Jong (1989b, 1991). This is also the model that Train (1986) and Hensher et al. (1992) used. This model is based on micro-economic theory, especially on the relationship this theory postulates between indirect utility functions for different car ownership states and demand functions for car use through Roy's Identity. As a result, the relationship between car ownership and car use is included in the model in a way that is consistent with economic theory. The basic idea is that households compare combinations of car ownership and car use with each other and choose the combination that gives then the highest utility. The model also contains fixed car cost and variable car cost as explanatory variables (besides the variables that are in the statistical model). The fixed car cost influence both car ownership and use, and so does variable car cost, and the model has been used for simulating these changes and variabilisation of car cost in the Netherlands.

In the course of developing a national model for Norway, the indirect utility model was extended to include the option of two cars per household (see HCG and TØI, 1990; De Jong, 1997). The model estimation took place on data from the Norwegian National Travel Survey. For both the models for one and for two cars in the household, significant terms were found 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.

The model has also been estimated on data for Israel. Attempts at estimating the indirect utility model for the UK, for use in the NRTF forecasts, have not produced stable results.

Train (1986) and Hensher et al. (1992) developed similar 'indirect utility' equations for car ownership and annual kilometrage, but embedded these models in a larger framework which also contains the choice of car type (discussed below), conditional on car ownership. The model system of Hensher et al. (1992) was developed on the basis of panel data for Sydney and contains both static and dynamic vehicle choice and use models.

2.7 Static disaggregate car type choice models

Unlike the former two disaggregate categories, this category contains discrete choice models that deal the choice of car type of the household, given car ownership. There are many older publications on static and (pseudo)-dynamic vehicle type choice models, such as: Berkovec (1985), Chandrasekharan et al (1991), Hensher et al. (1992), Mannering and Winston (1985), Manski and Sherman (1980) 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 (these submodels were discussed in section 2.6).

Whereas the disaggregate models for the number of cars per household have usually been developed to provide inputs for multimodal transport model systems, the disaggregate car type choice models usually form a part of stand-alone models to forecast the size and composition of the car fleet (and possibly also car use and emissions). TRESIS however, discussed in section 2.3, contains a multimodal transport model, household fleet size, vehicle types, car use and emissions.

Among the recently developed car ownership models, Page et al. (2000) for new vehicle purchasing, Brownstone et al. (2000), Hensher and Greene (2000) and Birkeland and Jordal-Jørgensen (2001) fall into this category, Page et al. (2000) 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 VMM also contains a model for vehicle scrappage (de Jong et al., 2001).

Both revealed preference (RP) and stated preference (SP) data were used. 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 SP interview data collected information from households who were either planning to acquire a new car, or had just acquired a new car. The household SP experiments presented many vehicle attributes to respondents, including: purchase prices, running costs, resale value, engine size, vehicle emissions, safety measures, fuel type (petrol, diesel or hybrid petrol-LPG) and fuel economy.

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. It 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 Fiat Punto 60, are not distinguished.

Brownstone et al. (2000) compare multinomial logit (MNL) and mixed logit models for data on Californian households' revealed and stated preferences for automobile type choice. 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 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. A key issue with the RP data 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.

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.

In the 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 was *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 marker 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.

Hensher and Greene (2000) 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 aimed at determining respondents' preferences with regard to conventional vehicles, as well as alternative fuel or electric vehicles.

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, fuel cost to travel 500km (variable described as approximate cost of filling a tank so respondents understood levels), fully fuelled range, acceleration 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.

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 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.

Birkeland and Jørgensen (2001) 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. The third dataset was an SP 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 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 has been used in subsequent analysis 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 seven 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 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, differentiation in registration tax alone cannot achieve the aims of substantial reductions in CO_2 emissions.

2.8 (Pseudo)-panel methods

In Kitamura (1987) a model was developed for the simultaneous determination of car ownership (0, 1, 2 or more) and the total (all modes together) number of trips in a week. The discrete choice is estimated using normal probabilities and the estimation of the continuous choice is done using Heckman's method. The data set consisted of the first waves from the Dutch National Mobility Panel (LVO). In total, ten waves were collected between March 1984 and March 1989. Kitamura’s model contains lagged effects. All equations are linear.

