

Development and application of a New Zealand car ownership and traffic forecasting model

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Tim Conder
Booz & Co (New Zealand) Ltd

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NZ Transport Agency
Private Bag 6995, Wellington 6141, New Zealand
Telephone 64 4 894 5400; facsimile 64 4 894 6100
research@nzta.govt.nz
www.nzta.govt.nz

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Abbreviations and acronyms

ADT	Average daily traffic
ASC	Alternative specific constant
BTRE	Bureau of Transport and Regional Economics (Australia)
DETR	Department for the Environment, Transport and the Regions (UK), now the DfT
DfT	Department for Transport (UK), formerly the DETR
EEM	<i>Economic evaluation manual</i>
GDP	Gross domestic product
VKT	Vehicle kilometres travelled
LMS	The Netherlands government transport forecasting model system,
MoT	Ministry of Transport
NRTF model	National road traffic forecasts model (UK)
NZTA	New Zealand Transport Authority (merger of Transit NZ and Land Transport NZ)
PEM	<i>Project evaluation manual</i> (now EEM vol 1)
PT	Public transport
RUC	Road user charges
STM	Strategic travel model (Sydney)
TDM	Travel demand management
TLA	Territorial local authority
Transit	Transit New Zealand
TRC	Transport Registry Centre
TTM	Tauranga transport model
VFEM	Vehicle fleet emissions model
VKT	Vehicle kilometres travelled
WoF	Warrant of fitness
WTSM	Wellington transport strategy model

Contents

- Executive summary 9**
- Abstract 10**
- 1 Introduction 11**
 - 1.1 Background and context 11
 - 1.2 Project purpose 11
 - 1.3 Project scope 12
 - 1.4 Project process 12
 - 1.5 Structure of the report 12
- 2 Appraisal of New Zealand car ownership and use trends 14**
 - 2.1 New Zealand vehicle ownership 14
 - 2.1.1 Sources for vehicle registration data 14
 - 2.1.2 Best database 15
 - 2.1.3 Project estimates of motor vehicle ownership in New Zealand 16
 - 2.1.4 Analysis of past trends 19
 - 2.1.5 Vehicle ownership in different areas: census data 21
 - 2.2 New Zealand car use trends 25
 - 2.2.1 New Zealand Household Travel Survey 25
 - 2.2.2 Ministry of Transport – warrant of fitness data 26
 - 2.2.3 Traffic count data 27
 - 2.2.4 Regional household interview surveys 28
 - 2.2.5 Impacts of transport fuel price changes 29
 - 2.3 Comparison with international data 30
 - 2.4 Conclusions 32
- 3 Update of a New Zealand aggregate car ownership model 33**
 - 3.1 The Booz aggregate car ownership model 33
 - 3.1.1 Introduction 33
 - 3.1.2 Basis for forecasting vehicle ownership 33
 - 3.1.3 Saturation level 33
 - 3.1.4 Growth to saturation 37
 - 3.1.5 New Zealand car ownership forecasts 40
 - 3.2 Comparison with other New Zealand model forms 41
 - 3.2.1 Prediction comparison: 1997–2006 43
 - 3.3 Conclusions 43
- 4 Development of policy and functional requirements 45**
 - 4.1 Car ownership and use ‘needs’ survey 45
 - 4.1.1 Respondents 45

4.2	Survey results	46
4.2.1	Current sources of car ownership and use data	46
4.2.2	Current uses of car ownership data	46
4.2.3	Future uses of car ownership data	47
4.2.4	Potential features of future car ownership model	47
4.2.5	Other comments	52
4.3	Conclusions	52
5	Review of New Zealand modelling practices	54
5.1	National modelling methodologies	54
5.1.1	MoT vehicle fleet emissions model	54
5.2	Regional modelling methodologies	57
5.2.1	Auckland regional transport model	58
5.2.2	Wellington transport strategy model	60
5.2.3	Christchurch transport model	64
5.2.4	Tauranga transportation model	66
5.3	New Zealand car ownership and use literature	68
5.3.1	Vehicle availability forecasting model, Travis Morgan (1992)	68
5.3.2	Model for forecasting vehicle ownership In New Zealand, Booz Allen Hamilton (2000)	70
5.3.3	Traffic growth prediction, Koorey et al (2000)	73
5.3.4	<i>Economic evaluation manual</i> , Land Transport NZ (2006)	76
5.3.5	National Land Transport Programme 2007/08	76
5.3.6	Impacts of transport fuel price changes, Booz Allen Hamilton (2006)	77
5.4	Conclusions	81
6	Review of international evidence and forecasting practices	83
6.1	Overview of car ownership modelling	83
6.1.1	Aggregate time series approaches	83
6.1.2	Static disaggregate approaches	84
6.1.3	The cohort approach	84
6.2	Discussion of general model archetypes	85
6.2.1	Aggregate time series model	87
6.2.2	Aggregate market model	89
6.2.3	Aggregate cohort model	90
6.2.4	Heuristic simulation model	90
6.2.5	Static disaggregate model	90
6.2.6	Indirect utility model	91
6.2.7	Dynamic transaction model	92
6.3	Features of key model types	92
6.3.1	Aggregate time series model	93
6.3.2	Static disaggregate model	95
6.3.3	Aggregate market model	98
6.3.4	Summary of key model types	99

6.4	Examples of international models	100
7	Development of a recommended New Zealand modelling framework.....	105
7.1	Introduction	105
7.2	Potential model types.....	105
7.2.1	Aggregate time series models	105
7.2.2	Static disaggregate models.....	106
7.2.3	Aggregate car market models.....	107
7.2.4	Recommendation.....	108
7.3	Recommended long-term future modelling methodology	108
7.3.1	Overview and structure.....	109
7.3.2	Data requirements	114
7.3.3	Model development and data collection process.....	116
7.3.4	Use of the model	116
7.4	Short- to medium-term modelling methodology	117
7.4.1	Short- to medium-term framework	117
7.4.2	National aggregate model: MoT VFEM.....	118
7.4.3	Agreed set of inputs and assumptions.....	118
7.5	Summary	119
8	Conclusions and recommendations.....	120
8.1	Conclusions	120
8.2	Recommendations.....	121
9	References.....	123
	Appendix A: New Zealand vehicle ownership data	126
	Appendix B: Components of general model archetypes.....	130
	Appendix C: Model archetypes influencing factors	133
	Appendix D: Summary of key model types.....	137
	Appendix E: Review of international models	142

Executive summary

This report investigates improved methods for forecasting car ownership and use in New Zealand. The research was conducted by Booz & Company (New Zealand) Ltd in 2007/08.

Car ownership and use in New Zealand

Examination of New Zealand car ownership and use data shows the following:

- Car ownership has continued to increase. In 1970 car ownership was 0.310 cars per person; by 2005 it had risen to 0.574 cars per person.
- There appears to be a relationship between times of increasing GDP per person and decreasing car prices corresponding to increased car ownership per person.
- New Zealand continues to have one of the highest rates of car ownership in the world.
- Information on vehicle kilometres travelled has been collected since 2001, using odometer readings taken during vehicle warrant of fitness inspections. This data shows that light vehicle travel per person increased between 2001 and 2005, but decreased in 2006. Average annual travel per vehicle has been decreasing since 2002.
- Previous research has shown that increased petrol prices result in less fuel consumption per person. This could explain why since 2002 light vehicle travel per person has decreased.

Aggregate car ownership model

As part of the research an aggregate car ownership model for New Zealand was updated. The following key conclusions have been reached from the development and application of this model, which can forecast future car ownership:

- The current level of car ownership in New Zealand, approximately 0.58 cars per capita, is below the saturation level of car ownership which is estimated to be in the range of 0.67 cars per capita (lower) to 0.75 cars per capita (upper). By 2041 the saturation level is predicted to increase, due to changes in age distribution, to between 0.71 cars per capita (lower) and 0.79 cars per capita (upper).
- Elasticities of GDP per capita and car price index can be used to predict future changes in car ownership, particularly in the short to medium term. These appear to be a strong set of relationships (ie economic conditions and car prices are predicted to have a significant impact on future car ownership).
- There is considerable uncertainty over factors that could have a significant impact on car ownership. For example it is unlikely that the real downward trend in the car price index that has occurred over the last 30 years will continue. The ability to forecast future car ownership is dependent on the ability to accurately forecast changes in GDP and car prices.

Development of a car ownership and use framework

The development of a New Zealand car ownership and use modelling framework was based on a user needs survey and a review of current New Zealand and international practices.

The user needs survey was conducted with transport practitioners in New Zealand. Results suggested that a modelling methodology for car ownership and use should ideally:

- be segmented by private vehicles (private and company ownership)
- be applied to national, regional and local contexts
- focus on forecasting within a 25-year horizon
- segment vehicles by fuel type/efficiency and split between private and business
- be sensitive to changes in fixed/variable costs, in particular changes in fuel taxes and road user charges, changes in income and the level of public transport supply
- have outputs which include vehicle numbers, usage, emissions and fuel consumption measures and to a lesser extent, government revenue.

The review of New Zealand modelling practices and literature identified a lack of a consistent approach to forecasting car ownership in New Zealand. While some of the regional models are regulated by national forecasts for car ownership, they are not the same forecasts. There does not appear to be a consistent set of key input assumptions for these model forecasts (eg future GDP or income, car prices). As these regional models are used to predict future transport requirements, the outputs forming an input to project prioritisation, it would be highly desirable if the forecasting of car ownership was undertaken on a consistent basis. As such, what appears to be lacking is an integrated framework for forecasting car ownership.

Following a review of user needs against local and international practice, it was concluded that the development of a national **static disaggregate model** was the recommended modelling methodology for car ownership and use. This is because it provides the desired level of functionality, is able to test many policy variables (eg public transport provision) and there is a large international body of experience to draw upon.

However it is recognised that developing a national static disaggregate car ownership model for New Zealand is a substantial undertaking and the development costs are likely to be significant. Consequently, there is merit in exploring a short- to medium-term modelling framework which would build upon existing models to provide the basis for forecasting car ownership and use, and ensure national consistency.

Abstract

This research investigated improved methods for forecasting car ownership and use in New Zealand. It compiled and reviewed current data and information on car ownership and use. From this data an aggregate car ownership model for New Zealand was developed. This model predicts that economic conditions and car prices will have a significant impact on future car ownership. A future framework for forecasting car ownership and use in New Zealand was developed, based on reviewing current New Zealand practice, international practice and by undertaking a user needs survey. The resulting recommended long-term framework is a national static disaggregate model. A short- to medium-term framework was also developed which provides an intermediate step to address some of the current shortcomings in New Zealand practices. The research was primarily undertaken in 2007/2008.

1 Introduction

1.1 Background and context

New Zealand does not have a national traffic forecasting model (unlike many countries), nor does it have a standardised methodology for traffic forecasting across the various major urban centres. Given that the majority of contemplated investment in increasing road network capacity over the next 10–20 years is planned to be in the major urban areas, this is a deficiency in terms of project planning and evaluation. The NZTA *Economic evaluation manual* (EEM) provides some guidelines on traffic growth forecasts, but these are largely based on the extension of historical trends, with little regard to issues such as population and age structure changes, increasing fuel prices and the potential approach of saturation levels of vehicle ownership and use. As stated in the EEM:

Historical traffic growth rates (in arithmetical terms) are generally considered to provide a sound basis for predicting future traffic demand provided there are no traffic restraints.

This is a simplistic approach compared with those adopted in most other developed countries: 'best practice' approaches adopted elsewhere could be expected to provide not only better 'central estimates' but also much improved information on the sensitivity of estimates to a range of significant variables.

The aim of the project was improve understanding on forecasting future car ownership and use (traffic growth) in New Zealand, and to provide a projection of likely future car ownership and the development of an appropriate model methodology. This methodology would provide a key input to the development of a New Zealand national traffic model (which, we understand, is currently under discussion), and also to the potential upgrading of the Ministry of Transport (MoT) vehicle fleet emissions model (VFEM).

1.2 Project purpose

In order to achieve its objective of developing and showing the application of improved methods for forecasting future car ownership and use in New Zealand, the project.

- focused on methods for forecasting car ownership and use at both national and regional/sub-regional levels, over a timescale of at least 20 years. Traffic trends by other vehicle types (including trucks) were not addressed by this research
- appraised and built on best practices in car ownership and use modelling adopted internationally
- had regard to and (as appropriate) built on practices adopted in New Zealand, particularly those incorporated in the regional transport models in the main centres
- had a primary emphasis on methodology and model structure, rather than on providing specific forecasts.

While the project provided some (illustrative) scenarios for future car ownership trends based on assumptions about input variables, it is likely that subsequent work will be necessary to further investigate likely trends in input variables (eg fuel prices) in order to generate a firm set of traffic trend scenarios for use in future traffic forecasting work.

1.3 Project scope

The scope of this research project was to develop two main outputs:

- 1 To update an aggregate car ownership forecasting model using historical data, and including some of the more traditional response variables such as car prices per GDP with saturation included. This model would provide forecasts of car ownership at an aggregate level and build upon work already undertaken in previous research (Booz Allen Hamilton 2000).
- 2 To develop a modelling framework (but no working model) for future development. This framework would be constructed by comparing policy and functionality requirements (through the use of a needs survey) with current modelling methodologies (international and New Zealand) and data availability. A recommendation would be made as to whether the modelling framework would be best delivered as an enhancement to an existing methodology, or as a new methodology.

As part of these two main outputs, the scope also included:

- appraisal of New Zealand car ownership data and use trends
- review of New Zealand modelling practices and literature
- review of international evidence and forecasting practices
- development of policy and functional requirements

1.4 Project process

The project was undertaken by developing seven separate working papers each of which focused on a particular aspect of the research. The working papers were peer reviewed and then combined into this overall report. Research was primarily undertaken in 2007/2008

1.5 Structure of the report

The structure of the remainder of this report is as follows:

Part A: New Zealand trends and an update of an aggregate model for NZ

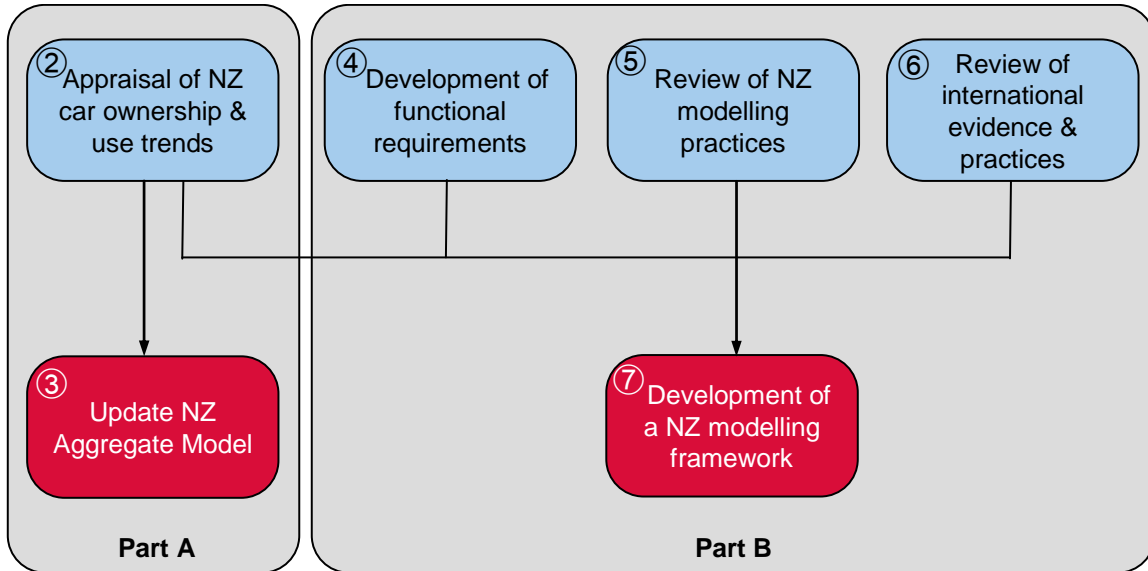
- Section 2: Appraisal of New Zealand car ownership and use trends
- Section 3: Aggregate model for car ownership

Part B: Development of a New Zealand modelling framework

- Section 4: Development of policy and functional requirements (user survey)
- Section 5: Review of New Zealand modelling practices
- Section 6: Review of international evidence and forecasting practices
- Section 7: Development of a recommended New Zealand modelling framework
- Section 8: Conclusions and recommendations

Figure 1.1 shows the general relationship between the two main parts of this report. The numerical circles in this figure represent the report section numbers. As shown in this figure, the two main outputs from this research are updating an aggregate model for car ownership (Part A) and the development of a recommended New Zealand modelling framework (Part B).

Figure 1.1 Relationship between report sections



2 Appraisal of New Zealand car ownership and use trends

2.1 New Zealand vehicle ownership

2.1.1 Sources for vehicle registration data

The various data sources for vehicle registrations in New Zealand have previously been investigated in considerable detail by Booz Allen Hamilton (2000) and Beca Carter Hollings & Ferner (Beca) (2003). The key conclusions from this work are detailed below:

It was originally expected that a time series of historical motor vehicle ownership in New Zealand could be taken directly from published statistics. However, this proved not to be the case, particularly because of changes in the last few decades in the 'standard' method of recording the number of motor vehicles registered. Hence considerable investigations were made to estimate a consistent and realistic time series of motor vehicle ownership at the national level. These investigations are summarised below and a 'best' time series has been derived.

New Zealand vehicle registrations are maintained by NZTA's Transport Registry Centre (TRC). Three time series, which have been derived from TRC data, are readily available:

- Tables of 'licensed motor vehicles' in the transport section of the New Zealand Official Yearbook. This series is based on the TRC March quarterly return. It presents the number of motor vehicles licensed at 31 March and 30 June each year. Figures are available from 1951, broken down by vehicle type.
- Tables of vehicles registered, in *Motor vehicle crashes in New Zealand*, a report produced annually by the MoT (previously titled *Motor accidents in New Zealand*). This series was originally based on the TRC December quarterly return, and represented the numbers of vehicles registered at 31 December each year. It records some vehicle categories not included in the yearbook series: exempt vehicles, tractors, trade plates and caravans. Only an aggregate figure is provided.
- Tables of vehicles licensed by quarter prior to 1987, and by month after 1987, held by Statistics NZ. This series is also based on the TRC returns, is available from 1970, and is broken down by vehicle type.

A new licensing system was introduced in 1987. No figures were provided by TRC in 1987, and the 1988 figures were some 10% lower than those for 1986. Given the long-running upward trend in motor vehicle registrations this was considered unrealistic, and prompted further investigations about the compilation of the figures. Previous discussions with the TRC and staff of the Land Transport Safety Authority (LTSA) (now NZTA) provided the following information.

Prior to 1986:

- motor registration had a manual recording system
- all motor vehicles were relicensed annually at the same time of the year

- deregistered vehicles were only deleted from the record of licensed vehicles once a year, following the end of the June quarter. All of the quarterly returns therefore included vehicles scrapped (deregistered)
- the quarterly returns represented the total number of licensed vehicles at the end of that particular quarter – that is, all vehicles licensed at the end of the quarter plus any other vehicles which were licensed from 1 July for which licences may have subsequently been deregistered.

From 1987, when a computerised recording system was installed, until the present:

- statistics represent the number of current licensed vehicles at the date of reporting
- deregistered vehicles are removed from the computer records immediately and therefore from the number of licensed vehicles at the date of reporting
- as the result of a new spread relicensing system also introduced in 1987, licensing periods of both six months and 12 months, and licence expiry dates are spread throughout the year
- the change to reporting statistics 'as at' a certain date rather than 'for the year ended', and the new spread relicensing system means that a significant proportion of vehicles are not recorded in the annual statistics because their licence was paid after the due date.

It was concluded from this that:

- TRC statistics prior to 1987 were an over-estimate of the number of vehicles licensed at any one time, due to deregistered vehicles not being removed from the totals
- TRC statistics after 1987 represent the number of vehicles for which licences were strictly valid at any one time, not allowing for any late relicensing. These should be added in to reflect the total 'active' vehicles at any one time
- census data is also readily available and is discussed in further detail in later sections of this report. However the census is only undertaken every five years and primarily records motor vehicles available to households on census night.

2.1.2 Best database

Having reviewed the three main sources of time series data for New Zealand motor vehicle ownership, it was decided to use the **Statistics NZ data** (September quarter) as the basis from which to derive a consistent time series.

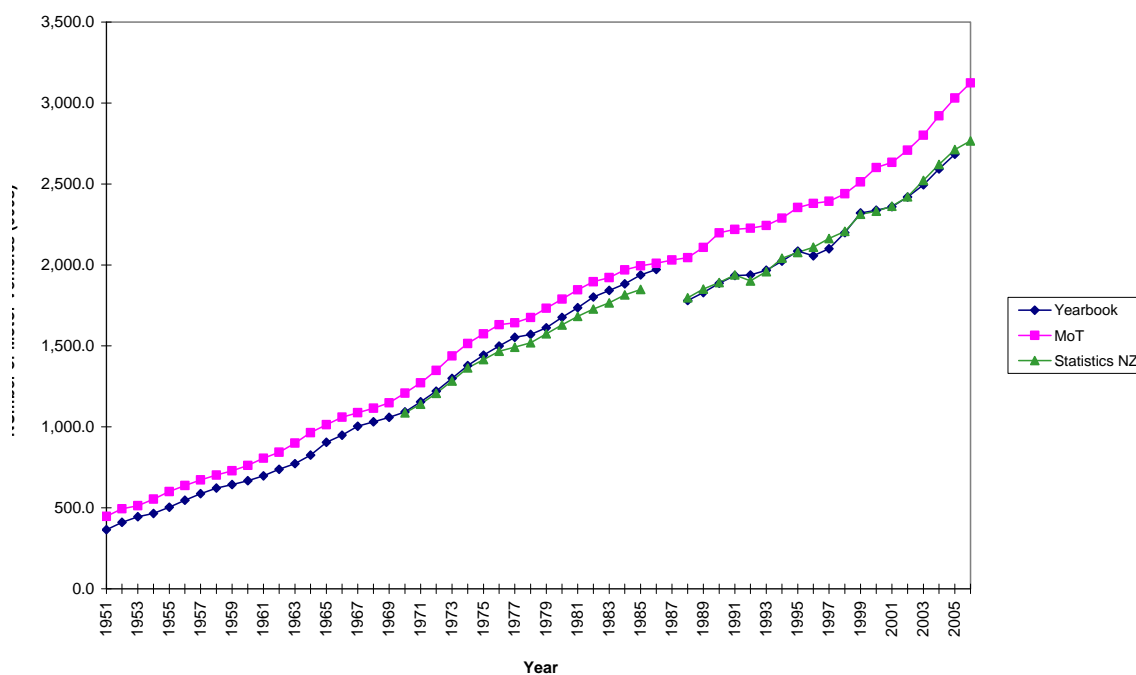
This decision was based on the following considerations.

- All three time series are based on the TRC data, and would be suitable as the basis for a historical time series.
- The New Zealand Official Yearbook data, which reports licensed vehicles at the end of March each year, includes a higher proportion of scrapped vehicles for the period prior to 1987 than does the Statistics NZ data. It would therefore be a less accurate representation of active vehicles than the Statistics NZ data.