In the paper by Golob and van Wissen (1989) an ordered-response probit model for car ownership in the household (0, 1, 2+) is combined with a standard tobit model for the continuous variables, which are the distances travelled per week by four modes. The overall framework is that of structural equations, with direct synchronous, indirect synchronous and lagged effects. The structural equations system is estimated with the LISCOMP procedure on panel data (the above-mentioned LVO). The model in Golob (1989) is similar to the above model in formulation and estimation, but it explains car ownership and travel time per week for three modes.

Kitamura and Bunch (1990) used four waves of the same LVO panel data set to develop an ordered-response probit model for the number of cars in the household (0, 1, or 2+). They included lagged variables to account for state dependence and individual-specific error components to account for unobserved heterogeneity across households.

The Ph.D. thesis of Meurs (1991) also contains car ownership models estimated on the panel data of the LVO. These models explicitly take account of the panel nature of the data. The car ownership models in the thesis include linear simultaneous equations models of car ownership and use, discrete choice car ownership models, estimated through mass point estimation, and joint car ownership and mobility models (also in Meurs, 1993). These models focus on the effect of income on car ownership; car cost variables are not included.

Hensher et al. (1992) used a dynamic analogue of Roy's identity to obtain a theoretically consistent system of total (intertemporal) indirect utility, the instantaneous (atemporal) indirect utility and instantaneous demand. For all these functions, empirical specifications were derived and estimated on household panel data for Sydney.

Recent panel models are Hanly and Dargay (2000) and Golounov et al. (2001). Recent pseudo-panel models can be found in Dargay and Vythoulkas (19991,b). These are discussed below.

In this paper, Nobile et al. (1996) estimated 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. 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. 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. 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. These were 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 did 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.

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). 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, such as the birth year 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

In Dargay and Vythoulkas (1999a) the pseudo-panel data set of five-year cohorts 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 Dargay and Vythoulkas (1999a) 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 were estimated to compare with the fixed effect model: OLS, random effect specification and random effect with a first order auto-regressive 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 were estimated and the lagged dependent variable was 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 three times as large as the short term elasticities, which indicates a considerable dynamics in car ownership.

In Dargay and Vythoulkas (1999b), the above analysis was extended by defining the pseudo-panel observations not only as five-year cohorts, but also in terms of area type (e.g. rural, urban).

In Hanly and Dargay (2000) 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. This is not a pseudo-panel, but a real panel 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 were 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 was 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 were 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.

In a paper presented at the 2002 Transportation Research Board annual meeting, Golounov, Dellaert and Timmermans (2002) first develop a theoretical model for the purchases and consumption of cars, other durable goods and other day-to-day and long-term purchases. This is an explicit dynamic model, based on the concept of (remaining) lifetime utility from economic theory. They -correctly- state that most existing dynamic car ownership models (duration models, panel models, cohort models) do not have a strong theoretical underpinning (an exception is the work of Hensher et al. (1992), which has a innovative theoretical section that however has not been followed since in econometric applications). Another theoretical foundation for a dynamic ownership and replacement model can be found in Rust (1987), who combined utility theory from micro-economics with optimal stopping process decision-making rules from dynamic programming. His application concerns the replacement of bus engines in a single firm over time.

Golounov et al. then present a model for an individual (not a household as in most disaggregate car ownership models), who is assumed to optimise the sum of discounted utilities for every period over the remaining lifetime. The utility in a period depends on the consumption in that period of four goods:

- Cars (internal to the model);
- Other optional durables (internal to the model);
- Long-term fixed purchases (external to the model);
- Fixed day-to-day purchases (external to the model).

Consumption in a period for the first three goods is defined as depreciation of the commodity. So car consumption (say in a year) is the decline in the value of the car (in the year). This definition of car consumption differs from that of De Jong (1989), where car consumption is defined in terms of car use (e.g. the annual number of kilometres). The model of Golounov et al. does not have a link to car use (except in the interpretation of some of the coefficients found), but it has the advantage of being dynamic.