- The MoT (previously LTSA) figures would also be a less accurate representation of active vehicles than the Statistics NZ data. They represent licensed vehicles at the end of December each year and, since 1986, have been estimated using a simple spreadsheet model.

The three time series are shown in table A.1 in appendix A and in figure 2.1 below.

Figure 2.1 Licensed motor vehicles time series



2.1.3 Project estimates of motor vehicle ownership in New Zealand

For purposes of previous research and this project, a consistent time series of annual figures for the number of ‘active’ motor vehicles (cars, motorcycles) in New Zealand was required.

As detailed in section 2.1.2 above, it was decided to use the September quarter data from the Statistics NZ database as the basis for this time series. However, as discussed below, several issues had to be addressed in developing the time series.

Scrapped vehicles

Prior to the introduction of the computer-based relicensing system in 1986 vehicles which were scrapped during the year continued to be counted as being licensed until the end of June, at which time all deregistered vehicles were removed from the records. Thus, the TRC-based records always included some ‘inactive’ vehicles, with the number of these increasing during the year from July to June.

Analysis conducted by the Land Transport Division of the MoT in the early 1990s concluded that the proportion of scrapped vehicles ranged from between 3% pa and 6% pa of licensed vehicles for the period 1970 to 1992, averaging out to 4.4% pa. Using the September quarter figures minimised the number of scrapped vehicles being counted as ‘active’; however, there would still be a small number of scrapped vehicles included in Statistics NZ’s numbers. The pre-1986 figures have therefore been adjusted downwards by 1% to reflect this (1% being one quarter of the average annual proportion).

Late relicensing

Prior to 1986 all vehicles were counted by the TRC as being licensed, unless they had actually been deregistered. This meant that vehicles which were relicensed late were also counted in the total of licensed vehicles. However, since 1986 the figures released by the TRC to Statistics NZ have been the actual number of vehicles with current licences. This means that the post-1986 figures are an under-estimate of 'active' vehicles as they do not include late registrations.

An analysis by the MoT Land Transport Division in 1992 over a six-month period concluded that about 8% of active vehicles were not relicensed at any one time. Booz Allen Hamilton (2000) analysed two sets of motor vehicle licensing data, one of which was gathered by the MoT and one by the LTSA. This analysis found that the number of all 'active' vehicles unlicensed at any one time was 4% and 5.5% of the total licensed vehicles (this analysis assumed that all vehicles relicensed within 12 months of their anniversary date were 'active'). We have therefore increased the Statistics NZ post-1986 data by 5% to account for late registrations.

Semi-permanently unlicensed

We have not made any adjustments for vehicles which are unlicensed for more than 12 months, although it could be argued these should be made. The MoT's broad estimates for these are about 1-2% of all vehicles (reliable data is not available).

Vehicle categories

Vehicle categories have changed over time. However, the Statistics NZ data is sufficiently detailed so that this variation could be accounted for in the vehicle totals.

2.1.3.1 Results

After applying the above adjustments to each vehicle type, table A.2 in appendix A shows our estimates of annual motor vehicle ownership in New Zealand, while table A.3 shows the estimate by vehicle type.

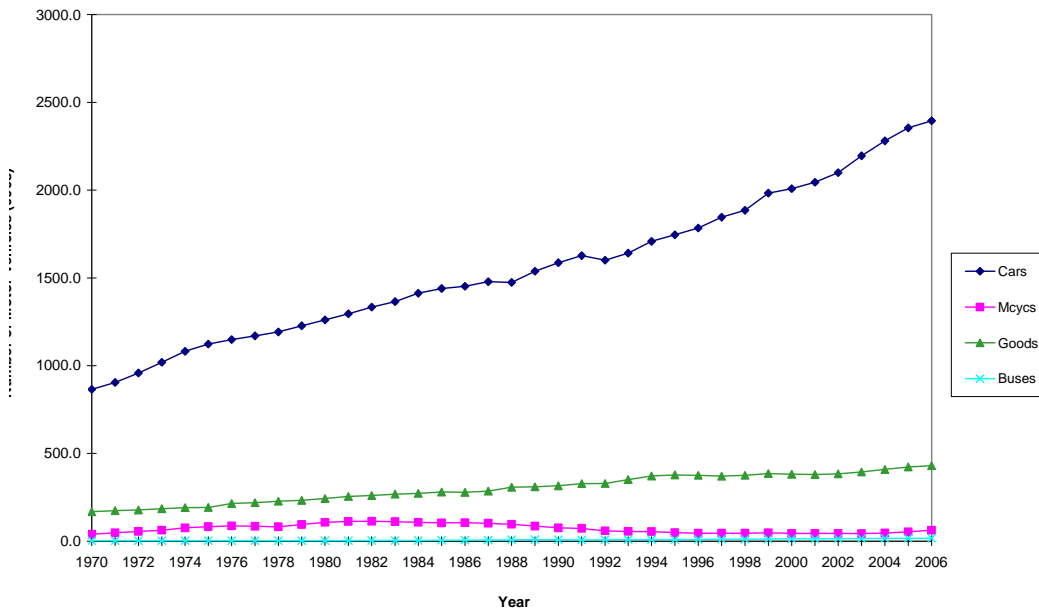
The adjustments involved:

- a reduction in the Statistics NZ September figures pre-1986 of 1%
- an increase in the Statistics NZ September figures post-1987 of 5%.

2.1.3.2 Trends in vehicle ownership

Figure 2.2 shows the trends in motor vehicle ownership in NZ during the period 1970-2006, using our best estimate, plus the breakdown into main vehicle categories, ie cars, motorcycles, goods and buses.

Figure 2.2 NZ motor vehicle ownership 1970–2006



Key features of the results include (based on the best estimate vehicle ownership):

- There was a total of 2.767 million motor vehicles at September 2006.
- This total comprised 82.4% cars, 2.2% motorcycles, 14.8% goods and 0.6% buses.
- Numbers of cars and good vehicles increased almost every year throughout this period. Apart from the 1986/87 'blip', which has been resolved partially by the adjustments made, the only recent exception to this steady upward trend was in 1992 when the number of cars dropped slightly for the first time in 20 years.

Numbers of motorcycles increased rapidly in the 1970s, peaked in the mid-1980s and have since decreased by almost half.

Figure 2.3 shows the trend in cars and motorcycles per person over the last 35 years. Table 2.1 summarises the increases in car ownership over the consecutive five-year periods during that time.

Figure 2.3 Motor vehicle ownership per person 1970–2006

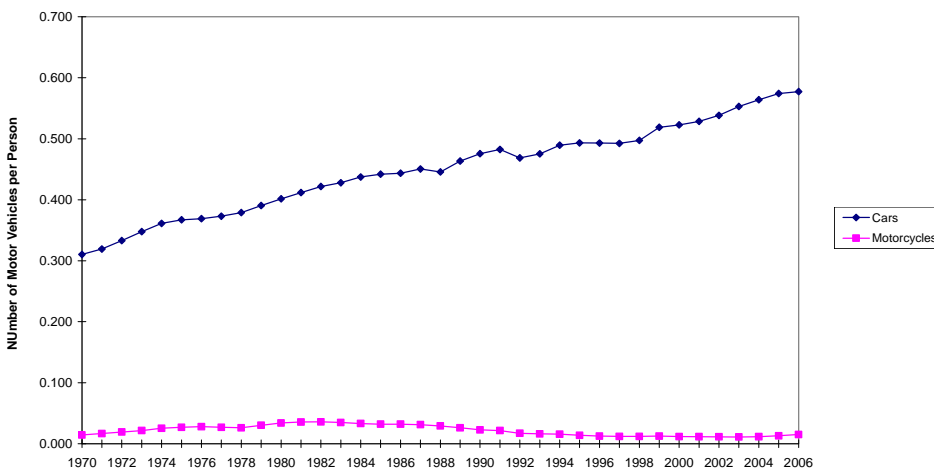


Table 2.1 Increase in car ownership 1970–2005

5 yrs ending	End cars per person	5-year increase in cars/person		
		Absolute	Total %	Ave % pa
1970	0.310	-	-	-
1975	0.367	0.057	18.3%	3.4%
1980	0.402	0.034	9.4%	1.8%
1985	0.442	0.040	10.0%	1.9%
1990	0.476	0.034	7.6%	1.5%
1995	0.493	0.018	3.7%	0.7%
2000	0.523	0.030	6.0%	1.2%
2005	0.574	0.051	9.8%	1.9%

It is apparent that:

- The absolute change in cars per person over each five-year period decreased between 1970 and 1995. However, since 1995 the absolute change has been increasing in each five-year period. The absolute change in cars per person was at its highest level in the five-year period to 1975, with an average of 57 cars per 1000 persons, and dropping to 18 cars per 1000 persons for the period to 1995. However, for the five-year period to 2005 the absolute change increased to 51 cars per 1000 persons.
- Similar to the absolute change, the average percentage change per annum fell between 1970 and 1995. However, the average percentage change has increased since 1995.
- The previous analysis of the trends used the data up until 1995 (Booz Allen Hamilton 2000). The data to 1995 showed that car ownership was increasing at a reduced rate over time, indicating that car ownership could be approaching saturation level. However, since 1995 the rate of change of car ownership has again been increasing. Following little change in car ownership per person during the mid-1990s, car ownership per person increased significantly during the late 1990s and early 2000s.

2.1.4 Analysis of past trends

2.1.4.1 Data sources

For analysis purposes, time series data has been assembled based on the following:

- 1 New Zealand population total (Statistics NZ data sources)
 - a mean population for year ending 31 March for years 1955–1996 (the mean population concept was discontinued in 1997 and replaced with a resident population estimate)
 - b resident population for year ending 31 March for years 1992–2006 (while the population numbers have been developed on different basis, analysis of the overlapping years when both data was available shows a difference of only 2% to 2.7%)
- 2 New Zealand real GDP (Statistics NZ data sources)
 - a annual GDP for year ending 31 March

- b for years 1955–1996, expressed in constant prices (\$1982/83)
- c for years 1988–2007, expressed in constant prices (\$1995/96)
- d all GDP data converted to \$1982/83

3 New Zealand average car purchase prices (Statistics NZ special analysis)

- a average prices of all cars purchased (new and second-hand) in New Zealand for year ending 31 March from 1970–2006, as used in CPI composition

2.1.4.2 Analysis of trends

An analysis was undertaken to investigate the extent to which car ownership levels might be affected by changes in real income (GDP per person) and changes in real car prices.

Figure 2.4 shows the increasing trend in GDP per person while figure 2.5 shows the generally decreasing trend in average real car prices. As shown in figure 2.3 there was an increase in car ownership per person during this period.

Figure 2.4 Trends in NZ GDP per person 1970–2006

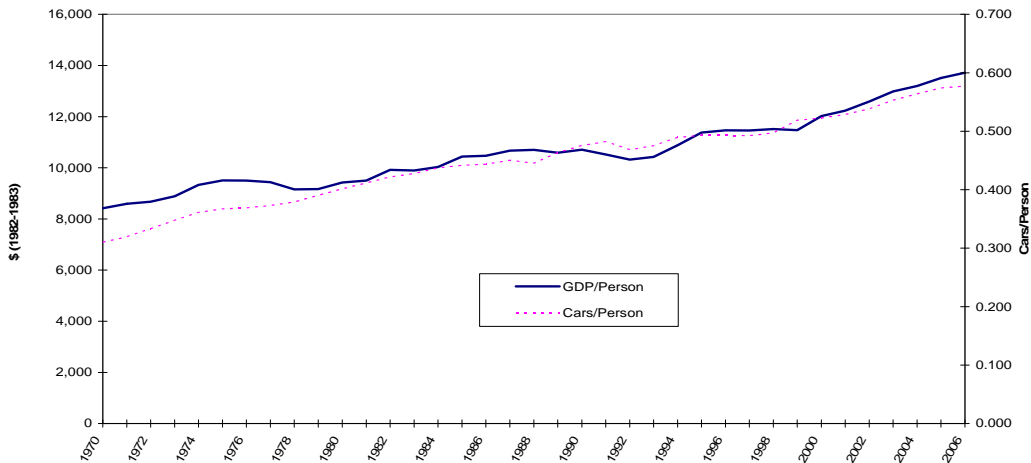


Figure 2.5 Trends in average real car prices: 1970–2006

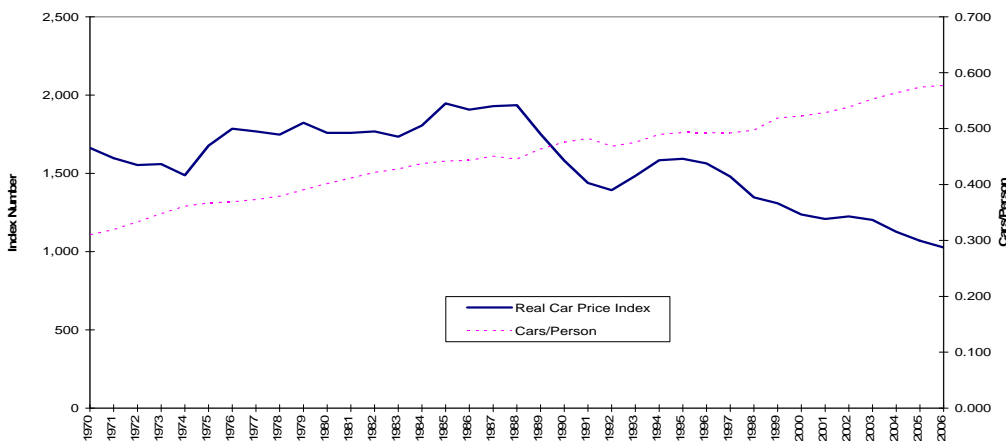
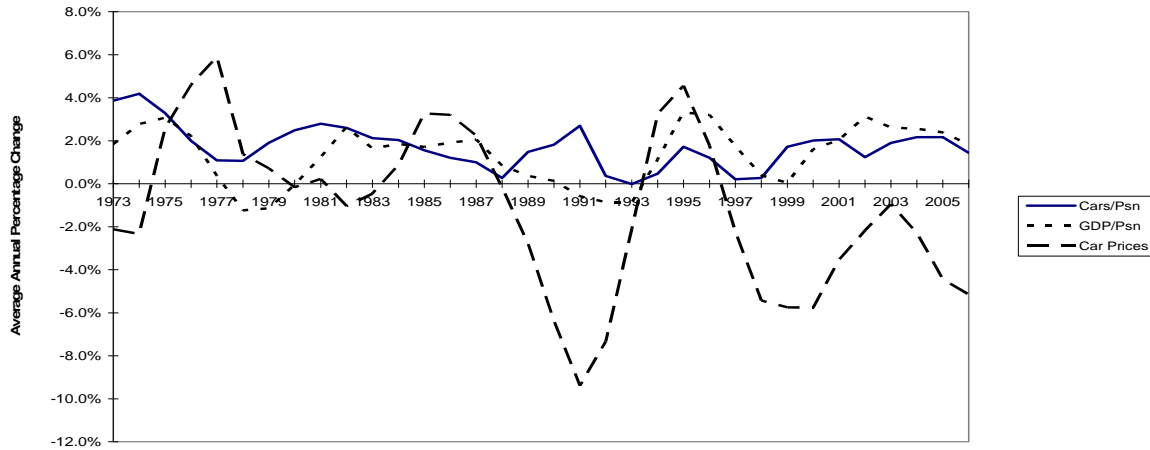


Figure 2.6 graphs the moving three-year average change in cars per person, real GDP per person and car prices since 1970.

Figure 2.6 Three-year change in cars per person, GDP per person and car prices 1973–2006



The above figure suggests that:

- There appears to be a relationship between growth rates in cars per person and in GDP per person. Times of increasing GDP per person and decreasing car prices tend to correspond to increasing cars per person. The cars per person growth rates are less volatile than those for GDP per person. There is no clear evidence that the car per person trend either leads or lags behind the GDP per person trend.
- The substantial reduction in car prices in the period after 1988 appears to be a major factor in influencing the strong growth in car ownership over the 1988–1991 period, when GDP growth was very weak (or negative).

2.1.5 Vehicle ownership in different areas: census data

2.1.5.1 Analysis of census data

Tabulations were obtained from the 1986, 1991, 1996 and 2001 censi of the proportions of households in each region owning different numbers of vehicles, the average vehicles per household and vehicles per person in each region (note 2006 census tabulations on a regional basis were not freely available at the time this research was undertaken). The motor vehicle ownership rate from each census by region is graphed in figures 2.7 and 2.8.

Figure 2.7 Vehicle ownership by region - vehicles per person

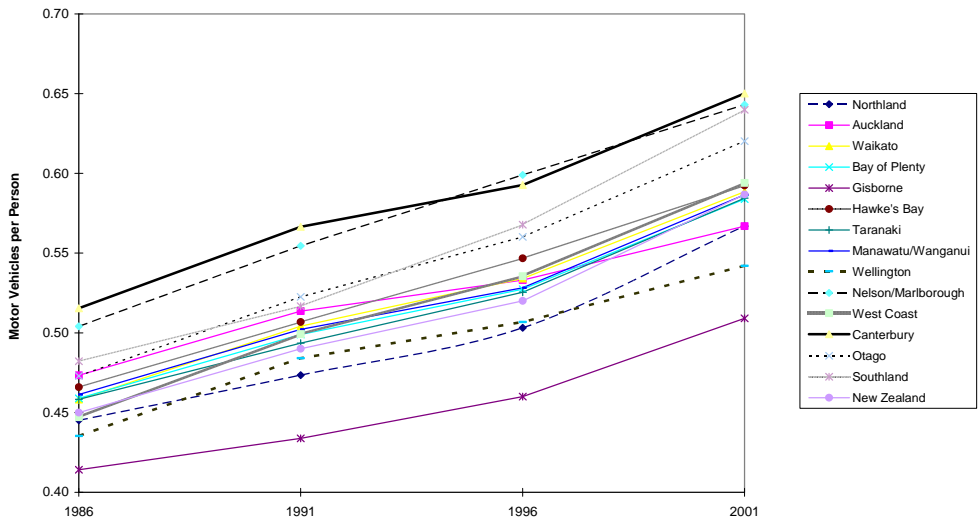
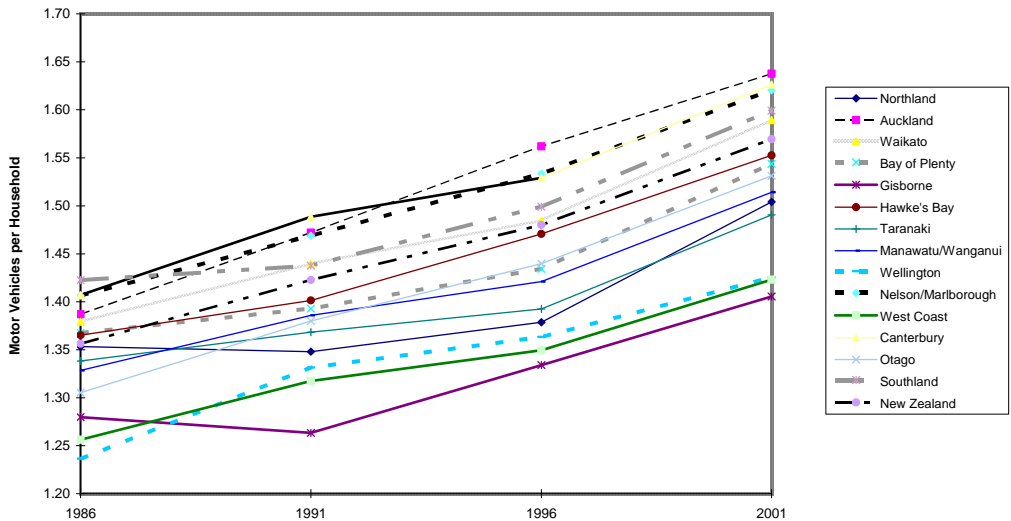


Figure 2.8 Vehicle ownership by region - vehicles per household



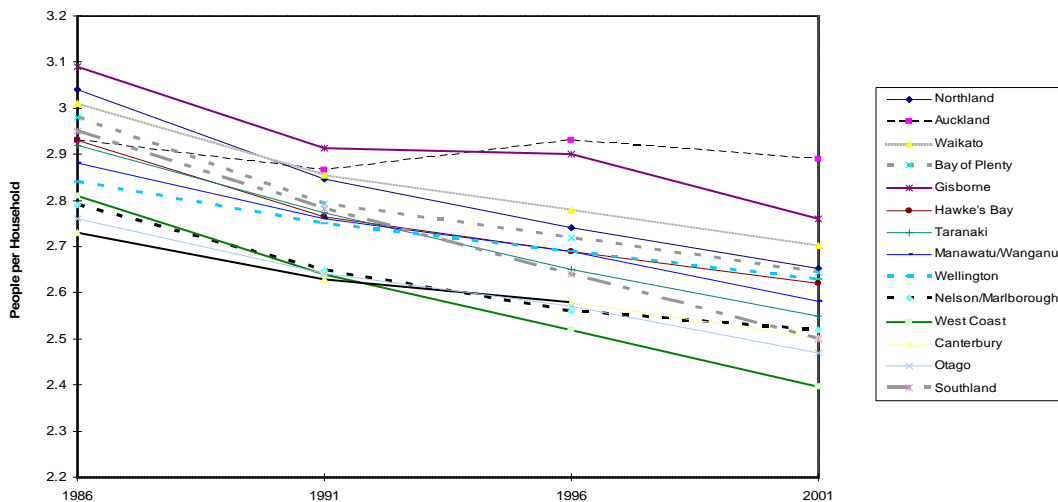
In this context, the numbers of motor vehicles recorded were those available for private use in the care of persons in the dwelling on census night. These included cars, station wagons, vans, trucks and other vehicles used on public roads, and also any business vehicles available for private use; but excluded motorcycles/scooters and tractors, and any business vehicles not kept at private dwellings (no breakdowns by vehicle type were available).

Notable features of these statistics were:

- nationally, the average vehicles per household increased from 1.36 in 1986 to 1.57 in 2001; and the average vehicles per person from 0.45 in 1986 to 0.59 in 2001
- nationally, the proportion of households with no vehicles decreased from 13% in 1986 to 10% in 2001. The proportion with more than one vehicle increased from 37% in 1986 to 49% in 2001

- Auckland had the highest level of vehicles per household in 2001 at 1.64; however, Canterbury had the highest level of vehicles per person in 2001 at 0.65, closely followed by Southland at 0.64 and Nelson/Marlborough/Tasman at 0.64. Auckland's ratio of vehicles per person in 2001 was 0.57. Gisborne had the lowest level of vehicles per household in 2001 at 1.41, and vehicles per person at 0.51
- there was a decline in household size over the 1986 to 2001 period, as shown in figure 2.9 below.

Figure 2.9 Household size 1986–2001



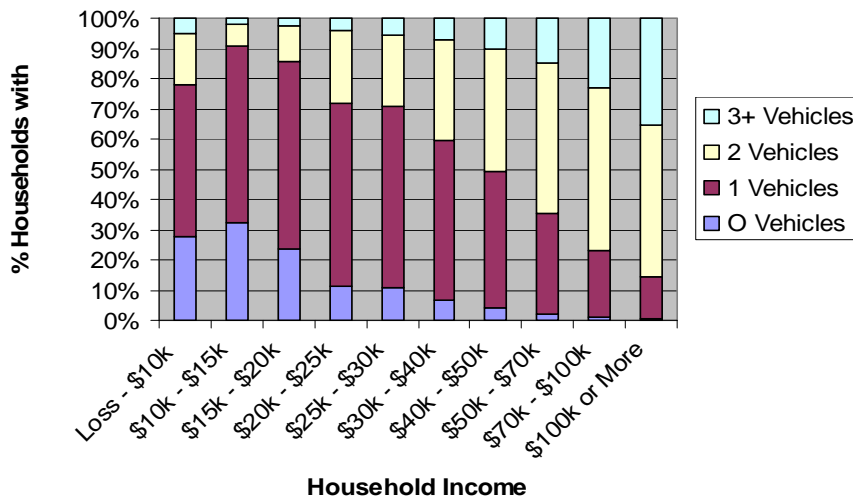
2.1.5.2 Motor vehicle ownership by household type and income

Tabulations from the 2001 and 2006 census data were obtained on the average number of motor vehicles per household and the percentage of households having 0, 1, 2 and 3+ motor vehicles available, with breakdowns by:

- household type
- household income.

Figure 2.10 below shows the percentage of households with different levels of vehicle ownership from the 2006 census. Higher levels of household income are associated with higher levels of car ownership.

Figure 2.10 2006 census – all family types



Other notable findings of the analysis included:

- overall the average vehicles per household increased by a factor of over two from the lowest income group (1.01 vehicles per household) to the highest income group (2.35 vehicles per household). However, part of this increase might be ascribed to household size effects
- households that contained a greater number of adults tended to have more vehicles per household:
 - couples with dependent children averaged 1.94 vehicles per household
 - couples averaged 1.79 vehicles per household
 - single adult with dependent children averaged 1.07 vehicles per household
 - single people averaged 0.90 vehicles per household
- households that contained retired people tended to have a fewer vehicles per household:
 - couples averaged 1.58 vehicles per household
 - single people averaged 0.74 vehicles per household.

2.1.5.3 Reconciliation of census and national statistics

The census data potentially provides the best basis for forecasting motor vehicle ownership levels at the regional level, or at more detailed levels (zonal or TLA): household number projections are available at the regional and more detailed levels, and the census motor vehicle ownership data is household based. However, the census data does not represent all motor vehicles: not only are motorcycles deliberately excluded, but company-owned vehicles which are not kept at private residences overnight are excluded.

The TRC statistics are the official records for motor vehicle ownership, and the project vehicle ownership time series is based on the TRC September quarterly returns. To enable estimates of motor vehicle ownership to be made at the regional level from census data, it is necessary to reconcile the census data with the TRC statistics (cars only).

An analysis was conducted of the differences between the 1991, 1996, 2001 and 2006 census and TRC data (March 1991, 1996, 2001 and 2006). The results are set out in table 2.2 below. Overall the census figures appear to be around 2%–6% higher than the adjusted TRC figures. The TRC figures are considered to be more reliable than the census figures as they are based on actual transactions rather than survey responses. There are differences in the definition of motor vehicles between the two data sets which could explain some of the differences in ownership figures. The census data includes cars (licensed and unlicensed) and vans, and could possibly include taxis, rental cars and some trucks. TRC data includes licensed cars, rental cars, taxis and trade plates.

Table 2.2 Comparison of vehicles per person

Vehicles per person – New Zealand	Vehicles per person			
	1991	1996	2001	2006
TRC ^(a) – original	0.459	0.469	0.504	0.550
– adjusted	0.482	0.493	0.529	0.577
Census ^(b)	0.492	0.521	0.544	0.586
Ratio – census: TRC adjusted	1.02	1.06	1.03	1.02

^(a) TRC figures (March) – all cars, including rental cars and taxis

^(b) Census figures – all vehicles used for personal use

2.2 New Zealand car use trends

This section details the various data that has been found on car use trends in New Zealand (ie the amount of travel occurring).

2.2.1 New Zealand Household Travel Survey

The New Zealand Household Travel Survey is a survey of household travel conducted for the MoT.

The first survey was undertaken in the period July 1989 to June 1990 and surveyed some 4000 occupied dwellings with 8700 responses received. The second survey was undertaken between June 1997 and July 1998 and surveyed some 7000 occupied dwellings with 14,000 responses received. The survey is now undertaken continuously where people in over 2000 households throughout New Zealand are invited to participate in the survey by recording all their travel over a two-day period. Data is available on the MoT website for the period March 2003 to June 2006.

The following table summarises some of the data from the travel surveys. Table 2.3 also shows a comparison in percentage change in car ownership. This comparison shows that driver travel has increased at a similar rate as car ownership. Between 1989/90 and 2003/06 car ownership increased by approximately 47.6% while driver travel increased by 45.1%. However, the number of driver trips increased at a lower rate than car ownership. Between 1989/90 and 2003/06 car ownership increased by approximately 47.6% while driver trips increased by 29.7%.

Table 2.3 New Zealand Household Travel Survey: trips and travel

	Year		
	1989/1990	1997/1998	2003/2006
Driver trips (millions)	2529	3093	3281
- % change since 89/90	-	22.3%	29.7%
Driver travel (100m km)	202	273	293
- % change since 89/90	-	35.4%	45.1%
Car ownership % change since 89/90	-	19.4%	47.6%

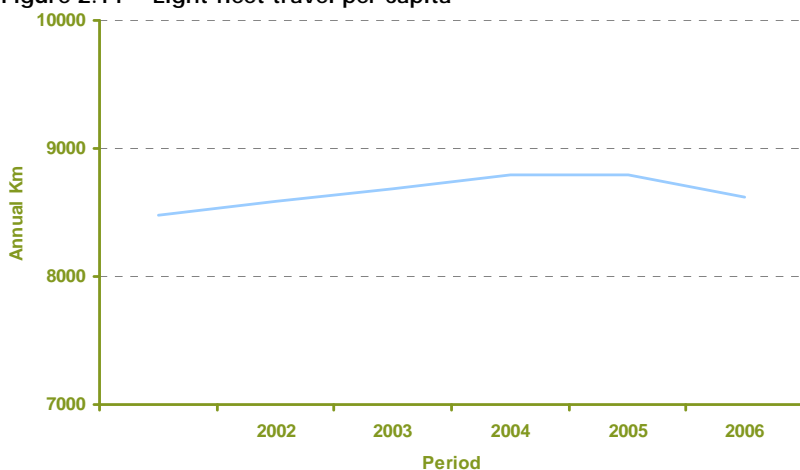
2.2.2 Ministry of Transport – warrant of fitness data

Information on vehicle kilometres travelled (VKT) was obtained from the MoT, based on odometer readings taken as part of the warrant of fitness (WoF) programme. Table 2.4 summarises the VKT estimates while figure 2.11 shows annual light vehicle travel per capita and figure 2.12 shows average annual travel per vehicle. While the data is only available since 2001, the following trends have occurred:

- light vehicle travel per capita increased between 2001 and 2005, but decreased in 2006
- average annual travel per vehicle has been decreasing since 2002.

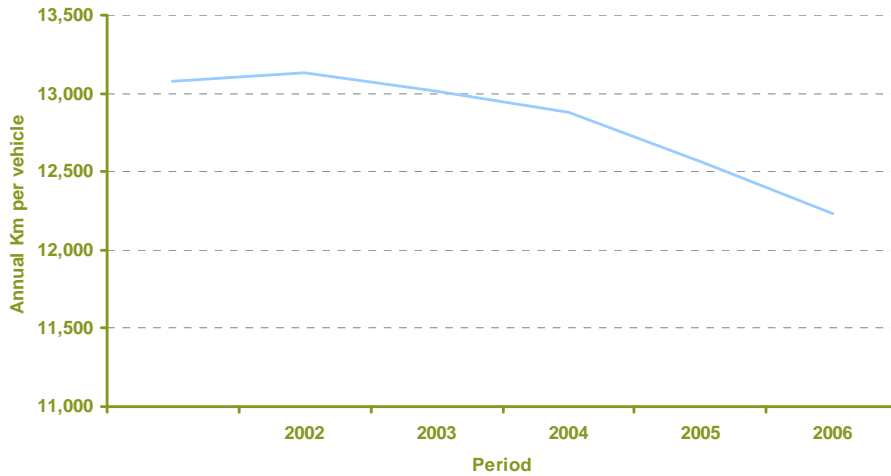
Table 2.4 WoF VKT estimates

Year	Light travel per capita (km)	Light travel per vehicle (km)
2001	8481	13,073
2002	8592	13,131
2003	8680	13,014
2004	8793	12,883
2005	8790	12,562
2006	8615	12,232

Figure 2.11 Light fleet travel per capita

Source: MoT (2007)

Figure 2.12 Light fleet average annual travel per vehicle



Source: MoT (2007)

2.2.3 Traffic count data

MoT undertook counts at around 2300 locations in 2000, 2001, 2003 and 2005 for the purpose of estimating car use, and as a proxy for car VKT. Traffic was counted for three hours per site and inflated to estimate annual traffic for each site. This has now been discontinued in favour of the WoF data (see section 2.3.2) which is deemed to be more reliable.

Figure 2.13 shows the estimate of total VKT in New Zealand, while figure 2.14 shows the breakdown by region. As shown in figure 2.13, the estimates derived from the traffic counts follow the same trend as those derived from WoF data, although they are 1% – 3% higher. Figure 2.14 shows that Auckland (which is home to 32% of the national population) contributes to approximately 28% of New Zealand's VKT.

Figure 2.13 Vehicle travel method comparison

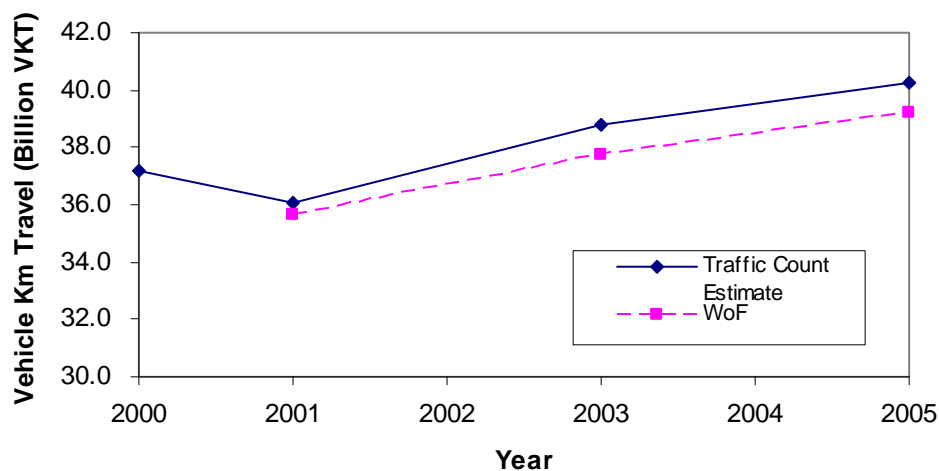
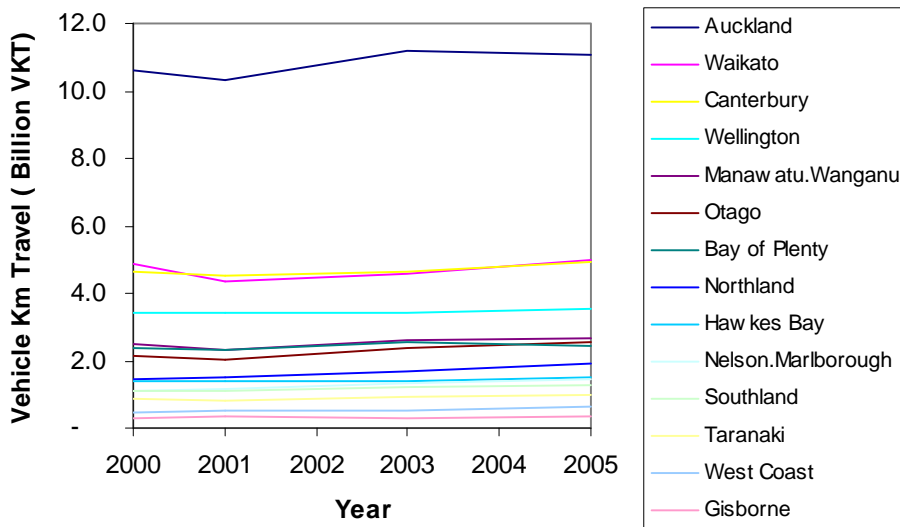
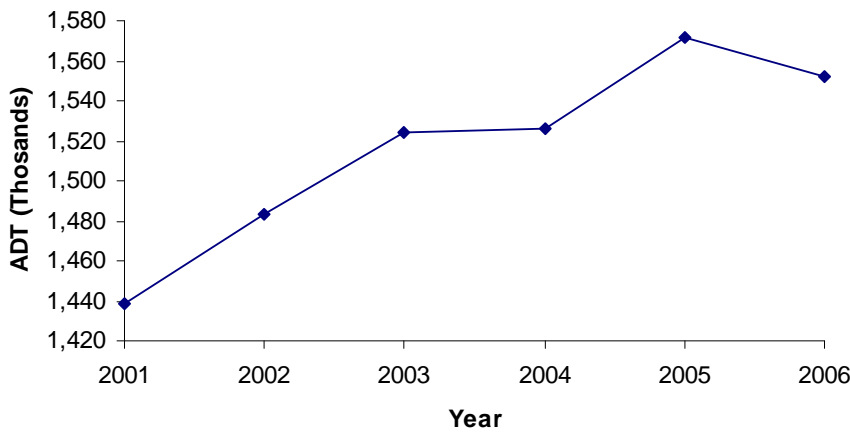


Figure 2.14 Vehicle travel by region



Traffic count data was also obtained from Transit NZ (now NZTA) from their Auckland continuous motorway count programme. Average daily traffic (ADT) estimates from 19 count sites were provided for 2001 to 2006. Figure 2.15 shows the total ADT across the 19 count sites. The trend is generally similar to the WoF data (figure 2.11) which shows increasing travel up to 2005 and then a decline in 2006.

Figure 2.15 Sample Auckland Transit NZ traffic counts



2.2.4 Regional household interview surveys

Larger regional councils conduct household interview surveys as part of their transport modelling programmes. These surveys capture information relating to household characteristics and trip-making behaviour (through the use of trip diaries).

Auckland has recently completed surveys as part of their ATM2 model development. The survey sampled some 10,000 households in 2006, of which final responses were received from 6000 households. Key information collected includes:

- number of residents in household
- age of people
- employment status
- type of vehicle
- travel information including:
 - trip purpose
 - mode of transport
 - driver or passenger.

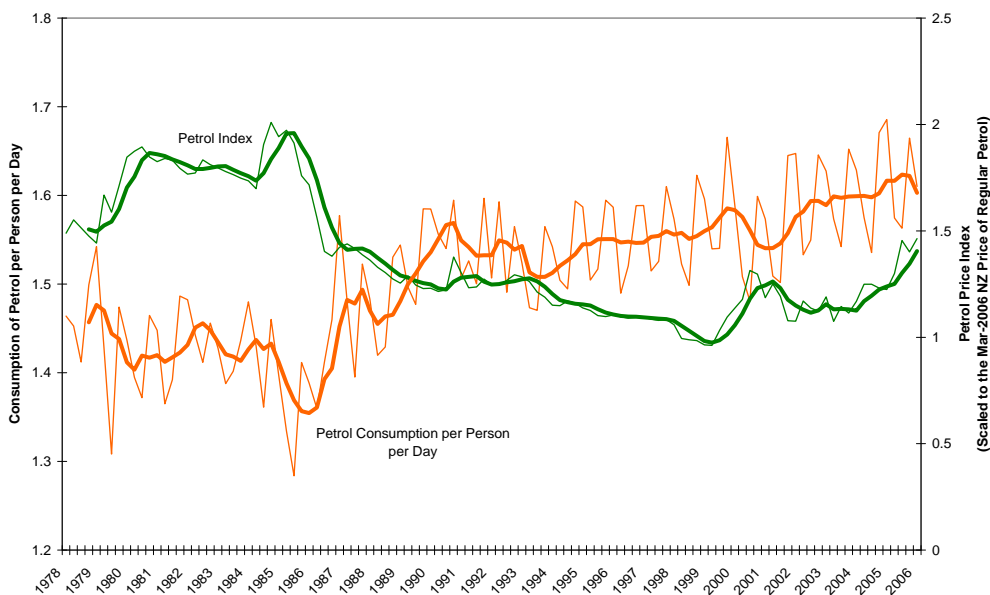
As these surveys are undertaken relatively infrequently they are of limited value in determining trends.

2.2.5 Impacts of transport fuel price changes

Booz Allen Hamilton (2007) undertook research to assess evidence on the impacts of petrol price changes on New Zealand petrol consumption, traffic volume and public transport patronage; and, in the light of this evidence and evidence from Australia and other countries, to recommend a set of 'best estimate' petrol price elasticities in the New Zealand context. The research was completed in 2007 and published as *Land Transport NZ research report 331*.

Figure 2.16 shows changes in petrol consumption (per person per day) as the petrol price index changed over the period 1978–2006. Both data sets were smoothed with four-quarter-moving averages. It appears that for most of the period analysed, petrol consumption trends 'mirrored' petrol price trends, ie increased petrol price resulted in less fuel consumption per person per day.

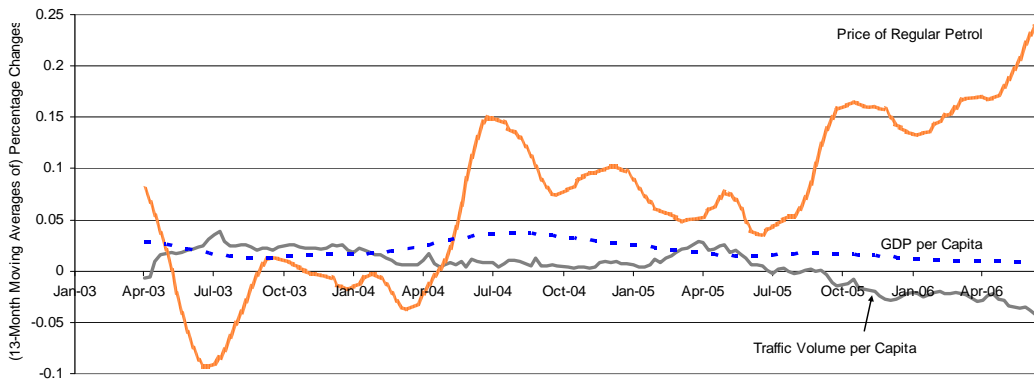
Figure 2.16 Trends in petrol prices and petrol consumption (1978–2006)



Source: Booz Allen Hamilton (2007)

Figure 2.17 shows the percentage change in total traffic volumes (per capita), petrol prices and GDP per capita. Throughout the period until mid-2005, car traffic volumes per capita increased continuously, generally at a rate of around 1% – 2% per year; since then, car volume trends have become negative, with the latest (mid-2006) data indicating an annual decline of 4% – 5%. The study suggested there was a relationship between traffic volumes and petrol prices, particularly in the periods around July 2003, April 2005 and since October 2005.

Figure 2.17 Changes in total traffic volume per capita, petrol price and GDP per capita



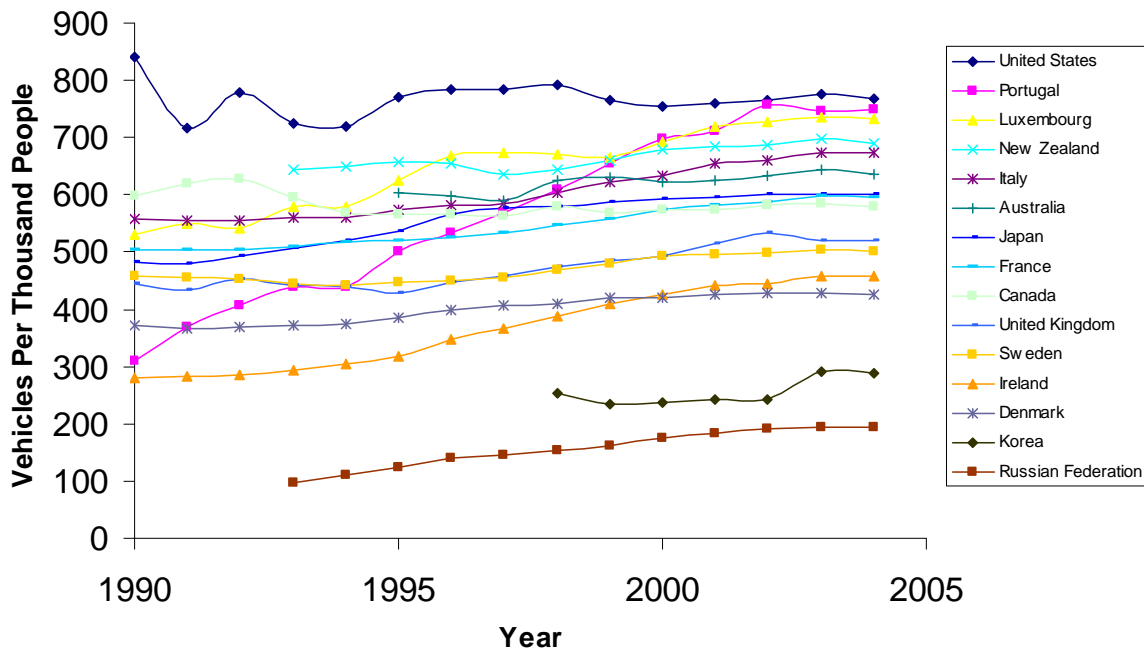
2.3 Comparison with international data

There is generally a wide range of international data available on car and vehicle ownership. However, due to differences in definitions and years where data is available, it is difficult to produce a consistent time series of data.

The Organisation for Economic Cooperation and Development (OECD) has produced vehicle ownership rates for a large set of countries between 1990 and 2004 based on available data. Figure 2.18 shows that New Zealand had amongst the highest vehicle ownership in the world (note this data includes all vehicles such as trucks and buses). Most countries showed an upward trend in vehicle ownership between 1990 and 2005. The notable exception was the United States, which although it had decreased vehicle ownership since 1990, still had the highest rate of vehicle ownership of the OECD data.

Transfund NZ research report 161 (Booz Allen Hamilton 2000) contained a figure showing car ownership between 1958 and 1988 for New Zealand, United States, United Kingdom, Canada and Victoria. Until 1988, New Zealand car ownership had closely matched that of Canada. However, as shown in figure 2.18, in the period 1990–2005, Canada’s vehicle ownership decreased while New Zealand’s continued to increase.