Besides the direct utility function to be maximised, the theoretical model also contains a number of restrictions, including a budget restriction with income, savings/loans, and purchases of the four types of goods. Consumption of durable goods (including cars) and expenditure on purchasing these goods can take place in different periods.

On the basis of the economic model, an econometric model for the purchases and consumption of cars and other optional durables was specified, which was estimated on seven waves (1993-1999) of data from a revealed preference consumer panel. This panel (CentER savings Survey) focusses on financial assets and liabilities of the persons. Additional assumptions had to be used to make this dataset suitable for estimation of the model. Also depreciation functions were adopted from the Dutch Automobile Association (ANWB/BOVAG). In estimation, parameters for the discounting function, the utility from cars and from other optional durables are estimated, as well as variance-covariance parameters. The model only contains 8 significant coefficients (besides the constants). Although the model used different brand-model-vintage combinations, it does not yield vehicle type choice probabilities. The major contribution is that car purchase behaviour over time has been formulated is an explicit dynamic theoretical model, and that this has been translated into an estimable econometric model, The authors have plans to collect new stated preference data and use this to develop and test the model further.

2.9 Dynamic car transactions models with vehicle type conditional on transaction

Early examples of vehicle transactions models are Hocherman et al. (1983), Smith et al (1989) and Gilbert (1992). Hocherman et al. used a nested logit model for vehicle transactions and the conditional vehicle type choice. The transaction options for a zero-car household are purchase a car or do nothing. For a one-car household the transaction options are replacement and do nothing. For the purchase and replace options, there are type choice models. Smith et al. only studied replacement behaviour of one-car households. They used a beta-logistic model, to account for unobserved heterogeneity, and estimated their model on panel data for Sydney (this discrete choice model could also be classified as a panel model). Gilbert (1992) already used duration models to explain car ownership duration. More recent examples of this category are Bunch et al. (1996) and the Dutch DVTM (dynamic vehicle transactions model). In these models, duration models determine whether a household will engage in a vehicle transaction. If a transaction involves purchasing a car, the conditional vehicle type choice model is used.

The model of Bunch et al. for California, contains transaction models for adding a car, disposing a car and replacing a car, both for single-vehicle households and multi-vehicle households. The overall dynamic simulation system also includes the type choice models described by Brownstone et al (2000), that were summarised in section 2.7, and car use equations.

The DVTM is a model, developed and tested by Hague Consulting Group in the period 1993-1995 for AVV (HCG, 1993, 1995a,b, De Jong 1996). The data used in estimation originate from a project for Novem to measure the effectiveness of a government campaign to increase energy efficiency of passenger cars ('Koop zuinig/Rij zuinig'). The main objective of the modelling exercise was to extend the disaggregate modelling approach for the size and composition of the car market into the domain of dynamic models. Static disaggregate car ownership models ('holding models') can only give a time path for the car fleet if one is prepared to assume that in each period a household compares all vehicles (or vehicle combinations for multiple car ownership) and chooses the alternative with the highest utility. This static equilibrium assumption for every period considered will lead to an unrealistically high number of transactions, unless this is made unattractive by introducing dummies for not changing the household fleet. A more detailed critique on static holdings models can be found in De Jong and Kitamura (1992). In the Dynamic Vehicle Transactions Model (DVTM) each household will keep its vehicle holdings the same unless it explicitly decides to engage in a transaction.

The DVTM consists of the following submodels

- Hazard-based duration models for the time that will elapse between two household vehicle transactions. Duration models explain how long the duration in some state – originally a person's life or an unemployment spell- will last. They use continuous time and are intrinsically stochastic models. The hazard function gives the probability of exit from a state immediately after time t, given that the state is still occupied at t. Several functional forms for the hazard function can be found in the literature, e.g. exponential, Weibull, lognormal. In the DVTM, duration models are applied to car ownership. Initially there was only a model for the duration of ownership of a single vehicle until its replacement. The preferred specification was the Weibull, which allows for a hazard that increases or decreases over time, with attributes of the person and household, attributes of the presents car and attributes that vary over time (e.g. fuel price index and a variable for quality of supply). Later on this model was extended to transactions such as adding to the household car fleet (e.g. from one to two cars) and disposal without replacement, in a competing risks model (see De Jong and Pommer, 1996). In a competing risks model there are several 'latent' hazard functions for different ways of exit from the state (e.g. replacing the present car or adding another car). The latent hazard that will end the state first will prevail, and the other hazards will remain latent. The advantage of a competing risks duration model over the standard duration model is that it gives multiple exit states.