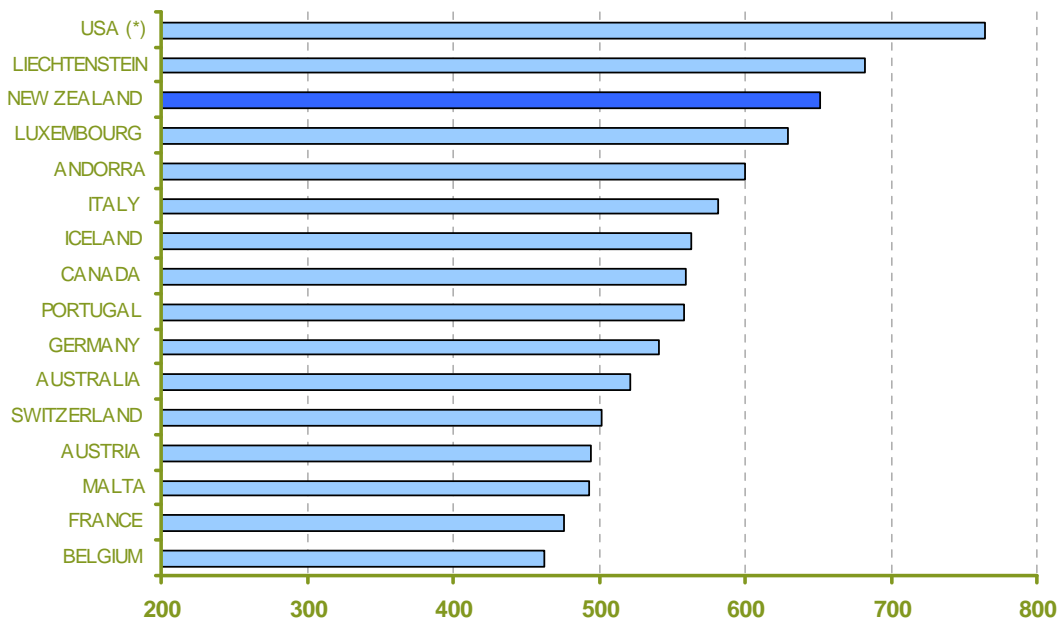
Figure 2.18 International vehicle ownership comparison



Source: OECD Factbook 2006 – selected countries

Figure 2.19 below shows a comparison of vehicle ownership rates, produced by MoT based on 2002 data. Again, it can be seen New Zealand, in that year, had one of the highest vehicle ownership rates in the world.

Figure 2.19 Vehicles per 1000 population (as at 2002)



Source: MoT (2007)

2.4 Conclusions

Examination of New Zealand car ownership and use data shows the following:

- Car ownership has continued to increase. In 1970 car ownership was 0.310 cars per person; by 2005 it had risen to 0.574 cars per person.
- There appears to be a relationship between times of increasing GDP per person and decreasing car prices corresponding to increased car ownership per person.
- New Zealand continues to have one of the highest rates of car ownership in the world.
- The census data provides the best basis for comparing car ownership between regions.
- The most comprehensive set of data on car use in New Zealand is the MoT New Zealand Household Travel Survey. This survey has been undertaken continuously since 2003 and shows that since about 1990, driver travel has increased at approximately the same rate as car ownership (approximately 45%).
- Information on VKT has been collected since 2001, using odometer readings taken during the vehicle WoF inspections. This data shows that light vehicle travel per person increased between 2001 and 2005, but decreased in 2006. Average annual travel per vehicle has been decreasing since 2002.
- Previous research showed that higher petrol prices resulted in less fuel consumption per person.

Regarding the data itself, the following conclusions have been reached:

- Due to changes in motor vehicle registration processes, there is some difficulty in determining accurate vehicle ownership in New Zealand, particularly a time series of data. This highlights the importance of collecting ongoing data in a consistent manner.
- There are different definitions used for car ownership levels. For example census data is not directly comparable to TRC figures due to the different definitions. It would be beneficial if these definitions could be brought into line or segregated to enable direction comparisons.

3 Update of a New Zealand aggregate car ownership model

3.1 The Booz aggregate car ownership model

3.1.1 Introduction

Booz Allen Hamilton (2000) previously developed an aggregate model for forecasting future car ownership. This section builds on the previous work and updates the model using latest data and research (note the previous research was based on data up to 1996). The approach adopted was a macro-economic model that estimates car ownership at a national level. See section 6 for the background to the selection of this model.

3.1.2 Basis for forecasting vehicle ownership

There are two critical elements in providing realistic vehicle ownership forecasts in macro-economic (aggregate time series) models:

- the growth path to saturation
- the saturation level.

A number of different methods have been used to predict these two elements. Most have used 's-curves' to model the growth path to saturation. In New Zealand, both MoT (as part of the vehicle fleet emissions model work) and Beca (2003) have used logistic form s-curves. These models assume a constant or fixed saturation level. By contrast, the previous Booz Allen Hamilton (2000) research used a changing saturation level, (reflecting changing demographics) but a more simplistic growth path to saturation. This approach was adopted for this research.

3.1.3 Saturation level

The saturation level of car ownership per capita is unclear and there appears to be considerable variation in the assumptions used in forecasting it. Two approaches are normally adopted to estimate the saturation level:

- use of statistical techniques on existing data to extrapolate a growth path: the saturation level is taken where this growth path levels off
- examination of the behaviour of the car-owning population with relatively high incomes: saturation levels estimated for this population are assumed to flow through to the remaining population of car owners as their real income levels increase over time.

The first of these approaches to forecasting a saturation level involves fitting a regression line to the annual growth rates of per capita car ownership, and extrapolating this line to the x axis. However, this approach fails to address the effect of economic influences (eg income, real cost of motoring) on the growth path. The development of a saturation level is a long-term effect and there is considerable uncertainty that the modelled relationship would continue to hold in the long term, even when economic influences are included in the model.

The second approach to forecasting car ownership looks at the behaviour of the car-owning population with relatively high incomes. This is considered a more sensible approach as economic influences have been shown to be a key determinant in car ownership.

It is also noted, and needs to be taken into account, that the saturation level of car ownership per capita will be influenced by the following factors:

- the proportion of the population who are permitted by law to drive
- the proportion of the potential car-owning population unable to drive because of physical or mental disability
- the proportion of the potential car-owning population who choose not to own a car.

3.1.3.1 New Zealand data and references

New Zealand census data for 2006 was reviewed and tabulations were obtained for car ownership (0, 1, 2 and 3+ cars), household structure and household income. The following key points were identified:

- Considering single adult households:
 - 77% own at least one vehicle
 - 94% with an income over \$50,000 own at least one vehicle
- Considering households of couples:
 - 65% own at least two vehicles (ie an average of at least one vehicle per adult)
 - 80% with a household income over \$70,000 own at least two vehicles
 - 82% with a household income over \$100,000 own at least two vehicles
- Considering households of couples with dependent children:
 - 75% own at least two vehicles (ie an average of at least one vehicle per adult)
 - 85% with a household income over \$70,000 own at least two vehicles
 - 88% with a household income over \$100,000 own at least two vehicles

This data suggests that a saturation level of car ownership of high-income adults in New Zealand could be between 80% (high-income couples) and 94% (high-income single adults). It is important to note that the above data is based on proportions of households that owned at least X vehicles, as opposed to average number of vehicles. This is because some household types averaged more cars than adults (this is discussed later in this section). For example, high-income single-person households averaged over one car per household.

Another source of information is the proportion of the population with a current driver licence. It is hypothesised that the saturation level could be everyone who has a licence would like to own a car, should income allow.

Data was obtained from the NZTA on the number of driver licences held, categorised by age and gender (as at the end of 2007). The following key points were identified:

- approximately 96% of the population aged between 15 and 65 have a driver licence
- approximately 76% of the population aged over 65 have a driver licence
- overall approximately 93% of the population aged over 15 have a driver licence or 74% of the total population
- assuming the current licence rates continue and with the projections for an aging population in New Zealand, in 2041 approximately 77% of the total population will have a driver licence.

It is noted that Beca (2003) adopted a saturation rate of 0.75 cars per capita (ie 75% of the total population) based on analysis of current and future licence holdings. By comparison the MoT VFEM uses a saturation rate of 0.65 cars per capita (see section 5).

3.1.3.2 Australian data and references

Beca (2003) reported that the Australian BTRE had raised its saturation level expectation to around 0.65 cars per capita. Booz Allen Hamilton (2000) reported that in Australia, about 5% of the potential car-owning population were unable to use a car because of disability, mainly because of advanced age or poor eyesight.

3.1.3.3 United Kingdom data and references

As cited in Booz Allen Hamilton (2000), the UK national road traffic forecasts (NRTF) model assumed a saturation level based on cars being owned by 90% of the driving age group, defined as 17–74 year olds.

3.1.3.4 United States data and references

Booz Allen Hamilton (2000) analysed historical data from the United States. Key findings of this data included:

- the ratio of cars to driving licences for the three states with the highest levels of car ownership in 1986 varied from 1.01 (Florida) to 1.13 (New Hampshire)
- US National Transportation Personnel Study data showed a levelling off at around 0.95 cars per adult at relatively high income levels.

3.1.3.5 Other comments

An initial plausible assessment is that the saturation level will occur when every person of driving age owns a car, with the exception of those who have a disability that prevents them from driving. However, the United States data, which indicates more cars than driving licences in some states and New Zealand census data which shows some household and income levels have more cars than adults, casts some doubt on whether this is really the saturation level of ownership: as cars get relatively cheaper to own, affluent people may well own more than one car, using different car types for different types of trips.

However, in cases where households have more cars than licence holders, not all the cars can be in use simultaneously and the marginal cars are unlikely to result in substantial increase in vehicle kilometres travelled. Hence for traffic planning purposes, it may be reasonable to estimate the 'effective' saturation level on this basis, while recognising that the physical saturation level may be higher.

The proportion of the potential car-owning population who choose not to own a car will vary depending on location. Vehicle ownership in major urban areas such as London, Tokyo and New York, is lower than in smaller cities and rural areas. However, much of this is due to physical constraints on car ownership and use, particularly congestion and parking problems. The effect of public transport provision on car

ownership levels in New Zealand was investigated by Booz Allen Hamilton (2000) and concluded to be equivalent to around -0.05 (-5%) vehicles per capita at current levels, based on United Kingdom, European and Australian analysis.

3.1.3.6 Adopted saturation level

The following table summarises the above discussion on saturation rates.

Table 3.1 Summarised sources of possible saturation rates

Source	Effective cars/ adult ^(a)	Effective cars/ capita	Comments
Booz Allen Hamilton: NZ census	80% – 94%	63% – 74%	Based on analysis of high-income singles and couples
Booz Allen Hamilton: NZ driver licence	93%	74%	Percentage of population that has a current driver licence
Beca (2003)	-	75%	Based on analysis of New Zealand driver licence data
MoT VFEM	-	65%	Unknown basis
BRTE Forecasts – Australia	-	65%	Cited in Beca (2003)
UK NFTF model	90%	-	Cited in Booz Allen Hamilton (2000)
USA data	95%	-	Cited in Booz Allen Hamilton (2000)

^(a) Person of driving age (in the New Zealand context this means persons 15 years or older)

Based on the above data and research, we propose the following range of saturation levels:

- likely upper saturation: 0.95 'effective' cars per adult (person of driving age)
- likely saturation: 0.90 'effective' cars per adult
- likely lower saturation: 0.85 'effective' cars per adult.

Based on the current (2008) New Zealand population profile this results in:

- likely upper saturation: 0.75 'effective' cars per capita
- likely saturation: 0.71 'effective' cars per capita
- likely lower saturation: 0.67 'effective' cars per capita.

The above likely saturation rates, relating to cars per driving-age population, appear to be broadly consistent with other cited experience and data. For example, with a starting point of 100% of the driving age population, the following reductions can be applied:

- A proportion of the driving age population will be unable to use a car because of disability. Some Australian data suggests this could be approximately 5% of the potential car-owning population.
- In practice, there will always be a proportion of the population who choose not to own a car (apart from reasons of disability etc). Based on United Kingdom experience, this could be approximately 5% of people of driving age.

- In addition, in urban areas car ownership levels are likely to be lower due to the availability of public transport and the constraints on car use (car parking limitations etc). This might reduce saturation levels by a further 5% of the people of driving age.

Table 3.2 shows the projected distribution of population in New Zealand by age group and the corresponding maximum and minimum saturation levels per capita (assuming that the minimum driving age is retained at 15). It indicates gradual increases in saturation levels over time, as the proportion of children in the population is predicted to decrease. The current saturation levels are in the range 0.67 cars per capita (lower) to 0.75 cars per capita (upper). By year 2041 these increase, due to changes in age distribution, to 0.71 cars per capita (lower) and 0.79 cars per capita (upper).

Table 3.2 New Zealand population distribution and car ownership saturation levels

Year	% Population by age			Saturation level (cars/capita)	
	0-14	15-64	65+	Lower ^(a)	Upper ^(b)
1996	23.0	65.4	11.5	0.654	0.731
2001	22.6	65.5	11.9	0.658	0.735
2006	21.2	66.5	12.2	0.670	0.748
2011	20.4	66.3	13.3	0.677	0.756
2021	19.2	63.6	17.1	0.686	0.767
2031	17.7	60.8	21.4	0.699	0.781
2041	17.0	59.2	23.9	0.706	0.789

Source: Statistics NZ 'New Zealand Population Projections' 2006 (base) – 2061 – Series 5 base

(a) Lower = 0.85 cars/capita of age 15+

(b) Upper = 0.95 cars/capita of age 15+

While it may appear confusing to have a saturation level that changes over time (when defined in terms of cars per capita), this is simply reflecting the changing proportion of the population that are of driving age. The saturation level, as defined in terms of cars per adult, is fixed and is not proposed to change over time.

3.1.4 Growth to saturation

The second element in forecasting future car ownership levels is the growth path taken to reach the saturation level. Key influences include:

- general level of economic activity (normally measured in GDP per capita)
- real cost of motoring (both car purchase and car use)
- household structure
- relative accessibility of private and public transport consumer taste.

As identified by Booz Allen Hamilton (2000), the evidence from many countries and from New Zealand data up to 1970 was that the 'underlying time trend' had been the major factor determining trends in car ownership; with growth in cars per capita being more or less linear and showing little signs of tailing off towards saturation. Relatively small variations from the linear trend line were related to variations in income

levels and motoring costs. However, analysis of New Zealand data since 1970 suggests that the apparent ‘unexplained’ time trend has reduced. With this reducing time trend, the effects from the trend of changes in GDP and the car price index (new and used) have become relatively more significant.

The approach adopted to determine the likely growth path to saturation was to make a range of projections based on multiple regression analysis of more recent New Zealand data and a range of estimates for future trends in GDP per capita, the car price index¹ and time trends.

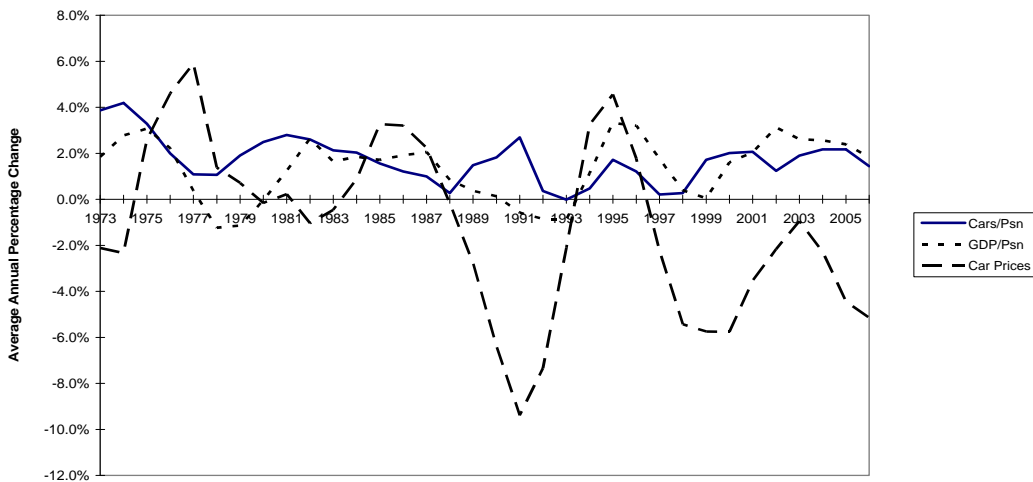
Using the same method previously adopted by Booz Allen Hamilton (2000), two multiple linear regressions were undertaken to further examine the relationship between the three-year moving average statistics for annual percentage changes:

Regression (A): Cars/capita against GDP/capita and car price index

Regression (B): Cars/capita against GDP/capita, car price index and time.

Figure 3.1 shows the three-year moving average in cars per capita, GDP per capita and the car price index.

Figure 3.1 Three-year change in cars per person, GDP per person and car prices 1973–2006



It was found that regression (A) provided little or no explanation of the trend in cars per capita ($r^2 = 0.15$). Regression (B) provided an improved fit ($r^2 = 0.64$), indicating a decrease in the annual time trend over the period. The results for regression (B) are summarised in table 3.3. All three variables are statistically significant to a 95% confidence level (using t test).

Table 3.3 Regression analysis results

Yearly time trend	-0.001
Elasticity of cars/capita with GDP/capita	+ 0.52
Elasticity of cars/capita with the car price index	- 0.18

The above regression analysis provided elasticities for GDP per capita and car prices per capita with respect to car ownership. This regression analysis also identified a downward time trend. However the

¹ The car price index incorporates new and second-hand car prices. It is noted that a better index would also incorporate other car ownership costs.

linear regression equation developed (B) did not take into account that the time trend would eventually reach zero. Therefore, the time trend component of regression (B) was modified to provide the following predictive equation:

Regression (C) = Cars/capita against GDP/capita, car price index and reducing time trend.

or

*% change in cars/capita = % change in GDP/capita * GDP elasticity + % change in car price index * car price index elasticity + time trend for year X (if greater than 0)*

The reducing time trend component of the equation consists of a starting percentage (at 1973) and a yearly reduction. Using the data set from 1973 to 2006 and the 'least squares' method to solve the equation, the starting percentage and yearly reduction were found to be:

- 2.6% starting percentage in 1973, reducing by 0.13% per year to reach a 0% time trend in 1993.

This indicates that changes in car ownership in New Zealand are no longer influenced by the unexplained time trend.

Therefore the final form of the regression (C) equation is:

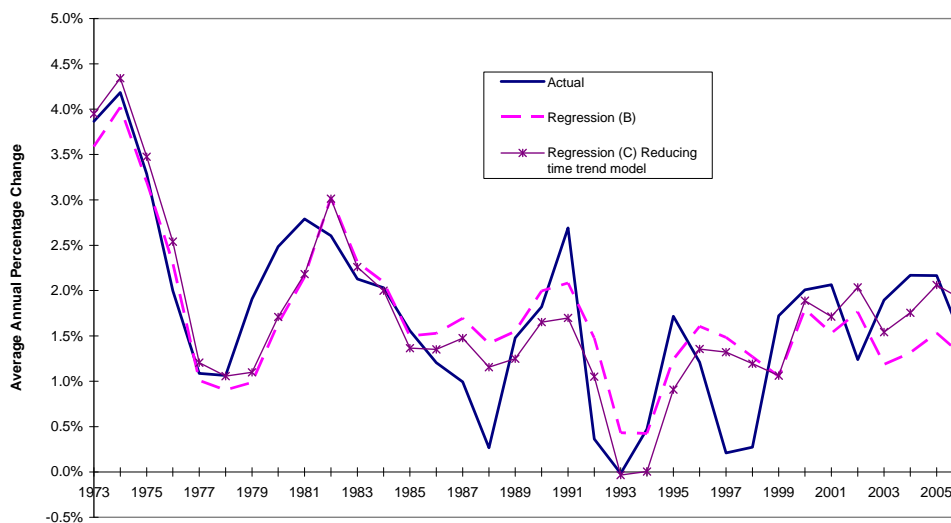
% change in cars/capita = % change in GDP/capita x 0.52 (Equation 3.1)

+ % change in car price index x (-) 0.18

+ 2.6% - (year-1973) x 0.13% {only included if positive}

The resulting regression (C) has an improved r^2 of 0.71 compared with an r^2 of 0.64 for regression (B). Figure 3.2 shows the actual cars per capita and modelled cars per capita. As shown the reducing time trend model (regression (C)) performs well when compared with regression (B) and the actual data.

Figure 3.2 Regression of three-year moving average of changes in real GDP/person and real car price against cars/person 1973–2006



3.1.5 New Zealand car ownership forecasts

The approach described above has been applied to developing a series of national New Zealand forecasts of car ownership per capita on the following basis:

- starting from the 2006 estimate of cars per capita, from the TRC figures, as adjusted (0.577 cars per capita)
- application of 'low', 'medium' and 'high' growth projections based on published forecasts for GDP and the regression analyses undertaken and plausible ranges for trends in GDP per capita and car price
- constraint of the 'low' and 'high' saturation levels as defined earlier.

Table 3.4 shows the inputs to the three sets of growth projections.

Table 3.4 Inputs to growth projections

Input	Annual change %		
	Low growth	Medium growth	High growth
GDP/capita ^(a)	+ 0.5	+ 1.5	+ 2.0
Car price index	+0.5	0.0	-1.0

^(a)Between 2007 and 2012 the actual Treasury forecasts for GDP/capita growth have been used (for all three scenarios).

The *Half year economic & fiscal update 2007*, produced by the Treasury, provides forecasts for GDP growth per capita until 2012. The forecast growth ranges from +0.5% to +2.0% with an average of +1.5%. By way of comparison, over the 36-year period 1970–2006 GDP per capita grew on average +1.8% per year.

Over the 36-year period 1970–2006 car prices fell on average by 1.1% per year. However, the decline in car prices is unlikely to continue at this rate for the following reasons:

- Some of the reduction of real car prices has been the result of one-off changes, such as the removal of import tariffs.
- The government has recently imposed stricter rules on the maximum age of imported vehicles, meaning that imported Japanese vehicles could be more expensive in the future.
- Growing environmental awareness is likely to lead to tougher standards and new technologies being required for vehicles, which could result in higher car production costs. With higher oil prices, as well as growing environmental awareness, there will be greater development of alternative fuel source vehicles (rather than the cheaper refinement of the existing petrol engine).

Based on these projections and the 2006 car ownership level, table 3.5 and figure 3.3 show projected car ownership levels up to year 2041, indicating that economic conditions and car prices are predicted to have a significant bearing on future car ownership.

Under these estimates, if growth were to continue according to the projections shown, eventually the postulated saturation levels would be reached. For instance, the 'high growth' projection line reaches the lower saturation level in about 2021 and the higher saturation level in about 2031.

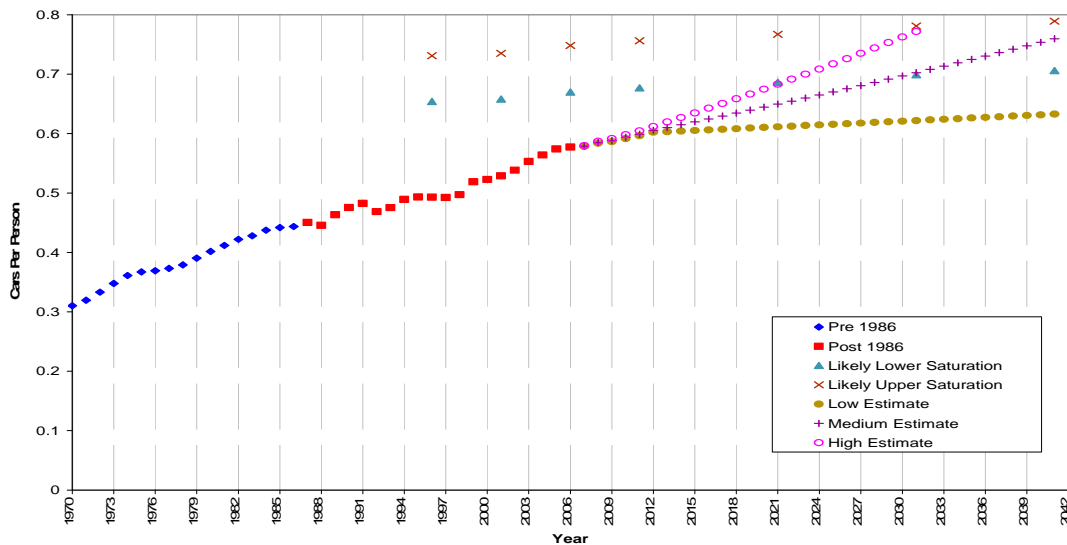
The Booz aggregate model is based on using developed elasticities to predict the change in car ownership. A disadvantage with this model form is that it does not model the ‘tailing off’ that might be expected prior to reaching saturation levels (as happens when an s-curve is used). In practice, therefore, while not shown in figure 3.3, a tailing off of growth for these projections is expected prior to the reaching of saturation levels. However some researchers (eg Romilly et al 1998) have argued that car ownership does not form a s-curve type trend in any event.

Table 3.5 Estimates of cars per capita to 2041

Year	Low growth	Medium growth	High growth
2006	0.577	0.577	0.577
2011	0.596	0.599	0.604
2016	0.606	0.625	0.643
2021	0.611	0.649	0.683
2026	0.617	0.675	0.726
2031	0.622	0.702	0.772
2041	0.633	0.760	0.789*

* Capped at the high estimate of saturation

Figure 3.3 Estimates of car ownership in New Zealand until 2041



3.2 Comparison with other New Zealand model forms

The Booz aggregate model described above has been compared with the two other model forms adopted in New Zealand:

- the vehicle fleet emissions model (VFEM) car ownership equation (MoT)
- the Tauranga transportation model (TTM) car ownership equation (Beca).

The forms of these models are as follows.

VFEM car ownership model:

$$cars / head = \frac{S}{(1 + e^a \cdot e^{bt})} \tag{Equation 3.2}$$

where:

- t = the year
- a and b = constants
- S = saturation level of car ownership

TTM car ownership model:

$$cars / head = \frac{S}{\{1 + a \cdot e^{b \cdot T} \cdot G^c \cdot CP^d\}} \tag{Equation 3.3}$$

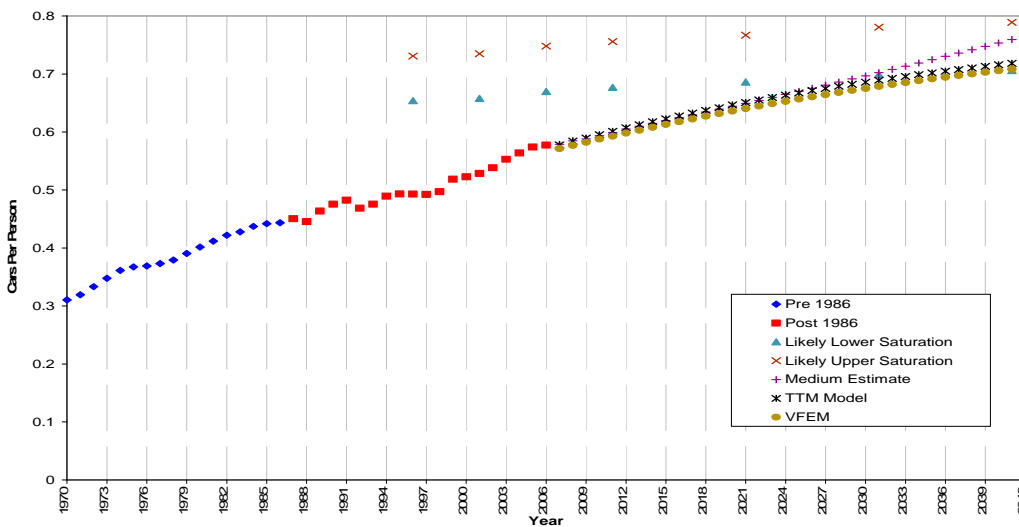
where:

- T = the year (eg 2007)
- G = GDP/capita
- CP = index of car prices
- a, b, c and d = constants
- S = saturation level of car ownership

The above models have been re-calibrated using the same data as used for the Booz aggregate model and adopting the same upper saturation ratio of 0.789 (in 2041).

Figure 3.4 shows the predictions from these equations compared against the aggregate elasticity model. As shown in this figure, the three models perform in a similar manner between 2007 and 2030 (approximately). Beyond 2030 the Booz aggregate model has a higher car ownership rate as it does not model the ‘tailing off’ that is expected to occur as car ownership approaches saturation.

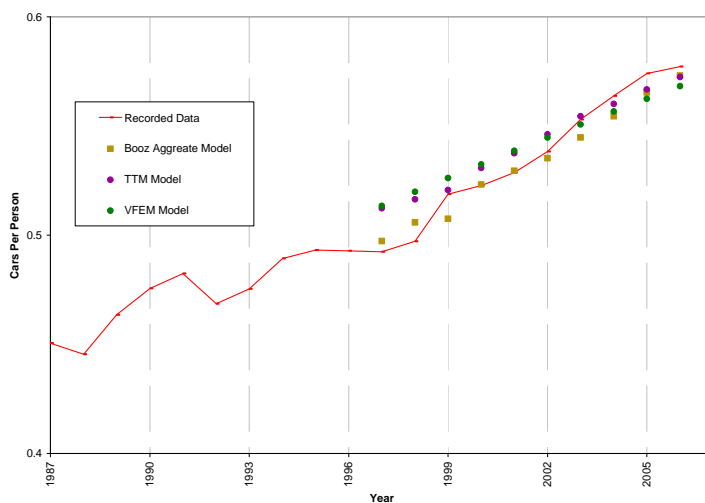
Figure 3.4 Comparison of equations against aggregate elasticity model



3.2.1 Prediction comparison: 1997–2006

In order to compare the performance of the three models, particularly in the short term, the three models were re-calibrated using data from 1970 to 1996. The predictions from these models for the 10-year period between 1997 and 2006 (inclusive) were then compared against actual car ownership data. The results are shown in figure 3.5 below. As shown, all three models appear to provide reasonable estimates of car ownership over the relatively short-term 10-year period. However, the Booz aggregate model more closely replicates the trend in car ownership over this period.

Figure 3.5 Comparison of model predictions 1997–2006



3.3 Conclusions

The following key conclusions have been made from the results presented in this section.

- The current level of car ownership in New Zealand, approximately 0.58 cars per capita, is below the estimated saturation level of car ownership. The current saturation levels are estimated to be in the range 0.67 cars per capita (lower) to 0.75 cars per capita (upper). By year 2041 the saturation level is predicted to increase, due to changes in age distribution, to between 0.71 cars per capita (lower) and 0.79 cars per capita (upper).
- Elasticities of GDP per capita and car price index can be used to predict future changes in car ownership (Booz aggregate elasticity model), particularly in the short to medium term. These appear to be a strong set of relationships.
- Using the Booz aggregate model under the 'high' scenario, car ownership could reach the lower estimate of saturation by approximately 2021.
- The aggregate elasticity model appears to perform better than the other examined aggregate models in the short-term (< 10 years). Over the medium term (10–20 years) the three models perform in a similar manner. In the longer term (>20 years) it is likely that the aggregate elasticity model will not perform as well as the other model types as it cannot replicate the 'tailing off' of car ownership growth that is likely to occur as saturation is approached
- Economic conditions and car prices are predicted to have a significant impact on future car ownership.

There is considerable uncertainty over factors that could have a significant impact on car ownership. For example it is unlikely that the real downward trend in the car price index will continue. The ability to forecast future car ownership is dependent on the ability to accurately forecast changes in GDP and car prices.

4 Development of policy and functional requirements

4.1 Car ownership and use 'needs' survey

A survey was developed as part of the scoping for this project to examine current and future uses of car ownership and use data, current sources of such data and possible features that might be included in the development of a New Zealand modelling methodology.

Members of the steering group and peer reviewers were given the opportunity to comment on the survey, with their suggestions being adopted by the study team.

The survey was distributed by email, and respondents were given around three weeks to reply. By the end of the allotted timeframe only 50% of the final sample had been returned and so respondents were given the opportunity to respond within the following week.

Responses were collated within a spreadsheet, and various statistics were developed.

4.1.1 Respondents

The survey was initially sent out to 26 individuals from 16 organisations. Two suggestions were made by the peer reviewers: the first was to include consultancies within the sample, and as such five consultancies were contacted; the second was to include Australian practitioners; however, it was felt that given this was a New Zealand needs survey Australian views would add little.

It was made clear in the survey preamble that the views given by the respondents were to be taken as their individual views, and not necessarily the views of the organisation they represented. As such, the conclusions drawn from this survey do not necessarily reflect organisational needs.

Where the survey was sent to a number of respondents within the same organisation, some respondents decided to pool responses together as one. By the end of the survey window, 17 responses were obtained representing the view of 22 individuals from 15 organisations. The following organisations took part in the survey:

- Land Transport NZ
- Ministry of Transport
- Transit NZ
- Ministry of Economic Development
- The Treasury
- Automobile Association
- Auckland Regional Transport Authority
- Auckland Regional Council

- Greater Wellington Regional Council
- Christchurch City Council
- five consultancies.

4.2 Survey results

4.2.1 Current sources of car ownership and use data

Respondents were asked to list their current sources of historical and forecast data for car ownership and use. The responses have been categorised into broad sources, with the number of times the source mentioned recorded. Note that many respondents recorded more than one source for their car ownership and use data. The top five sources are shaded.

Table 4.1 Sources of car ownership and use data

Source	Number of times recorded	Percentage of responses
Statistics New Zealand (including census)	12	71%
Transport Registry Centre	5	29%
Regional household travel survey	5	29%
Third party publications	4	24%
Transport models	4	24%
Traffic count data	3	18%
Ministry of Transport HH travel survey	2	12%
Motor Industry Association (MIA)	1	6%
Membership data	1	6%
Fuel sales/road user charges (RUC)	1	6%

The most significant source for car ownership and use data was Statistics NZ, and in particular its census car ownership data (journey to work data was also mentioned). Motor vehicle registration data and regional household travel surveys were also frequently mentioned. Transport models (such as the VFEM and regional transport models) were mentioned by four practitioners, while others referred to third party publications for source data. It should be noted that transport model outputs are in effect a secondary data source as they are built on other data sources.

4.2.2 Current uses of car ownership data

Respondents were asked to list their current uses of car ownership and use statistics. Many of the answers were varied, and as such were allocated into broad categories of usage. There were significant overlaps between categories; for example, many respondents used car ownership data in transport models, but these models were in turn used to provide inputs into funding, policy, planning and monitoring functions.

Table 4.2 Current uses of car ownership data

Current uses	Number of times recorded	Percentage of responses
Policy analysis	10	59%
Transport models	7	41%
Evaluation	3	18%
Funding/value for money	2	12%
Project planning	2	12%
Monitoring	2	12%

The three most stated uses of car ownership and use data were for policy analysis, and for use in transport models and in project evaluation.

4.2.3 Future uses of car ownership data

Respondents were asked what their future uses of car ownership and use data would be if there was a source that met their needs. A certain amount of interpretation of the responses has been undertaken by the researcher to categorise them into broad themes.

Table 4.3 Future uses of car ownership data

Future uses	Number of times recorded	Percentage of responses
No change in requirement	8	47%
Improve/update transport models	3	18%
Improve spatial understanding	3	18%
Better understanding of usage drivers	2	12%
Impact of new technologies	2	12%
Impact of changes in fleet mix	2	12%
Improve performance monitoring	1	6%

For many, the current data sources met their anticipated future needs. Some responses highlighted better data as a source for improving and updating transport models. Others mentioned the identification of spatial (geographical) differences as a potential future use of an improved modelling methodology.

4.2.4 Potential features of future car ownership model

Respondents were asked to provide a priority ranking for potential features of a car ownership and use model. These features were grouped into the following categories:

- modes
- level of geographic context
- forecasting horizon
- vehicle characteristics

- policy measures
- possible outputs
- other features not included in this list.

Rankings were given for 'not relevant', low, medium and high priorities, and converted into scores using a scale 0 (not relevant) to 3 (high priority). Respondents were also given the opportunity to comment further.

Average scores have been provided for each feature, with those obtaining a score higher than 2 (on average, better than medium priority) shaded. Variations in response scores are also provided (standard deviation) to indicate a large variety of priority views between respondents.

4.2.4.1 Modes

Respondents were asked to provide a priority ranking for private cars, motorcycles and light commercial vehicles (LCVs). Almost all respondents gave private cars a high ranking, with many giving the same ranking to LCVs. Motorcycles were seen as less of a priority and, as one respondent put it 'are only of interest when considering safety issues'. Respondents suggested there should be a clear distinction between private and company-owned cars (available for private use). Heavy commercial vehicles were also mentioned; however, they are outside the scope of this study.

Table 4.4 Priority modes

Modes	Average response	Variation in response
Private car	2.94	0.24
Light commercial vehicle	2.47	0.72
Motorcycle	1.47	0.72

Private vehicles (including segmentation into private and company ownership) and LCVs are an important part of a car ownership forecasting methodology.

4.2.4.2 Geography

Respondents were asked to provide a priority ranking for the geographical scope of a car ownership forecasting methodology. Car ownership at a regional level had the highest ranking and most consistent level of responses, and at a local level the lowest ranking and largest variation.

Table 4.5 Priority geography

Geography	Average response	Variation in response
National	2.41	0.87
Regional	2.71	0.47
Local	2.29	0.99

All geographic contexts had a high score, highlighting that any car ownership methodology would need to have the ability to be applied at all spatial levels.

4.2.4.3 Forecasting horizon

Respondents were asked to provide a priority ranking of the forecasting horizons important to them. Forecasting within the next 25 years was clearly the most important timeframe, with 5/10/25 years all

providing scores significantly greater than 2. Forecasting out to 50 years received a more mixed priority ranking, with some respondents highlighting the significant amount of uncertainty associated with this timeframe.

Table 4.6 Priority forecast horizon

Horizon	Average response	Variation in response
5 years	2.56	0.63
10 years	2.76	0.44
25 years	2.50	0.61
50 years	1.47	0.87

The survey results indicated that the modelling methodology needed to perform well in the short to medium term (within 25 years). While it should have the ability to forecast further out beyond 25 years, less resources should be put into this.

4.2.4.4 Vehicle characteristics

Respondents were asked to provide a priority ranking for some of the vehicle characteristics that a forecasting model could capture. There was less consensus on the importance of each of these characteristics, as indicated by the larger variation in values. Fuel type (both current and future) and fuel efficiency were very important on average. Also, the split between private and business use as well as the level of car ownership (first/second/third car in household) were important. Finally, fixed and variable car costs also had a high ranking; this finding is consistent with the high ranking in the policy measures.

Engine size, vehicle weight or age, new or second-hand, or used import were not seen, on average, as important distinctions. Many respondents saw vehicle safety attributes as not being relevant to their work.

Respondents' comments included:

- fuel type distinction was required for emissions modelling
- hybrids were already here, but they were not captured very well in the Motor Vehicle Register
- future fuel efficiency, rather than fuel types, might be more useful given uncertainties about future fuel types.

Table 4.7 Vehicle characteristics

Characteristics	Average response	Variation in response
Current fuel types	2.29	0.77
Private/business use	2.24	0.90
Costs	2.13	0.89
Fuel efficiency	2.00	0.94
Future fuel types	2.00	0.79
First/second/third car in household	2.00	0.71
Age	1.76	1.15
Engine size	1.53	0.94
New/second-hand	1.38	1.02

Characteristics	Average response	Variation in response
NZ new/imported	1.38	1.15
Weight	1.19	0.91
Safety	1.06	1.12

The survey results indicated that the modelling methodology needed to segment vehicles by fuel type and efficiency and split between private and business.

Also it would be desirable to include segmentations for fixed and variable costs and to determine whether the vehicle was the first, second or third in the household. However, the inclusion of many segments would make data collection and modelling more difficult. It was therefore important to select the characteristics that were most important to practitioners.

4.2.4.5 Policy measures

Respondents were asked to provide a priority ranking for some of the policy measures that a car ownership and use model could be sensitive to. It should be noted that there is possible overlap between some of these measures. For example, sensitivities to subsidies and taxes could be represented in a model that included fixed and variable car costs. Road user changes could also be included in a similar way.

Of all the policies presented, the inclusion of fixed and variable costs, fuel taxes, sensitivity to income, road user charges, sensitivity to the level of public transport supply, and to a lesser extent sensitivity to subsidies and taxes were all seen as being very important. Lease market policies, scrappage subsidies, penetration of future vehicle types and import restrictions were all seen as less important.

Table 4.8 Policy measures

Policy	Average response	Variation in response
Fuel taxes	2.35	0.93
Public transport supply	2.31	0.95
Road user charges	2.24	0.83
Fixed/variable costs	2.12	0.78
Income effect	2.06	0.90
Subsidies/taxes	1.94	0.90
Future vehicle	1.73	0.88
Import restrictions	1.60	0.91
Scrappage	1.44	0.96
Lease market	1.24	0.83

The survey results indicated that the modelling methodology should focus on being sensitive to fixed and variable car costs, and in particular include sensitivities to fuel taxes and road user changes. The methodology also needed to be sensitive to changes in income and the supply of public transport.

4.2.4.6 Outputs

Respondents were asked to provide a priority ranking for the types of outputs that could come from a car ownership and use model. All outputs presented (apart from government revenue) were universally supported with average scores over 2. The most important outputs related to cars per household and

vehicle use; and it should be recognised that all other outputs could be constructed by knowing both of these quantities and applying average factors to them.

Respondents commented that some of these outputs needed to be linked with the vehicle characteristics previously identified. In particular:

- vehicle use and fuel consumption could be segmented by vehicle type, geography, private or company ownership, or household structure
- emissions could only be readily estimated by including the vehicle fuel/age mix.

Table 4.9 Outputs

Outputs	Average response	Variation in response
Vehicle use	2.65	0.61
Cars per household	2.53	0.51
Cars per person	2.41	0.62
Fuel consumption	2.41	0.62
Emissions	2.35	0.93
Government revenue	1.59	0.87

The survey results indicated that the modelling methodology needed to be able to provide vehicle numbers, use, emissions and fuel consumption measures and to a lesser extent government revenue. Segmentation of these outputs should relate directly to the vehicle characteristics.

4.2.4.7 Other features

Respondents were given the opportunity to list other features that were not included in the survey list and to apply priority rankings to them. Some of these features were:

Vehicle characteristics

- relationship of vehicles to household structure and demographic factors (high)
- segmentation by income (high)
- consumer preferences (high)

Policy

- links to local public transport (PT) penetration, regional PT/TDM spending (low-high)
- land-use impacts – housing/development density, mixed land use (low)

Outputs

- fuel efficiency per km (high)
- cost of ownership over time (high)
- Impacts of all-electric vehicles on electricity demand (medium).

4.2.5 Other comments

Respondents were given the opportunity to provide other comments on the survey. These comments have been simplified into the following general themes:

- methodology needs to include key predictors that are easily definable and measurable both now and in the future
- an emphasis on what possible policy changes affect car ownership and use (or vice versa), and the impacts on future transport energy demands and emissions
- the importance of saturation of car ownership, and whether this is a realistic assumption
- motorcycle substitution effects under various policy options – however, there appears to be little interest from the survey in models that relate to motorcycles
- interest in a vehicle purchasing model, including preferences for various classes of vehicles – however, there appears to be little interest from the survey in models that relate to purchasing and scrappage.

4.3 Conclusions

A car ownership and use modelling needs survey was conducted with transport practitioners in New Zealand. The purpose was to examine the needs of users of car ownership and use data. Conclusions drawn from this survey will be used as an input to the development of a New Zealand modelling methodology

Many respondents felt that the current level of data met their needs and this will need to be considered when decisions are made about whether to progress development of a New Zealand modelling methodology. Some identified improvements in transport models and geographical differences in car ownership and use as being advantages of an improved modelling and forecasting methodology.

It can be concluded from the survey, that a car ownership and use modelling methodology should ideally have the following features:

- segmented by private vehicles (private and company ownership) and LCVs
- can be applied to national, regional and local contexts
- should focus on forecasting within a 25-year horizon
- vehicles segmented by fuel type/efficiency and split between private and business
- should be sensitive to changes in fixed and variable costs, and in particular changes in fuel taxes and road user charges, changes in income and the level of PT supply
- outputs should include vehicle numbers, usage, emissions and fuel consumption measures and to a lesser extent, government revenue.

It is important to note that the more segments or characteristics required, the more the data collection and complexity of modelling will increase. It is therefore important to select the segments or characteristics that are most important.

Respondents were also given the opportunity to list other factors that had not been included. A common theme was the link between car ownership and household structure and demographic factors. The impact of PT and TDM policies was reinforced, as well as the possible impact of land-use changes.

There were some areas where there was a strong priority for a particular output, but less of a priority for some of the inputs that might affect that output. An example of this was the desire to predict fleet emissions while classifying engine size as a lower priority. For these situations, global factors would likely be used but with the possibility to segment in the future.

The features identified here will be used to determine a possible car ownership and use modelling methodology for New Zealand.

5 Review of New Zealand modelling practices

5.1 National modelling methodologies

Currently there is no national land transport model for New Zealand. However, in the late 1990s, the MoT developed a vehicle fleet emissions model (VFEM). The VFEM includes future projections of vehicle fleet mixes and usage. The outputs from this model are used for policy developments in New Zealand.

5.1.1 MoT vehicle fleet emissions model

5.1.1.1 Overview

The technical report *Vehicle fleet emissions model: New Zealand vehicle fleet database and model development* (MoT 1998) provides an outline of the design of the VFEM.

The VFEM is a dynamic emissions inventory for the New Zealand road vehicle fleet and is used to examine future scenarios of fleet turnover and evolution. The model is based on the following basic structure:

$$\text{Vehicle numbers} \times \text{utilisation} \times \text{emission rate} = \text{quantity of emissions}$$

Although the basic structure is simple, there are a number of complex methodologies and projections behind each of the three terms.

For this research project, the relationships behind the 'vehicle numbers' and 'utilisation' terms from the above equation are relevant. The 'emission rate' is specific to the estimation of vehicle emissions, as opposed to car ownership and traffic forecasting and as such is not relevant to this research.