- Vehicle type choice models, for households replacing or extending their fleet. Vehicle types are distinguished by brand and model (for instance Volkswagen Golf 1.6 diesel and Toyota Starlet 1.3) and by vintage. For each brand/model/vintage combination, the engine size, weight, average fuel efficiency, fuel type, type of catalytic converter (if any) and fixed and variable cost are known, which are used in this multinomial logit type choice model. The outputs can be aggregated over these categories. The most expensive car types were not included in the sample; company cars were not included either.
- A model for annual car use (similar to the indirect utility model)
- A model for style of driving determining a possible deviation from the average fuel efficiency.

The DVTM has been used to simulate the impact of changes in fixed and variable car cost and income on the size and composition of the Dutch car fleet for the short and medium run (1-5 years ahead). For application to the long run a car (type) supply component would have to be added. The outcomes of these simulation runs generally speaking were quite plausible.

In a dynamic vehicle transaction model, such as the DVTM or the model for California of Bunch et al., the number of cars per household is predicted on the basis of current car ownership of the household. The duration model predicts the time (e.g. in months) until the next vehicle transaction and the type of transaction (e.g. replacement, disposal, adding a car). In application, this model is used in discrete time steps, for instance a year. For every household that does not transact in this year, the vehicle ownership situation of year t+1 will be equal to what it was in year t. For other households there will be a transaction and, if this involves replacing a car or adding a car, the conditional type choice model will be used to get new type choice probabilities. In this way the duration model can be used step by step, each time predicting transactions on the basis of the car ownership situation of the previous year. Vehicle scrappage transactions could also be integrated in such a model: with the passage of time, vehicles age and scrappage (other than accident-related scrappage) becomes more likely.

Because duration models predict changes in continuous time, they can give all intermediate time steps. If one uses Markov models for car ownership changes, then the time steps need to be determined by the researcher (e.g. years, five-year periods). As soon as the time interval has been chosen, the Markov model cannot predict for shorter time intervals.

Both for a duration model and a panel model of vehicle transactions, short run predictions (up to five years ahead) might be done without updating the population in the sample used. For medium and long run forecasts, the population needs to be updated. The most sophisticated method for this is dynamic micro-simulation of ‘birth’ and ‘death’ of households and changes within households. This can be done by using duration models for the time that a household spends in a certain state (household lifecycle stages). Such duration models for household demographic and socio-economic changes can be combined in a consistent way with duration models for vehicle holdings, as has been done in the Californian car ownership project. The micro-simulation of household change needs inputs from medium and long term scenarios (e.g. on income and population over time), but also additional restrictions to remain consistent with the scenarios.

A simpler method is to use the model for a specific sample recursively and afterwards reweigh the sample to reflect the changes in the household distribution between the present and the situation 10, 15 or 20 years ahead (based on information from the scenarios). The latter method avoids the spurious accuracy and complication of modelling the generation and termination of households, but loses the dynamic aspect of ageing of the households themselves.

Conditional on specific vehicle transactions, the discrete vehicle type choice model is applied. Here the choice alternatives are the brand-model-vintage combinations, e.g. Opel Astra, 1.8 diesel of 1999. In the DVTM about 1000 such alternatives were distinguished. Most of the vehicle type choice models in the literature also use brand-model-(vintage) alternatives instead of more aggregated vehicle categories. This distinction is not used because the researchers want to predict by brand (interesting for General Motors, not so much for government), but because:

- This specification is clear, for the researchers but especially for the consumers: this is the kind of vehicle alternative that one can refer to when interviewing a respondent. Moreover, this is the kind of choice alternative that many consumers will have in mind when deciding on the type of vehicle.