The model includes a large database of historical data as well as projections of vehicle fleet characteristics, including disaggregation of the vehicle fleet by vehicle type, ownership, road and driving conditions and geographic characteristics.

5.1.1.2 Model details

Mode of operation

Vehicle fleet profile

Vehicle types are classified into a number of groups, including separate groups for passenger cars (also subdivided into three engine size groups) and light commercial vehicles (similarly subdivided). Vehicle types are also classified by:

- age
- type of fuel
- ownership (domestic or business)
- country of origin
- whether imported, new or used.

The data is utilised in a fleet turnover model, as factors such as the age of a vehicle will affect emissions.

Vehicle utilisation

The technical report defines vehicle utilisation as 'the amount of travel carried out by the vehicle over a period of time and the conditions under which the travel occurs, such as the road type and driving conditions'. The VFEM uses kilometres travelled per year as the measure for vehicle utilisation. Utilisation is classified by vehicle type, size, age and ownership.

Vehicle utilisation has been based on analysis of the TRC records. In general the data shows a reduction in vehicle use with age. The data also shows higher vehicle use for diesel vehicles compared with petrol vehicles.

For cars, vehicle utilisation is derived from the vehicle fleet size and kilometres of travel per head of population which in turn is derived from vehicle ownership and fuel prices. As such, increasing real prices of petrol will reduce the rate of growth in vehicle utilisation. This is discussed in further detail later in this section.

Other factors

The VFEM includes other factors which influence vehicle emissions:

- fuel consumption and carbon dioxide emissions
- road types and driving conditions (for emission calculations)
- corridor flow profiling (for emission calculations)
- emission types and rates.

The VFEM forecasts to the year 2040.

Projection methodology

The following sections describe how the various factors in the VFEM, such as population growth, have been derived (historic trends and projections).

Population growth and age distribution

Population growth and population age distribution have been based on forecasts undertaken by Statistics NZ. There are three factors to population changes – fertility, mortality and migration – each with high, medium and low projections. The base case for the model is medium fertility, medium mortality and low migration.

Population changes are also considered on a region-wide basis, based on historic regional changes between 1981 and 1991.

Vehicles per capita

A key component of the model is the forecast of changes in vehicles per head of population (ie per capita). Historically vehicle ownership per capita has been growing; however, in the future it is expected to reach saturation in New Zealand (and other developed countries).

There is no universal agreement about the ultimate saturation level. Some consider that saturation will only be achieved when every person of driving age owns a car (which currently is approximately 65% of the population). Others consider it is likely to be lower than this level.

The VFEM has adopted a Tanner model, based on previous work undertaken by the Ministry of Energy in the 1980s. The model has been recalibrated, using more recent data. It was found during the calibration that inclusion of GDP per capita was of little significance and as such was excluded.

The resulting equation for the rate of car ownership in the VFEM is:

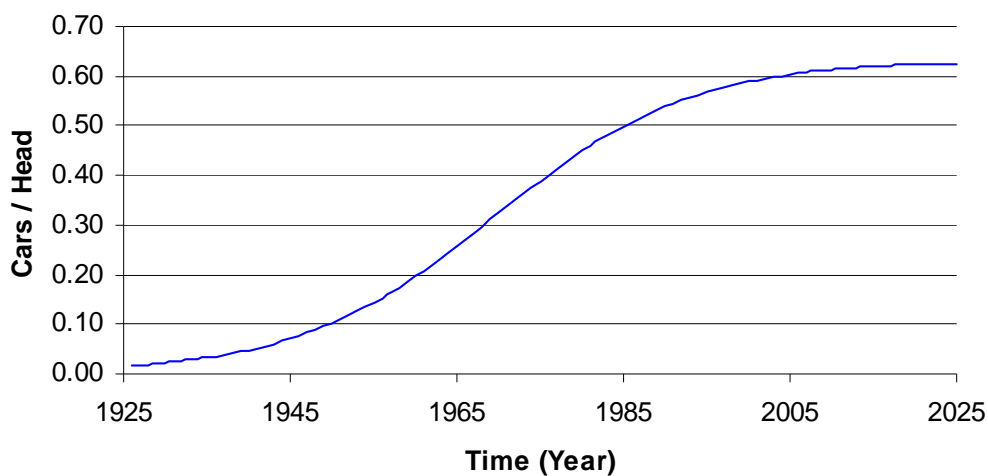
$$Car + LCVs \text{ per head} = Yt = \frac{0.633}{(1 + e^{-0.0476} \cdot e^{-0.0847t})} \quad (\text{Equation 5.1})$$

Where:

t = the number of years from a base date of zero in 1970

The only explanatory variable in the above equation is time. Further in this equation the saturation level of cars plus light commercial vehicles per head is 0.633 or 63%. Figure 5.1 shows a graphical representation of the above equation. The 'S' shape to the curve shows that as cars per capita near saturation, the rate of growth decreases.

Figure 5.1 Model of cars/capita over time



Vehicle utilisation

The total amount of vehicle kilometres travelled (VKT) is not solely related to the number of vehicles in service, ie there is variation in the annual VKT. The possible variables which influence car use include:

- real GDP
- real GDP per capita
- number of vehicles
- vehicle ownership
- real fuel price
- other motoring costs.

The approach adopted in the VFEM is to assume annual utilisation remains constant for non-private car VKT (eg company cars, buses and goods service vehicles). For private vehicles, which make up the largest component of VKT, a multiple linear regression analysis was used to find a suitable model.

The resultant equation (with an R² of 0.91 showing a good representation) has VKT per capita as the dependent variable with household cars per capita, real petrol prices and real GDP per capita as dependent

variables. The details of the variable values of the vehicle utilisation equation were not provided in the technical report.

An outcome of the VKT projections is a levelling off of car kilometres per capita as a result of vehicle ownership nearing saturation in approximately 2010. It is noted that the model assumes that the real price of petrol remains constant in future years. This assumption (made in 1998) was based on the reduction in real petrol prices in the decade up until 1998, although significant petrol price increases in 2006–07 draw into question whether this is still a realistic assumption.

Other factors

The VFEM includes other projections which are used to determine vehicle emissions:

- vehicle fleet turnover
- vehicle new registrations
- road space provision and traffic density effects
- vehicle emissions technology evolution and emission assigns.

5.1.1.3 Revision to model

It is understood that the car ownership equation used in the VFEM model has been revised and now only predicts cars per capita (as opposed to cars and light commercial vehicles). The adopted saturation level is now 0.65 with the other equation co-efficients also updated. The base year of the model is now 1978.

5.1.1.4 Model strengths and weaknesses

The following table provides a summary of what is considered to be the model's key strengths and weaknesses (based on the reviewed information):

Table 5.1 VFEM car ownership model

Strengths	Weaknesses
Takes into account saturation	Does not take into account changes in population age distribution
Can provide national and regional predictions	Does not take into account economic changes (eg GDP/person)
	Is not sensitive to household structure changes
	Is not sensitive to PT accessibility
	Is not sensitive to car purchasing costs

5.2 Regional modelling methodologies

This section reviews the major current car ownership modelling methodologies that have been adopted at a regional level in New Zealand. These methodologies mostly form part of large regional transportation models; in particular regional multi-modal models in Auckland and Wellington, and road-based models in Christchurch and Tauranga.

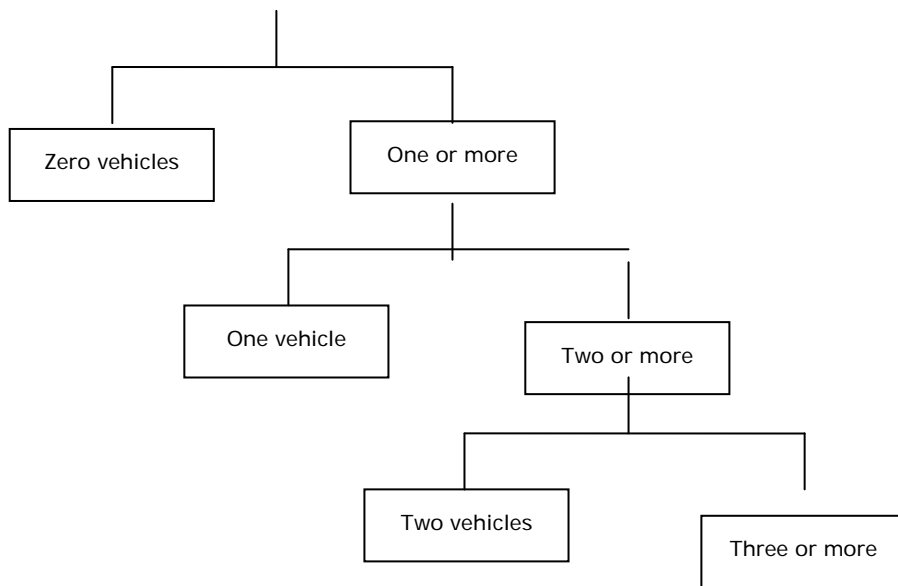
5.2.1 Auckland regional transport model

Information has been provided by the Auckland Regional Council on the modelling of car ownership for regional transportation forecasting in the Auckland regional transport (ART2) model.

The ART2 model is a conventional four-stage transport model implemented using Emme/2 modelling software; the four-stages being trip generation, trip distribution, mode split and assignment functions. The ART2 model has been continually updated since 1991 (usually in conjunction with census years) to provide better estimates of base year data, although the model structure has remained broadly the same over the last 15 years. It currently provides projections to 2021. The ART2 model is being replaced by the ART3 model following a significant update but at the time of this research the model was not available for review.

Car ownership forecasting provides an important function within the model structure, and forms part of the trip generation stage. Car ownership is determined on a household basis by estimating the proportion of households within a given area that own a certain number of cars. This is achieved through a series of binary choices – the first being the probability of owning zero versus more than one car. The second choice is then represented as the probability of owning one car versus more than one car given the household owns at least one car. The third choice then determines the probability of owning two cars versus three or more cars given they own at least two cars. The series of binary choices can be represented as a nested logit model with the nest as given in figure 5.2 below.

Figure 5.2 ART vehicle ownership structure



Each series of binary choices are made through the use of a logit equation with the following structure:

$$p_i = \frac{e^{-U_i}}{(1 + e^{-U_i})} \tag{Equation 5.2}$$

Where:

- p_i =the probability of owning more than i cars
- U_i =the utility of owning more than i cars

The level of car ownership within an area is therefore dependent on the utility within that area. The utility function is a linear equation that has been calibrated using vehicle ownership patterns from around 10,000 Auckland households, and initially included the following household variables:

- the number of adults
- the number of fulltime/part-time employed, and 'not working' adults
- the number of children
- the number of school children/infants
- income
- accessibility to employment by both car and public transport (as calculated using an accessibility measure which includes a weighted measure of travel costs and employment).

Utility functions were calibrated for each of the three levels of the logit structure. It was found that the main differentiators of car ownership when choosing to own or not own a car (the uppermost level) were the number of adults by employment status (fulltime, part-time or unemployed), household income, and both car and public transport accessibility; with income and employment being the biggest factors.

When choosing to own one or more cars, given they already owned a car, employment status, income and public transport accessibility were all explanatory factors. Interestingly, car accessibility was not found to be significant and was replaced by the number of children in the household. This suggests that when choosing to get an additional car, the existence of children in the household is a differentiator. The main explanatory factors were employment status and income.

When choosing more than two cars, the explanatory factors were employment status and income only, with income being the most significant factor. Finding income to be a significant factor at higher levels of car ownership is consistent with international evidence.

Performance of the car ownership models, presented as a comparison of observed versus modelled household ownership by level (zero, one, two or three plus), showed the methodology gave a broadly consistent view of existing car ownership levels, with a few outliers for very low (zero) and very high (three plus) levels of ownership.

Future vehicle ownership (from a base year of 1991) assumes average real household incomes increase by 17% between 1991 and 2001, 20% between 2001 and 2011, and 20% between 2011 and 2021. Model constants were adjusted for future years as well as the number of cars in three plus households, although the basis for this adjustment is not entirely clear.

The ART2 model documentation provides car ownership forecasts to 2021, which have been reproduced in table 5.2. The forecasts indicate a continuing increase in car ownership levels, as illustrated by the reduction in the proportion of zero and one-car households, and subsequent increase in two and three-car plus households.

Table 5.2 ART2 model car ownership by year

Year	Number of households					Proportion of total				Cars
	Zero	One	Two	Three+	Total	Zero	One	Two	Three+	
1991	38,167	125,118	95,085	38,075	296,445	13%	42%	32%	13%	458,069
2001	38,000	140,080	104,189	62,900	345,169	11%	41%	30%	18%	642,830
2011	30,000	140,100	140,855	77,500	388,455	8%	36%	36%	20%	762,810
2021	26,000	149,412	170,353	86,772	432,537	6%	35%	39%	20%	865,841

The ART2 car ownership model predicts that vehicles per capita will increase from 0.52 in 1991 to 0.70 in 2021.

In summary, the ART2 model uses a series of binary choices to form a decision tree to determine probabilities of different levels of car ownership within a given area. The probabilities are determined primarily by the employment status of adults and average income of households. At lower levels of car ownership, accessibility to employment by car and public transport is also a determining factor. The decision to get an additional car when one is already owned is influenced by the existence of children in the household.

5.2.1.1 Model strengths and weaknesses

The following table provides a summary of what is considered to be the model’s key strengths and weaknesses (based on the reviewed information):

Table 5.3 ART2 car ownership model

Strengths	Weaknesses
Takes into account changes in population age distribution Sensitive to household structure changes Takes into account PT accessibility Sensitive to economic changes (eg income)	Does not take into account saturation Is not sensitive to car purchasing costs Does not provide national predictions or consistency

5.2.2 Wellington transport strategy model

Information has been provided by the Greater Wellington Regional Council on the modelling of car ownership undertaken in the Wellington transport strategy model (WTSM).

The history of the WTSM dates back to the 1980s, when a model was calibrated based on a household interview survey conducted in 1988 using the Tracks software package. In 1996, the model was converted to the Emme/2 software package and between 1996 and 2000 a number of model updates were undertaken, including recalibration based on new census information and additional model functionality. In 2003, the model was respecified and rebuilt based on a new household survey. A further update is currently being undertaken based on the 2006 census which will also include some changes to model functionality.

5.2.2.1 1996–2000 model

It is understood that throughout its history, the form of the car ownership model in WTSM has changed. In particular, the 1996–2000 update included a significant respecification of the car ownership model.

The 1996–2000 model is detailed in the *Wellington area transport strategic model report* (Booz Allen Hamilton 1999).

Trip generation is based on the characteristics of households (18 household categories). Households are categorised by:

- number of adults, children, infants and old age pensioners
- number of employed/unemployed adults

- car ownership.

Future population forecasts are able to take into account issues such as:

- an ageing population
- declining numbers of children.

Prediction of car ownership levels

The adopted definition for car ownership is the number of cars that are owned and consistently available to members of that household. The model had three levels of car ownership being no vehicle, one vehicle and two plus vehicles.

The form adopted for the car ownership model expressed the probability of owning no vehicle, one or two plus vehicles as a function of:

- household category
- private and public transport accessibility
- income.

The key steps in the process were as follows:

- Utility functions were calculated for owning a car and owning two or more cars. The utility functions were equations which included average income, income growth factor, public transport accessibility and ratio of PT to car accessibility.
- Based on the utilities, probabilities were calculated for the number of households owning no car, one or two plus cars.
- The probabilities were used to determine the number of households at each level of car ownership by zone.

The above approach is similar to that used in the ART2 model.

Accessibility

In the Wellington region, public transport trips are competitive with private vehicle trips to and from certain areas. The level of accessibility was considered to be a determinant of car ownership levels, particularly for trips to and from employment. The accessibility index was determined from the 1988 model calibration and includes:

- total employment in the zone
- generalised cost between zones for the mode being considered
- measure of sensitivity.

Levels of car ownership

Probabilities are calculated for each household category and zone to obtain the number of households that own a particular number of vehicles. Binary choice equations are used.

Results

The results of the above methodology show future projections that are similar to other studies and models with:

- a decrease in households with 0 cars
- an increase in households with more than one car.

5.2.2.2 2003 Beca/SKM model update

The WTSM was substantially rebuilt in 2003 by Beca Carter Hollings & Ferner (Beca) and Sinclair Knight Merz (SKM). The car ownership model for the transport model is detailed in the report *TN15.1 Car ownership report* by Beca and SKM (final version, dated July 2003) and as at 2008 is still current.

The car ownership model is in three parts. The first part of the model forecasts the proportion of households owning no car, or one or two plus cars in each zone. The second part of the model adjusts the results to match census car ownership statistics for each zone. The final part of the model adjusts future forecasts of the car ownership model to overall predicted figures for car ownership growth, economic growth and car prices.

Each of these parts is discussed in further detail below.

Initial choice models

The mathematical structure of the household car ownership model is as follows:

$$P_m = \frac{S_{mh}}{[1 + e^{(LP_{mh})}]} \quad \text{(Equation 5.3)}$$

where:

P_m is the car ownership probability for model m. m=1 refers to the probability of owning one of more cars, m= 2 refers to the probability of owning two or more cars for the groups of households that own at least one car

S_{mh} is the saturation level for each model which can be a function of the household type h

LP_{mh} is the 'linear predictor'

$$LP_{mh} = \alpha_{mh} \cdot f(I) + \delta_{mh}$$

α is the coefficient of some function of household income I

δ is a constant.

The values vary by model m and household type h.

The above models were calibrated to household survey data.

Census fitting

The above models, which provide estimates of the level of car ownership for individual households, must also be implemented in a way that is consistent with census zones data on car ownership.

To do this, the basic process is as follows:

- The household survey is divided into the same five household types used in the model (eg one adult (employed), one adult (non-employed)).
- Using the census data, for each of the above household types, the range of car ownership probabilities is determined. These are then put into 50 bands of car ownership (minimum to maximum).
- For these bands and for each model, an adjustment factor is calculated to replicate the census data.

Car ownership growth

The report notes that while car ownership is linked to income and household composition (as represented by the above models) there is also a relationship of car ownership to GDP, car prices and time. As such the overall regional car growth is controlled by an externally generated forecast.

The model uses an updated time series model of car ownership growth, based on the work undertaken by Booz Allen Hamilton (see section 3.1.1). This model has the dependent variables of economic growth (GDP) and car prices.

While based on the work undertaken by Booz Allen Hamilton, the model has been updated with more available years of data and recalibrated.

The Booz Allen Hamilton form of the time series model was:

$$\Delta C = \Delta GDP^\alpha \cdot \Delta P^\beta \cdot (1 + \gamma - t \cdot \eta) \quad (\text{Equation 5.4})$$

where:

Δ is the year on year change

C is cars per person

GDP is gross domestic product per person

P is car price

t is the number of years from the start of the period

$\alpha \beta$ are elasticities

$\gamma \eta$ are the time trend and incremental reductions to this time trend

The Beca/SKM approach then applied a log transformation so it approximated a linear equation and could be estimated using linear regression. The calibrated model resulted in similar parameters to the original Booz Allen Hamilton work it was based on.

The predicted growth of GDP and car price trends has been based on trends recorded over the previous 10 years which was a 1.7% increase and 1.8% decrease per annum respectively.

5.2.2.3 Model strengths and weaknesses

Table 5.4 provides a summary of what is considered to be the model's key strengths and weaknesses (based on the reviewed information):

Table 5.4 WTSM car ownership model (2003 update)

Strengths	Weaknesses
Takes into account changes in population age distribution	Does not take into account PT accessibility
Is sensitive to household structure changes	
Takes into account car purchasing costs	
Sensitive to economic changes (eg income)	
Takes into account saturation	
Links regional forecasts to national forecasts	

5.2.3 Christchurch transport model

Information has been provided by the Christchurch City Council on the modelling of car ownership for regional transportation forecasting in Christchurch.

The overall future car availability is based on forecasts of census data. The following table details the car availability projections up to 2021. Details of how these projections were derived were not provided.

Table 5.5 Christchurch transport model car ownership by year

Cars/1000 population	Year								
	1981	1986	1991	1996	2001	2006	2011	2016	2021
National low	400	437	496	540	580	607	625	629	629
National 'most likely'	400	437	496	540	580	611	638	656	669
National high	400	437	496	540	580	620	653	674	686
Christchurch study area	464	488	543	577	599	625	649	664	671

The trip production model requires categorisation of households by vehicle availability as well as life cycle. In the Christchurch model the global car availability (to be precise, the population of vehicles available within the study area for private use) was estimated externally to the model (see above). Furthermore the distribution of these to each zone was also estimated externally in predictions for the future.

The global availability is forecast using projections of population combined with time series based data on car availability per person and alternative scenarios for the level of saturation. Once the number of cars within the study area is known, or estimated, these then have to be distributed across both the traffic zones and between household categories. The Christchurch model adopted a vehicle allocation model to perform this task (given an externally made estimate of the mean availability in each traffic zone). In summary, the revised vehicle allocation model works as follows:

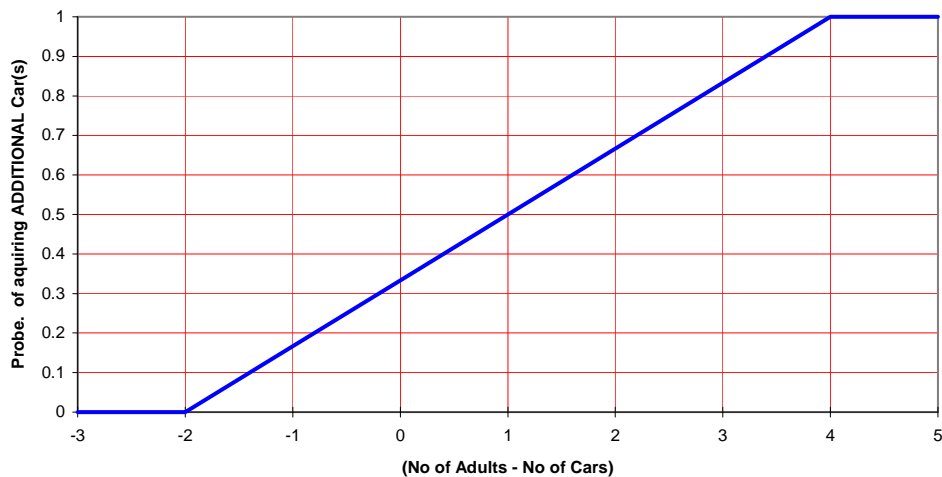
A base-year distribution of households across each of the household categories was made. This was achieved through knowledge of the mean car availability in each zone (across all households). A strong relationship was apparent between this mean availability and the proportion of households in each car-availability category.

As the total households in each household category were known (or could be predicted) and an estimate could be made of the total number which would be in each car-available category (on average) using the

above relationships, then a furness procedure was employed using these column and row totals to estimate individual cells in a 32-cell household/car-availability 'matrix' for each zone.

As the car-availability curves in figure 5.3 are essentially calibrated using 1991 data, the mean performance of the model in this base-year allocation closely matched the observed distribution.

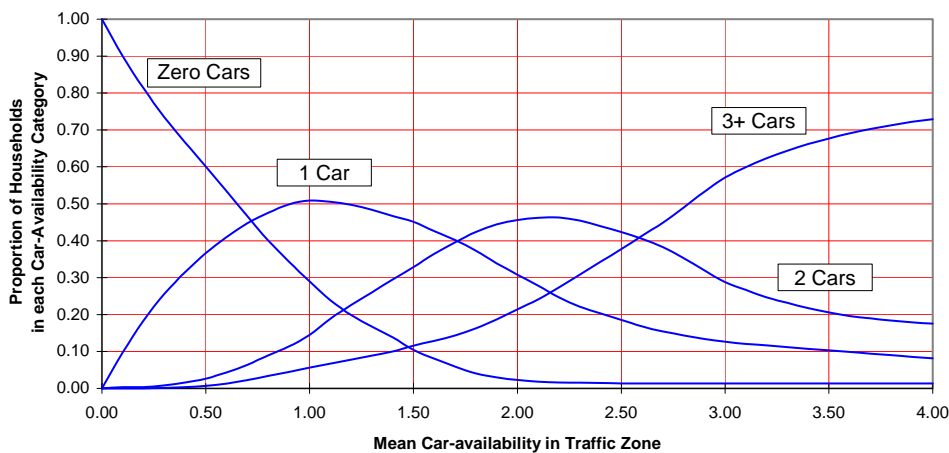
Figure 5.3 Car availability proportions by zone



The key task was, however, to have an allocation model with robust predictive qualities. If the global study area car-available population is known or is predicted (for the future) then the total 'difference' in study area cars available from 1991 could be estimated. These additional cars are then distributed across zones and between households according to the relative probability that any particular household (or rather groups of households) will acquire one or more of the cars.

The relative probability of acquiring an additional car was assessed using an assumed relationship with the number of 'spare' adults in a household - that is the number of adults to the number of cars. Figure 5.4 indicates the relationship assumed between the 'spare adults' and probability of car-acquisition.

Figure 5.4 Car acquisition probability used in allocation model



The above relationship was used, in combination with base and forecast year household distributions, to establish a weighted probability for each zone acquiring any additional cars. This was then used to obtain

the new 'future' mean car availability for each zone. It was then a matter of carrying out a furness procedure on the implied row and column totals, in the same manner as for the base year, to obtain the household category/car availability matrix required for each zone as an input to the next stage of trip production.

The inputs required for the model are base-year data and the future total of cars-available in the study area. The performance of the model was been validated by back projection to 1986 and 1981.

The Christchurch model is currently going through a full re-development using 2006 census and household interview survey data. The upgrade to the model is being undertaken by Traffic Design Group and MVA.

5.2.3.1 Model strengths and weaknesses

The following table provides a summary of what is considered to be the model's key strengths and weaknesses (based on the reviewed information):

Table 5.6 CCC car ownership model

Strengths	Weaknesses
Sensitive to household structure changes	Is not sensitive to economic changes (eg income)
Regional forecasts are linked to national forecasts	Is not sensitive to car purchasing costs
	Does not take into account PT accessibility

5.2.4 Tauranga transportation model

The Tauranga transportation model (TTM) is a strategic transportation model of Tauranga city and surrounds. The model is used as a tool for 'Smartgrowth' which is a programme aimed at developing and implementing a plan for managing growth in the Western Bay of Plenty over the next 50 years.

The car ownership forecasting for the model is detailed in the report *Smartgrowth - car ownership forecasting* (Beca 2003). The TTM uses mean trip rates per car per household to predict future trip movements. There are 16 categories of household car availability and household sizes in the model.

Beca reviewed various methods available for forecasting vehicle ownership. The adopted logistic model includes time, GDP per capita and the car price index. This model was considered to give the best fit to the historical data.

The form of the model adopted was:

$$cars / head = \frac{S}{\{ 1 + a \cdot e^{b \cdot T} G^c CP^d \}} \quad \text{(Equation 5.5)}$$

where:

- T = the year (eg 2007)
- G = GDP/capita
- CP = index of car prices
- a, b, c and d = constants
- S = saturation level of car ownership

This is a similar form to that adopted by the MoT for the VFEM (section 5.1.1.2).

The adopted saturation level of car ownership (S) is 0.75. The adopted saturation level is based on 90% of the driving age population. This is higher than the saturation level adopted by the MoT (of 0.65); however,

Beca considered this value too low, compared with the number of number of people who could hold a driver licence.

The car ownership model is based on national data. As it was unlikely that car ownership rates would vary significantly between regions and regional GDP data was not readily available, it was concluded that a regional model could not be constructed.

Future GDP per capita has been based on analysis of the past 32 years of data and using a linear growth projection.

Analysis of car price index has shown that car prices have reduced over the years, although many of the reductions have come from one-off factors such as the removal of duties. The model assumes a value of 1.0 over the forecasting period (ie no further reductions).

Future trip productions are modelled by multiplying the numbers of households in each category with their trip production rates (which are assumed to remain constant). The future number of households and people in each area has been estimated by Tauranga City Council. The number of future trip productions at the model level is made by factoring the base-year car ownership level with the future car ownership level. For each area, the total number of cars is distributed to future household numbers in 16 categories, taking into account the change in households, persons per household and cars per person. The adopted methodology makes the assumption that growth in vehicle availability is not significantly influenced by geographic, economic or demographic differences. However, higher-density urban zones positioned near public transport could exhibit lower levels of car ownership than other areas.

The overall effect of the car ownership model on the TTM will be to increase trip productions by about 7% in 2051.

The Beca report also notes limitations on the methodology adopted, including:

- As car ownership approaches saturation, additional cars will have less influence on the total kilometres travelled, which implies that trip production rates will decrease.
- The projections are considered suitable for short- to medium-term forecasting.

5.2.4.1 Model strengths and weaknesses

The following table provides a summary of what is considered to be the model's strength and weaknesses (based on the reviewed information):

Table 5.7 TTM car ownership model

Strengths	Weaknesses
Takes into account changes in population age distribution	Is not sensitive to PT accessibility
Takes into account saturation	Is not sensitive to household structure changes
Provides national and regional predictions	
Takes into account economic changes (eg GDP/person)	
Is sensitive to car purchasing costs	

5.3 New Zealand car ownership and use literature

The following sections detail the key findings from the literature review of New Zealand car ownership.

5.3.1 Vehicle availability forecasting model, Travis Morgan (1992)

This project, undertaken for Transit NZ, had two principal objectives. The first was to build a model which would predict total car availability at a national and regional level, and second to build a model which distributed these vehicles among various categories of households. The following is a summary of key outcomes from the project.

5.3.1.1 Past trends and influences on vehicle ownership

A literature review was undertaken as part of the research. Key points included:

- The level of car ownership in New Zealand was approximately half way between the United Kingdom (lower) and United States (higher) and similar to Canada and Victoria (Australia).
- Car ownership per capita had grown steadily over the last 30 years in all countries studied.
- Levels of car ownership in major English-speaking countries were thought to lie in the middle of the s-shaped curve. Statistical analysis had not succeeded in identifying the turning point.

Major influences on the level of car ownership were found to be:

- the general level of economic activity
- real cost of motoring
- PT availability
- household structure
- consumer taste.

The saturation level of car ownership

The saturation level of car ownership per capita was uncertain. Two techniques have normally been adopted: statistical techniques on historical data and examination of the behaviour of relatively high-income earners. It was considered that using statistical techniques was unreliable. Research of the car ownership of high-income earners in the United States suggested that car ownership would peak at around 0.95 cars per adult.

The major influences on the saturation level were from:

- the proportion of the population lawfully able to drive a car
- the proportion of the population unable to drive a car due to physical or mental disability
- the proportion of the population who chose not to own a car (eg due to parking shortages, availability of public transport).

5.3.1.2 Potential modelling approaches

The project included a literature review of approaches to modelling car ownership. An overview of three identified approaches is presented below:

Macro-economic approach

The macro-economic approach uses a time series analysis to relate observed changes in car ownership over time to variables such as population, GDP and the cost of motoring. The advantage of this method is that significant data is not required and that it generally performs well over the short to medium term. The main disadvantage of this approach is that it does not include many of the variables that affect car ownership at the household level.

Micro-economic approach

The micro-economic approach uses analysis of cross-sectional data, usually households. A large number of variables are included, even though some of the variables do not contribute significantly to the explanation of changes. The main disadvantage of this approach is that experience has shown it tends to perform badly over time and underestimates the growth in car ownership.

Cohort processing approach

The cohort processing approach is based on modelling car ownership behaviour of people as they age (ie people exhibit different car ownership characteristics as they age). There are a number of features of this approach that make it attractive, including:

- as cars become a more personal item (as opposed to a household item) it makes sense to model in relation to persons
- household characteristics are changing significantly and forecasts based on personal behaviour are more readily available
- the models can separate changes in car ownership due to an ageing population, from other changes due to such things as increasing income.

However the main disadvantage for this approach is the extensive data requirements, most of which are unavailable in New Zealand.

5.3.1.3 New Zealand trends and data sources

The research identified the difficulty in obtaining a consistent and correct series of vehicle ownership in New Zealand over the last 40 years. A new licensing system was introduced in 1987. The official public figures in the annual yearbook showed a fall in registrations of around 10% between 1986 and 1988, which was determined to be nonsensical.

Analysis of the trends in New Zealand vehicle ownership showed that total registered vehicles grew by a compound growth rate of 4.2% between 1951 and 1991. The absolute rate of increase in cars per person remained relatively constant over the period, with little evidence of approaching saturation.

5.3.1.4 Proposed modelling approach

Based on a review of the data, it was concluded that statistical methods based on past data to estimate a saturation level and growth path would not be sufficient to provide the basis for modelling future ownership.

Therefore the approach adopted was to:

- identify a saturation level based on a review of United States high-income earners (a maximum and minimum range was given)
- adopt a growth rate to saturation based on a simple trend extrapolation from past data, modified as the saturation level was approached.

Forecasting at a zonal level

The above model structure can be used to estimate a range of future cars per person. However, the rate of change in car ownership will not be uniform across all areas.

The recommended approach is based on known relationships between household vehicle ownership and the explanatory variables of income and public transport accessibility. It uses a logistic expression and utility function.

5.3.2 Model for forecasting vehicle ownership In New Zealand, Booz Allen Hamilton (2000)

This project was initially undertaken for Transit NZ and was carried out between 1996 and 1997 (unpublished). Transit NZ's research responsibilities were transferred to Transfund NZ and the material was edited and published as *Transfund NZ research report 161* in 2000. The study had two principal objectives: to provide a basis for forecasting motor vehicle ownership at national and regional levels for the next 20 years, and to provide a set of forecasts based on the model.

5.3.2.1 International literature review

The first part of the project was an international literature review on vehicle availability forecasting.

Major influences in car ownership

The review highlighted five key influences on car ownership:

- economic activity
- real cost of motoring
- public transport availability
- household structure
- consumer taste.

Each of these influences is discussed in further detail below.

Economic activity

It appears universally accepted that car ownership is related to economic activity. Growth in economic activity (most often measured by GDP) generally results in increased car ownership rates.

Real cost of motoring

The level of car ownership increases as the cost of motoring decreases and vice versa. The elements that contribute to the cost of motoring include the prices of new and used cars, fixed costs of ownership such as registration and insurance and the variable costs of car ownership (eg fuel).

Public transport availability

The research indicated that the level of public transport has little impact on the rate of first car ownership, but a more significant impact on the rate of second and third car ownership.

Household structure

The household structure may significantly impact on the patterns of car ownership. For example a household of two working age adults would be more likely to own two cars than a household of two retired people. Potential future influences include an aging population and smaller household sizes.

Consumer taste

Consumer taste can be demonstrated in the changing view of car ownership. While the car was once viewed as a luxury, it is now commonly viewed as a necessity. Historically, the time factor has been used in car ownership models to explain changing taste.

The saturation level of car ownership

The saturation level of car ownership is the peak level that car ownership will reach (normally defined per capita or per driving age population). As car ownership has been increasing over time, historical data is inconclusive on what the saturation level could be.

Two approaches were adopted to estimate the saturation level:

- extrapolation of existing data, the saturation level being where the growth path levelled off
- examination of the behaviour of car-owning people with relatively high incomes.

The first approach of extrapolating existing data appeared to work well in the short to medium term. However, this approach does not address the effect of economic changes on the saturation level.

The second approach considered how high-income earners behaved with respect to car ownership. It was hypothesised that those with relatively high incomes would have saturated level car ownership and as the remaining population's incomes grew, these saturation levels would flow through. Data from the United States suggested that approximately 95% of adults with a driver licence would own a car. In some states the ratio of car ownership to driver licences exceeded one. This indicated that it might be more appropriate to forecast adults with car availability (as opposed to cars per adult) as only one car could be driven at a time per person.

Further data from Australia indicated that approximately 5% of the potential car-owning population was unable to drive a car due to disability. It was noted that as the population aged, this proportion might increase.

5.3.2.2 Potential modelling approaches

The report provided a similar discussion to the 1992 Travis Morgan research, with three suggested approaches:

- macro-economic (or aggregate)
- micro-economic (or disaggregate)
- cohort processing.

5.3.2.3 Vehicle ownership in New Zealand

The various sources of data relating to vehicle ownership in New Zealand were reviewed. These sources, all based on data from the TRC, were published in the NZ yearbooks, *Motor vehicle crashes in New Zealand* (MoT) and statistics published by Statistics NZ. It was decided that the data published by Statistics NZ was the most suitable as it was likely to be the most accurate.

Using the available data, trends in vehicle ownership were reviewed. The key conclusions from this review were:

- the number of cars per person increased almost every year between 1970 and 1996
- the proportional rate of increase in cars per person fell
- since the 1950s New Zealand car ownership per person has closely matched Canada and Victoria (Australia) – 0.49 cars per person in 1995
- the average annual changes in cars per person were strongly correlated with changes in GDP per person and real car prices
- Auckland had the highest level of vehicles per household in 1996; however, not the highest level of vehicles per person (Nelson/Marlborough)
- households with a greater number of adults tended to have more vehicles per household
- households with retired people tended to have fewer vehicles per household.

5.3.2.4 Proposed modelling approach

From the international research undertaken, it was concluded that a macro-economic model was the more effective approach to adopt. There are two key elements required for the macro-economic model: an appropriate saturation level and the growth path to saturation.

The adopted saturation level was based on recent trends in the United States of high-income earners, Australian data on those unable to drive and United Kingdom data on those who chose not to own a car. Based on this the following 'plausible' maximum and minimum values were obtained:

- maximum – 0.95 effective cars per person of driving age
- minimum – 0.85 effective cars per person of driving age.

The growth path to reach saturation included the following time-scale variables:

- level of economic activity (GDP per person)
- real cost of motoring (car purchase and use)
- household structure

However, analysis of New Zealand data suggests there was a reducing time trend influence, with the effects from changes in GDP and car prices becoming relatively more significant.

The final form of the proposed national vehicle ownership model included the following for forecasting car ownership per person:

- starting point of the 1996 estimate of cars per person
- application of 'low', 'medium' and 'high' linear growth projections for GDP per person, car price and time trend
- constraint to the "low' and 'high' saturation levels.

The above model should be tailored to provide regional forecasts by:

- adjusting the cars/person based on regional census data
- adopting the same growth projections as detailed above.

5.3.2.5 Potential areas for further research

Over the course of the study a number of issues were identified that needed further research or clarification. These were:

- the apparent discrepancies in data from the 1996 census and the TRC
- international evidences and recent research on:
 - saturation levels
 - use of cohort approaches and data requirements
 - influence of economic variables on car ownership trends.

5.3.3 Traffic growth prediction, Koorey et al (2000)

This research for Transfund NZ and published as *Transfund NZ research report 191*, reviewed previous investigations on traffic growth predictions in New Zealand and overseas, and studied factors that had the most influence on traffic growth.

The key tasks undertaken during the research were:

- a literature review of New Zealand and overseas growth prediction methods
- a survey of road controlling authorities on current growth forecasting practice in New Zealand
- a review of the *Project evaluation manual's*² recommendations on traffic growth
- identification of factors and the context for factors affecting traffic growth.

The results from each of the above tasks are discussed below.

5.3.3.1 Literature review

A review of Great Britain, United States, Australia and New Zealand literature was undertaken, with the following key conclusions:

² The *Project evaluation manual* has now been replaced by the *Economic evaluation manual*, volume 1. See sections 5.3.3.3 and 5.3.4.

In Great Britain, national level traffic growth is forecast up to 35 years out by a central government agency. Two models are used to predict car ownership. The first model is based on surveyed data from the Expenditure and Food Survey and the second model uses information from the National Travel Survey. In both models, income is the key determinant in car ownership. Growth in car use is predicted from travel survey results and historical trends, again related to income and real fuel price.

At a district level, two sub-models are used, the first is a district car ownership model and the second is a national trip end model.

In the United States, there is no single method and practice varies from state to state. Some states use network modelling, others extrapolate historical data, and others use hybrid methods.

In Australia, there is no national procedure; however, the Bureau of Transport Economics has undertaken a research project on national traffic growth. Traffic was first divided into three categories, inter-regional car travel, rural and local car travel, and commercial travel.

Inter-regional car travel was forecast using a gravity model covering all modes between pairs of cities. Rural and local travel was assumed to vary with growth in VKT and vehicle ownership.

Literature by Hounsell (1989) on urban travel forecasting was also reviewed. It was noted that there were more factors affecting traffic growth in urban areas than rural areas, including:

- modal choice
- traffic restraint
- peak spreading
- travel/work habits.

Failure to take into account these factors can result in an over-estimate of traffic growth in urban areas.

Three New Zealand works on traffic growth prediction were reviewed. Read (1971) considered that extrapolation from observed data was not sufficiently accurate and that effects of car ownership saturation could limit growth. Similar to Read, Clark (1982) considered that a national traffic forecasting model was desirable. Reference was also made to the research by Booz Allen Hamilton (2000) which is discussed above in section 5.3.2.

Literature was reviewed for factors identified to have a significant effect on traffic growth. These were found to include:

- land use
- demographics
- economy
- car use
- vehicle ownership
- induced traffic/roadway improvements
- freight movement
- technology.

5.3.3.2 Survey of road controlling authorities

Road controlling authorities (regional councils, local district/city councils and Transit NZ) were surveyed with regard to their current practice of traffic growth predictions.

This survey concluded:

- city authorities typically used transport models to estimate growth
- the traffic growth prediction methods used by district authorities varied
- there was widespread use of the *Project evaluation manual* procedures
- most authorities varied traffic growth by either type of vehicle and/or time of day
- fuel consumption was identified as another predictive measure.

5.3.3.3 Review of the *Project evaluation manual*

As noted above, *Project evaluation manual* procedures for predicting traffic growth were widely used. The manual has subsequently been updated and replaced by the *Economic evaluation manual*, volume 1 (see section 5.3.4).

The review of the *Project evaluation manual* concluded that:

- there was a need to provide further guidance on the likely uncertainty of the default growth values provided
- disaggregation by other factors such as time of day would be useful
- it would be worthwhile considering an empirical Bayesian approach whereby local historic growth data could be combined with generic growth data
- it would be useful to provide further guidance on how to modify traffic growth predictions in congested situations.

5.3.3.4 Identification of factors

Literature was reviewed to identify significant factors affecting traffic growth. An analysis was conducted for a number of different locations to see if strong relationships could be established. However the analysis did not find strong associative factors.

An alternative approach to traffic growth prediction was also proposed whereby factors would be examined in a highly localised study.

5.3.3.5 Recommendations

The study recommendations included:

- considering the use of traffic growth relationships other than the standard 'arithmetic growth' method.
- developing a national traffic growth forecasting programme, including a defined approach and data collection

- carrying out further work to identify, provide and maintain key 'non-traffic' data sources for growth prediction
- considering further how to relate national growth estimates to local circumstances.

5.3.4 *Economic evaluation manual*, Land Transport NZ (2006)³

Appendix A2 of the *Economic evaluation manual*, volume 1 (V2.1) provides guidance on measuring and estimating traffic volumes and growth.

The appendix recommends that when there is a properly calibrated and validated transportation model it should be used to predict future traffic volumes.

The manual also recommends that actual traffic counts be used, with linear regression analysis, to estimate traffic growth. Where local traffic growth cannot be readily established, default arithmetic growth rates are provided for a 25-year period on a regional basis.

The default traffic growth rates in the manual were determined principally from counts taken over the 1980–2000 period and take into account factors such as trends including:

- population growth
- gross domestic product
- car ownership.

However no details are provided on how the above factors were taken into account.

5.3.5 National Land Transport Programme 2007/08

The National Land Transport Programme (NLTP) is the mechanism by which the NZTA identifies significant upcoming transport issues, funding allocations and forecasts. The version consulted for this research was the NLTP 2007/08. The NLTP used to be produced on an annual basis, but has now shifted to a three-year cycle.

The NZTA and other transport agencies are directed by the New Zealand Transport Strategy and the Land Transport Management Act 2003. This requires that funding for transport activities works towards an integrated, safe, responsive and sustainable land transport system.

The document identifies a number of trends, including the growth in transport demand from increasing desire for mobility as household incomes increase and the general preference for travel by private motor vehicle.

The NLTP identifies a number of significant issues that will be faced by the transport sector over the coming years. These issues include:

³ The Land Transport NZ (2006) *Economic evaluation manual* was the version current at the time the research was undertaken. With the 2008 merger of Land Transport NZ and Transit NZ the manual is now published by the NZTA and the latest edition (2008) is also referred to in this report.

- The New Zealand government commitment to the Kyoto Protocol, which obligates greenhouse gas emissions to be reduced to 1990 levels, will require future changes in travel patterns, fuel choices and energy consumption.
- The widespread consensus that oil supplies will peak in the next 50 years. This is expected to result in increased oil/petrol prices that could be four or five times current levels. The general conclusion is that the era of cheap travel is over and the cost of travel will be significantly higher in the future.

In order to make the transportation sector more sustainable in the future, the NZTA has identified a number of trends that need to occur, including:

- a reduction in CO₂ emissions
- more people choosing active and shared modes of transport
- development patterns that reduce the need for people to travel.

The NZTA has identified its approach to meeting its statutory objectives and government priorities. Some of these approaches are likely to influence car ownership and traffic forecasting, including:

- reducing the need for travel
- further developing roads with a focus on completing networks and improving connections
- providing greater choice of modes and investing in public transport services
- managing demand through road pricing.

5.3.6 Impacts of transport fuel price changes, Booz Allen Hamilton (2006)

This research was undertaken to assess evidence of the impacts of petrol price changes on New Zealand petrol consumption, traffic volume and public transport patronage; and, in the light of this evidence and evidence from Australia and other countries, to recommend a set of 'best estimate' petrol price elasticities in the New Zealand context.

The project was commissioned by Land Transport NZ and undertaken by Booz Allen Hamilton in 2006.

5.3.6.1 Project background, objectives and scope

Transport fuel prices in New Zealand (as in other countries) have varied considerably over the last five or so years, with a generally increasing trend. It is likely that in the future petrol prices will increase further, but could also be quite volatile.