- This specification can be aggregated in many different ways to yield relevant outcomes:

  - Fuel type
  - Weight
  - Vintage
  - New or second hand
  - Energy consumption label, safety label.

Also average emission rates and fuel consumption for the brand-model-vintage combination can be used to give outcomes on these variables.

Vans and pickups can be included as a number of special brand-model–vintage combinations, if data on the household possession of these would be available.

3. Comparison of the model types on the basis of sixteen criteria

In Table 1, the nine model types are compared on the basis on sixteen criteria (listed in the first column). The perspective here is the use of the car ownership models for transport planning in the public sector. Some models which are less appropriate in this respect, might be a good choice (also given the data availability) for other purposes, such as assisting the macro-/meso-economic planning in developing countries.

Aggregate time series, cohort models and aggregate car market models do not appear very promising for the development of a full-fledged car fleet model, since they lack vehicle types and policy variables. They could only be used to predict a total number of cars in a future year (especially medium to long run), which would then be used as a starting point in other more detailed models. But even for this, other types of models offer more possibilities of making the predictions policy sensitive (which is important for simulating large car cost changes). However, for situations in which data are very scarce (e.g. application to developing countries), aggregate time series models, might be the only method available for forecasting. Within this category there is scope for testing mode advanced econometric models for time series data (e.g. the co-integration approach, as in Romilly, et al. 1998). Cohort models remain useful for predicting licence holding, itself a potentially important determinant of car ownership.

Heuristic simulation models of car ownership do not offer extensive possibilities for including many car types either. On the other hand they can fruitfully be used for predicting the total number of cars with some policy sensitivities.

The static car ownership models and the discrete car type choice models with many car types are less suitable for short-run and medium-run predictions, due to the assumptions of an optimal household fleet in every period. For such time horizons it is much better to predict only the *changes* in the car fleet, instead of predicting the size and composition of the entire car fleet in each period. For a long term prediction of the number of cars and the distribution over households and car types these models are more suited, though cohort effects on total car ownership might not be well represented.

Discrete car type choice models can be added to panel models for the transitions between car ownership states of households. The panel models could then be used to give the evolution of the fleet, starting from the present fleet. For medium and long term forecasts, this can only be carried out if there also is a mechanism for predicting changes in the size and composition of the population (e.g. dynamic micro-simulation, or sample enumeration at different points in time). To include the impact of accelerated scrappage subsidies in the model, in countries without such policies, it is necessary to base the scrappage transactions decisions on stated preference data (as in de Jong et al, 2001).

Pseudo-panels offer an attractive way to get short and long-run policy-sensitive forecasts of the total number of cars (including the cohort effects), but can not take over the role of a choice-based model for the number of cars and car type.

Table 1. Comparison of types of car ownership models

Aspect	Aggregate time series model	Cohort models	Aggregate market models	Heuristic simulation models	Static disaggregate ownership models	Indirect utility models	Static disaggregate type choice models	Panel models	Pseudo panel models	Dynamic transaction models
Demand-supply	Usually only demand	Demand	Demand and supply of 2nd hand cars; Equilibrium mechanism	Demand and supply of 2nd hand cars; Equilibrium mechanism	Demand	Demand	Demand	Demand	Demand	Demand
Level of aggregation	Aggregate	Aggregate	Aggregate	Disaggregate	Disaggregate	Disaggregate	Disaggregate	Disaggregate	Aggregate	Disaggregate
Dynamic or static model	Dynamic	Dynamic	Dynamic	Static, but shift from new to old cars over time	Static	Static	Static	Dynamic	Dynamic	Dynamic
Long or short run forecasts	Short, medium and long (saturation)	Medium and long	Short, medium and long	Medium and long	Long	Long	Long	Short and long	Short and long	Short & medium
Theory	No strong links	No strong links	Economic market equilibrium theory	Strong basic assumptions, can be at odds with theory	Can be based on random utility theory	Strong links	Can be based on random utility theory	Can be based on random utility or lifetime utility theory	Weak links with random utility theory	Parts can be based on random utility
Car use	Not included	Not included	Not included	Can be included, but insensitive (can be amended)	Included in some models (logsum)	Included	Included in some models (logsum)	Sometimes included, but in ad hoc way	Not included, but can be	Sometimes included, but in ad hoc way
Data requirements	Light	Light	Light	Moderate	Moderate	Heavy	Heavy	Very heavy	Moderate	Very heavy
Special treatment of business cars	Usually not, but possible	Usually not, but possible	Usually not, but possible	Usually	Done in recent models	Usually not, but possible	Usually not, but possible	Usually not, but possible	Usually not, but possible	Usually not, but possible
Car types	No car types	No car types	Limited number of car types	Limited number of car types	Very limited number	Very limited number of car types possible	Often very many car types (brand-model-age)	Very limited number of car types possible, but could be combined with a type choice model	Very limited number of car types possible	Very limited number in duration model, but very many in car type choice model
Impact of income	Yes	Yes	Yes (average and distribution)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Impact of car cost	Fixed and or variable cost sometimes included	None	Fixed and variable	Fixed and variable	Fixed cost often included; logsum includes variable cost	Fixed and variable (also on car use)	Purchase cost and fuel efficiency often included	No policy runs reported, but might be possible	Fixed and variable	Fixed and variable

Aspect	Aggregate time series model	Cohort models	Aggregate market models	Heuristic simulation models	Static disaggregate ownership models	Indirect utility models	Static disaggregate type choice models	Panel models	Pseudo panel models	Dynamic transaction models
Car quality impacts	No	No	No	Can be included, might have to work through cost	No	No	Yes	No, unless type choice added	No	Yes in type choice
Impact of licence holding	No	Yes	Yes	No	Possible	Possible	No	No, but possible	No, but possible	No, but possible
Socio-demographic impacts	Limited	Many possible	Limited	Many possible	Many possible	Many possible	Many possible	Many possible	Limited	Many possible
Attitudinal variables	Hard to include	Cohort-specific attitudes can be included	Hard to include	Hard to include	Can be included if specific questions in dataset	Hard to include	Can be included if specific questions in dataset	Can be included if specific questions in dataset	Can be included if specific questions in dataset	Can be included if specific questions in dataset
Scrappage included	No	No	Can be included	Can be included	No	No	No	Can be included	No	Can be included

Dynamic transaction models include duration models for the changes in the car ownership states of the households, and in this respect are a continuous time alternative of the discrete time panel models. They have been combined with detailed policy-sensitive type choice models. For short to medium term forecasts this combination seems a highly attractive option. For longer term forecasts (10-20 years ahead), as for panel models, a population refreshment procedure needs to be included. Long term changes in the supply of car types can be simulated through scenarios (this also goes for panel models combined with type choice).

4. Summary and conclusions

In this paper, models explaining car ownership were reviewed, using a classification in nine types of car ownership models. The focus was on models developed recently (since 1995) or that are still in use, but for some of the car ownership model types (where there are few recent applications) older systems have been described as well. The nine model types distinguished are aggregate time series models, aggregate cohort models, aggregate car market models, heuristic simulation models, static disaggregate ownership models (explaining the number of cars per household), indirect utility models of car ownership and car use (joint discrete-continuous models), static disaggregate car type choice models (often with choice of brand-model-vintage), panel models and pseudo-panel models and dynamic car transactions models (with models for the duration until replacement, acquisition or disposal, and with conditional type choice).

These model types were compared on the basis of sixteen criteria, ranging from the treatment of supply, through level of aggregation and data requirements, to the treatment of scrappage. A final ranking of model types has not been provided in this paper, because this depends on the relative weights of the criteria. These weights in turn are influenced by the policy objectives and availability of data and of other models in a specific application context. In a data-rich environment, where the policy requirement for car ownership modelling is to provide the future number of cars by vehicle type from year to year for forecasting energy use and emissions (and simulation of policy impacts on these), the criteria 'dynamic', 'car types' and 'impact of car cost' are quite important. In a long run model of global mobility on the other hand, the criteria 'data requirements' (for many countries, only very aggregate data will be available) and 'impact of income' will be relatively more important. As a result, the most preferred model type will vary from context to context.

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