Knowledge of the likely market responses to fuel price changes is important, including for:

- forecasting transport demand and its associated energy demand
- forecasting traffic growth trends for use in road investment planning and evaluation (current New Zealand traffic forecasting practices are often based on a continuation of past traffic growth rates).

The overall objective of the project involved obtaining and combining recent information on petrol price elasticities from two sources:

- an econometric analysis of the impacts of petrol prices in New Zealand on the following:
 - petrol consumption (short and longer term)
 - road traffic levels (VKT by peak/off-peak, urban/rural)
 - public transport patronage.
- an appraisal of evidence on petrol price elasticities relating to New Zealand, and other countries, with a strong emphasis on Australia.

The impact of New Zealand petrol prices on petrol consumption was investigated using a number of econometric models. Most of these models explicitly estimated the relationship between percentage changes in petrol prices and percentage changes in petrol consumption.

The preferred econometric model had several favourable features:

- The coefficients for petrol prices and GDP per capita all had the expected signs.
- The coefficients for petrol prices and GDP per capita were statistically significant.
- The coefficients for petrol prices followed a plausible pattern, so that the initial impact was -0.15, falling to -0.05 the next year and then about zero thereafter.
- There was no evidence of multicollinearity among explanatory variables.
- The time trend was insignificant and very close to zero.

The preferred model implied the following: a 10% (real) rise in the price of petrol would have the following effects on petrol consumption:

- petrol consumption would decrease by 1.5% within a year
- petrol consumption would decrease by 2% after two years

(ie short-run (SR) elasticity=-0.15 and medium-run (MR) elasticity=-0.20)

Further modelling indicated that the short-run elasticity (the impact of prices on petrol consumption over the first year) was expected to be constant over time. This elasticity showed no indication of increasing or decreasing with time.

The impact of petrol prices on state highway traffic volumes for cars was also investigated, using a model that related percentage changes in petrol prices to percentage changes in traffic volumes.

Again, the preferred econometric models had several favourable features:

- The coefficients for petrol prices and GDP per capita all had the expected signs.
- The coefficients for petrol prices were statistically significant (although GDP per capita was not, apparently due to the short five-year time period which the traffic count data covered).
- The coefficients for petrol prices followed a plausible pattern, so that the initial impact was -0.22, falling to -0.08 the next year.
- There was no evidence of multicollinearity among explanatory variables.

The urban traffic models implied that the impacts of a 10% (real) rise in petrol prices on urban car traffic would be as follows:

- The impact on urban off-peak traffic would be relatively large and most of this impact would feed through immediately – traffic would fall by 2.7% within a year, and by 3.6% after two years. (ie SR = -0.27, MR = -0.36).
- The impact on urban peak traffic would be smaller and would feed through in a more prolonged manner – traffic would fall by only 0.9% within a year, and by 2.4% after two years. (ie SR = -0.09, MR = -0.24).

The rural traffic model implied that the impacts of a 10% (real) rise in petrol prices on rural car traffic would be more subdued: rural traffic would fall by 1.6% within a year and by 1.9% after two years. (ie SR = -0.16, MR = -0.19).

The estimates above suggest an apparent inconsistency: highway traffic is more responsive to petrol prices than petrol consumption, despite the fact that traffic is a major driver of petrol consumption. One possible explanation for this inconsistency is that highway traffic (which consists of long-distance trips) may not be representative of overall traffic.

Models relating percentage changes in petrol consumption to percentage changes in public transport patronage (for Wellington bus and rail and Christchurch bus) were also considered. Unfortunately, the models were unable to produce reliable results due to noise in the data and a number of missing variables.

5.3.6.2 Comparison with international evidence

Table 5.8 summarises the evidence from the research as well as other New Zealand and international analyses.

Table 5.8 Summary of elasticity evidence

Source	Elasticity estimates (short-run/long-run)				Notes
	VKT/traffic vol.		Consumption		
	SR	LR	SR	LR	
Study results	-0.20 to -0.25	-0.35	-0.15	-0.20+	Traffic figures relate to 2002–06; consumption figures relate to 1974–2006.
Other NZ results	-		-0.1	-0.15	
Australian results	-0.1	-0.25	-0.1	-0.15	Some studies indicate much higher LR consumption elasticities.
International results:					
US/Canada	} -0.15	-0.3	-0.2	-1.0	
UK			-0.1	-0.5	
Europe average			-0.3	-0.9	

Focusing on the short-run results, the findings from the research were:

- In terms of traffic volume elasticities, the New Zealand estimates (based on recent data, 2002–06) were higher than typical Australian and international values. These VKT elasticities appeared to be inconsistent with consumption elasticities, and might only be representative of the impact of petrol prices on state highway traffic.

- In terms of consumption elasticities, the New Zealand estimates (based on a long-term data series, 1974–2006) were on the high side of previous New Zealand and Australian studies, slightly lower than the United States/Canadian estimates and substantially lower than the European average (but above the United Kingdom estimates, at least in the short-run).

Goodwin et al (2004) stated in their most recent international review that:

The overall picture implied is....if the real price of fuel rises by 10% and stays at that level, the result is a dynamic process of adjustment such that the following occur:

- a) Volume of traffic will fall by roundly 1% within about a year, building up to a reduction of about 3% in the longer run (about 5 years or so)*
- b) Volume of fuel consumed will fall by about 2.5% within a year, building up to a reduction of over 6% in the longer run.*

Comparing the research results with this statement suggests that the New Zealand traffic volume (VKT) effects were greater than these international averaged estimates; but that the New Zealand consumption effects were rather less than these international estimates.

One of the most interesting aspects of the elasticity results was the differences between urban peak, urban off-peak and rural responses. All indications were that the urban peak elasticity were lower than the urban off-peak elasticity: this result reflected the less elastic nature of the commuter market overall, which was not offset by the availability of more competitive public transport services for many of these trips.

5.3.6.3 'Best estimate' elasticities for petrol consumption and traffic volume elasticities

Drawing on all the results from the research, for future policy analysis purposes the following elasticity values were suggested as being most appropriate for New Zealand:

- fuel consumption elasticities:
 - overall: short-run -0.15, long-run -0.30
- VKT elasticities:
 - overall: short-run (<1 year) -0.12, long-run (5+ years) -0.24

5.3.6.4 Applications to traffic forecasting models

The highway traffic elasticity estimates determined by this research could be incorporated into traffic forecasting models. To do this, a 1% petrol price increase would be assumed to have the following impacts on total highway traffic per capita:

- car and van traffic would fall by 0.22% within a year
- car and van traffic would fall by 0.08% the next year.

Similar assumptions could be used to develop specific forecasting models for subsets of traffic (rural, urban off-peak and urban peak).

These forecasting models could be used when estimating future traffic flows. The forecasting models could be fed known or expected changes in petrol prices.

The traffic elasticities indicated that state highway traffic was responsive to petrol prices – a 1% increase in petrol prices would cause about a 0.3% (or more) reduction in car and van traffic. This could have implications for the assessment of road projects given the possibility of rising petrol prices in the future.

5.4 Conclusions

The review of New Zealand modelling practices and literature has highlighted that there are a range of approaches that have been proposed and used to forecast car ownership and use. However a number of the approaches have similar elements.

The vehicle fleet emissions model developed by the MoT appears to be the only nationally adopted model that forecasts car ownership levels. This model, developed in the late 1990s, only has time as an explanatory variable for changes in car ownership.

Regional transport models generally have more complex approaches for forecasting vehicle ownership, particularly at the household level.

The Wellington, Christchurch and Tauranga models all use a form of national car ownership forecasting to govern car ownership growth. However, the form of the predictive car ownership models is different among the three models. The Tauranga model uses a similar equation to the VFEM; however, it uses GDP per capita and car prices, as well as time, as explanatory variables. The current Wellington transport model uses a time series car ownership model based on the Booz Allen Hamilton (2000) research.

Table 5.9 provides a summary of the key model types, their structure and explanatory variables.

Table 5.9 Vehicle ownership models summary

Model	Structure	Explanatory variables
MoT VFEM	Tanner equation based saturation model Only predicts cars/person	<ul style="list-style-type: none"> Time
Auckland (ART2)	Binary choice models for household car ownership	<ul style="list-style-type: none"> Household variables: Number adults and children Employment Income Accessibility (car + PT)
Wellington (2003 update)	Initial choice models to determine household car ownership, adjusted to census data	<ul style="list-style-type: none"> Household variables Number adults and children Employment Income
	Adjusted to national time series model for car ownership	<ul style="list-style-type: none"> Time GDP/capita Car prices
Christchurch	Uses national predictions of cars/person. Distributed to household groups using curves calibrated to 1991 census.	<ul style="list-style-type: none"> N/A
Tauranga (2003 update)	Tanner equation based saturation model.	<ul style="list-style-type: none"> Time GDP/capita Car prices

This review has identified the lack of a consistent approach to forecasting car ownership in New Zealand. While some regional models are regulated by national forecasts for car ownership, they are not the same forecasts. There does not appear to be a consistent set of key input assumptions for these model forecasts (eg future GDP or income, car prices). As these regional models are used to predict future transport requirements, the outputs forming an input to project prioritisation, it would be highly desirable if the forecasting of car ownership was undertaken on a consistent basis. At present an integrated framework for forecasting car ownership is lacking in New Zealand.

The regional models reviewed use fixed trip production rates, ie trip productions are stable over time for the defined category. However, as car ownership nears saturation, it is likely that trip production rates will decrease.

Some research has been undertaken in New Zealand on car ownership and traffic forecasting. This has identified a number of influences on both car ownership and traffic forecasting. Some of these influences have been investigated in detail, such as fuel prices, while other influences do not appear to have been investigated in such detail. Overall there appears to be a lack of good data on all of the factors that influence car ownership and traffic forecasting. This could limit the methods by which car ownership and traffic forecasting methods can be applied at this time.

There is a lack of national guidelines for transport professionals who want to take into account changes in car ownership and traffic growth. The mostly widely used document, the *Economic evaluation manual*, is simplistic in its approach, providing only default linear traffic growth rates.

6 Review of international evidence and forecasting practices

6.1 Overview of car ownership modelling

Car ownership forecasts have an important role in determining trip generation and mode use travel behaviours, and form part of most transport modelling structures. Button (1974) outlined the origins of car ownership estimating as being part of aggregate (ie time series) national forecasting techniques, but a subsequent growth in the sophistication of transport planning methods (primarily through better data and computing capabilities) has allowed for more disaggregate (ie cross-sectional data) analysis to be undertaken.

The history of car ownership/use modelling has been dominated by three general model types:

- aggregate time series approaches
- static disaggregate approaches
- aggregate cohort approaches.

It should be noted however that there can be overlap of these broad model types. For example, some disaggregate approaches can include a saturation parameter that is more commonly used in an aggregate time series approach.

The three general model approaches are discussed below drawing upon the literature summarised in appendices B, C, D and E.

6.1.1 Aggregate time series approaches

Aggregate time series models use existing data on car ownership per capita and extrapolate it into the future. These models have very limited data requirements, especially when compared with models that use disaggregate data, such as the static disaggregate approach. The only data required is aggregate time series data on car ownership, population, GDP per capita and any other variables of interest (eg car prices). In these models, car ownership forecasts are affected by two components:

- the saturation curve⁴ and a saturation level
- the explanatory variables (GDP per capita, time, motoring costs, etc).

In aggregate time series models, the long-term forecast for car ownership per capita is determined by the saturation level (which can be either assumed or estimated).

However, the path towards 'saturation' car ownership per capita is influenced by the growth rates of explanatory variables such as GDP per capita. As car ownership per capita gets closer to 'saturation' these

⁴ Most aggregate time series models assume a saturation curve of some type (ie logistic function, power function, Gompertz function). However, there are exceptions: Romilly, Song and Liu (1998) employ a linear co-integration time series model.

explanatory variables have less influence – hence the s-shaped curves associated with most aggregate time series models.

The key functionality of aggregate time series models is that they enable estimation of the impacts of time series variables such as GDP per capita, car prices, etc. Aggregate time series models also enable the estimation of saturation levels using econometric methods, but the accuracy of these saturation levels has been questioned by some researchers.

The key output of aggregate time series is an estimate of car ownership per capita. These models can also produce estimates of elasticities (eg car price elasticities) which may be of interest to transport planners.

The key advantages of aggregate time series models is that they have limited data requirements. The key disadvantages include the limited ability to include demographic distinctions and model effects of policy variables.

6.1.2 Static disaggregate approaches

Static disaggregate models use household data (eg household income, household structure) to predict the probability of a household owning at least one car. The models also estimate the probability of a household owning more than one car, given that they own at least one car and so on.

Static disaggregate models require household data on car ownership and on the explanatory variables that influence car ownership. Common explanatory variables are household income, household structure, location and licence holding.

Static disaggregate models usually build on other models. In particular models are used to predict future household incomes and future household structures. Also, a licence-holding cohort model is often used to predict future licence holding.

The key functionality and therefore advantage of static disaggregate models is that they enable transport planners to predict the impacts of anticipated changes in household structure and household income. The key output of static disaggregate models is car ownership per household, which can be used to predict total car ownership.

Static disaggregate models have one disadvantage compared with aggregate time series models: estimating the impact of variables such as car prices is difficult because static disaggregate models generally estimate parameters based on household data at a particular point in time (or at a few points in time). Static disaggregate models also have large data requirements.

6.1.3 The cohort approach

Aggregate cohort models segment the population into cohorts (ie groups of people born in the same period). They are similar to aggregate time series models in that they take aggregate data and (in effect) extrapolate it into the future. These models forecast car ownership per cohort based on licence holding and income growth forecasts for each cohort. A licence-holding model is used to predict licence holding for each cohort and an income growth model is used to predict income growth for each cohort.

The key functionality and therefore advantage of aggregate cohort models is that they take into account inter-generational trends that may be anticipated. In particular, these models take into account the ‘cohort effect’: cohorts born before World War II never established a car-owning lifestyle, but cohorts born

after the war were more likely to drive. There are also gender differences between cohorts: the incidence of licence holding is relatively low among women from older cohorts; but the incidence of licence holding among women from younger cohorts is almost the same as men's. The key disadvantage of cohort models is that they are static.

The outputs from aggregate cohort models are licence holding per person and the number of cars per person.

6.2 Discussion of general model archetypes

During the course of the research, seven general model archetypes (generic models) were identified. These model archetypes can be divided into models that use aggregate data (ie time series data) and models that use disaggregate data (ie cross-sectional data or panel data):

The main identified model archetypes were:

- aggregate time series model
- static disaggregate model
- aggregate cohort model
- aggregate market model
- heuristic simulation model
- indirect utility model
- dynamic transaction model.

The following sections contain an overview of the various model types, including:

- how the model is structured or built
- what the key functionalities of the model are (ie what is the model able to produce, what scenarios can it reflect)
- what the outputs are (ie output = car ownership statistics at aggregate level vs cars bought and sold)
- the inputs required for the model.

Table 6.1 provides a summary of the various car ownership model types. As shown in the table, models vary by factors such as functionality, forecast horizon and data availability.

Appendix B summarises each model's structure, attributes and required inputs and Appendix C contains summary details of various influences relating to model archetypes.

Table 6.1 Summary of car ownership model types

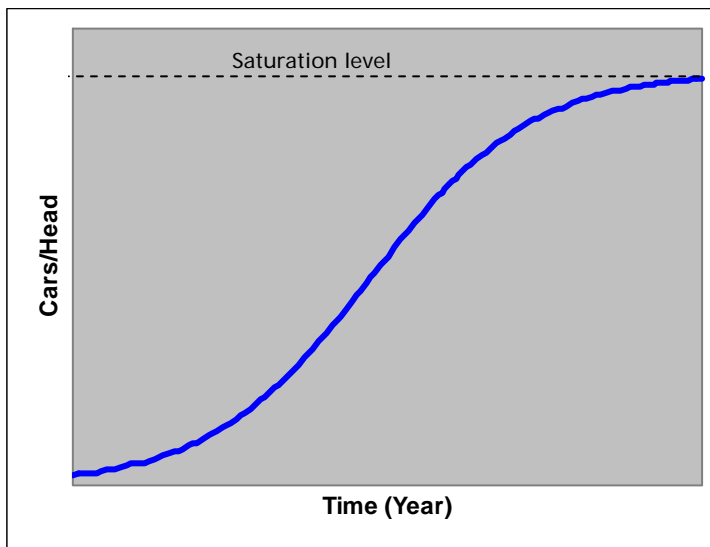
	Uses aggregate data				Uses disaggregate data		
	Aggregate (saturation) time series models	Aggregate market models	Aggregate cohort models	Heuristic simulation models	Static disaggregate ownership models	Indirect utility models	Dynamic transaction models
General model structure	Car ownership per capita follows a saturation curve	The size and composition of the car fleet is affected by scrappage	Car ownership per capita is forecast for each cohort	Car ownership is a function of discretionary income	The probability of owning a car(s) is a function of household characteristics	The probability of owning a car/s (and km driven) are a function of household characteristics	The purchases and disposals that a household makes are a function of household characteristics
Dependent variables	Car ownership per capita	Size and composition of the car fleet	Car ownership per cohort	Proportion of households owning certain car types	Proportion of households with 0,1,2+ cars	Proportion of households with 0, 1,2+ cars and km driven	Purchases, retentions and disposals of cars by households
Common explanatory variables	<ul style="list-style-type: none"> GDP per capita Motoring costs Car prices 	<ul style="list-style-type: none"> Scrappage rates Used car prices Car purchases 	<ul style="list-style-type: none"> Licence holding Income 	<ul style="list-style-type: none"> Household car cost expenditure Car prices Motoring costs 	<ul style="list-style-type: none"> Household income Household structure Licence holding Location 	<ul style="list-style-type: none"> Household income Household structure Licence holding Location 	<ul style="list-style-type: none"> Household income Household structure Licence holding Location
Key functionalities	Forecasts the impact of income growth, petrol prices changes and car cost changes	Forecasts the impact of scrappage on the car fleet	Forecasts the impact of inter-generational changes on licence-holding and car ownership	Forecasts the impact of income growth	Forecasts the impact of household structure and income growth	Forecasts the impact of household structure and income growth Forecasts both car ownership and car use	Forecasts the impact of household structure and income growth Forecasts car purchases, car disposal and car ownership
Forecast horizon	Short, medium and long	Short, medium and long	Medium and long	Medium and long	Long	Long	Short and medium
Data requirements	Light	Light	Light	Moderate	Moderate	Heavy	Very heavy

Each of these model archetypes is discussed below.

6.2.1 Aggregate time series model

Aggregate time series approaches formed the earliest models and were developed during the 1950s by Farrell (1954), Cramer (1959) and Tanner (1962). These models fitted an s-curve as a function of time, with car ownership per capita growing rapidly at moderate levels of car ownership but tapering off as car ownership approached saturation. The s-curve (see figure 6.1) was used to simulate the product life cycle of other consumables, with a slow increase in sales during the early years of marketing, a rapid rise as product acceptance became widespread, and a 'tailing off' of new sales as saturation was approached (ie everyone who wanted one had one). Car ownership was extrapolated into the future, based on an assumption that car ownership would follow a certain saturation curve.

Figure 6.1 The car ownership s-curve



These aggregate approaches made forecasts using aggregate (ie national) time series data, with the dependent variable being car ownership per capita and the explanatory variables initially including time and GDP per capita. Later models such as Tanner (1975) were modified to incorporate other explanatory variables such as motoring costs. These models implied that a growth in income or motoring costs could speed up or slow down the approach towards saturation.

Tanner (1977; 1979) introduced a power growth function which approximated a slower approach to the saturation level. Tanner (1983) then modified the power growth model to accommodate inertia effects. Other researchers have employed power function curves and Gompertz curves. Dargay and Gately (1999) estimated Gompertz functions using partial adjustment models, which enabled estimation of short-run and long-run dynamics.

Aggregate time series models described above have been criticised on a number of grounds. Booz Allen Hamilton (2000) noted that the initial Tanner model had since been discredited, largely based on the ad hoc nature of saturation levels (see section 6.2.1.1). Romilly et al (1998) criticised aggregate time series models that incorporated saturation curves. They argued that hindsight showed that car ownership per capita did not follow a sigmoid trend (ie s-curve). This criticism was also reflected in the comments of Whelan, Wardman and Daly (2000).

Romilly et al (1998) developed their own linear aggregate time series model, based on a linear co-integration model. They compared the forecasting performance of a range of different models, including their own linear co-integration model and a range of saturation-based models similar to those described above. In summary they found that:

- the basic logistic (s-curve) model performed poorly
- the power growth model performed better
- the lagged power growth model performed better than any of the other saturation-based models
- the linear co-integration model performed better than any of the saturation-based models.

Aggregate time series models are still commonly used, particularly given the relative simplicity of developing and updating such a model.

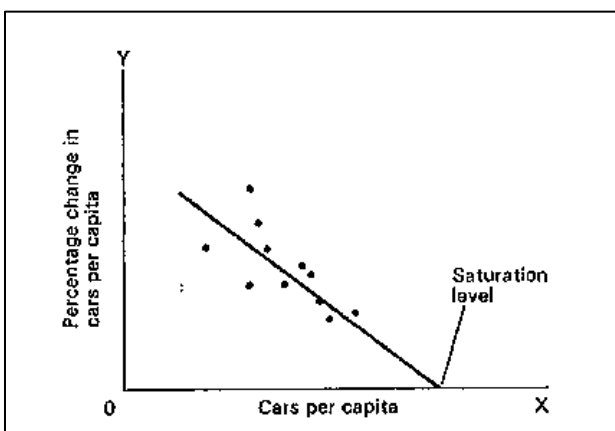
6.2.1.1 Saturation

The earliest aggregate time series models fitted s-curves based on a logistic function, with saturation levels an input. Since then, saturation levels have been determined through one of three methods:

- statistical methods to determine a saturation level
- asserting saturation based on other evidence
- by examining the behaviour of the licensed and unlicensed population and relating it to car-owning households, particularly those with higher incomes.

Statistical methods for determining saturation levels can be very complicated, although historically this has been achieved through a simple process of comparing year-on-year change in car ownership per capita against the absolute level of car ownership. A scatterplot (see figure 6.2) of the two variables would provide a downward-sloping linear line showing where as the absolute level of car ownership increased, the incremental change in ownership levels would decrease. Saturation would occur at the point where this line crossed the horizontal axis.

Figure 6.2 Estimation of saturation level



Source: Button (1974)

Booz Allen Hamilton (2000) was critical of this approach for determining saturation levels. While it recognised that this approach would perform reasonably well in the short to medium term, the approach

ignored changes in economic influences (eg income, real costs of motoring) on the growth path. It was also likely that the make-up of the driving population would change over time. For example, recent years have seen a significant increase in the proportion of female licence holders, due primarily to changes in social expectations – this change would undoubtedly have increased the level of saturation. It is therefore feasible to think that saturation levels change through time, thus calling into question statistical approaches for estimating saturation.

The second approach that has commonly been used is to assert a saturation level using evidence from other markets. This approach is unsatisfactory due to the factors that are apparent in these markets – in particular, car ownership levels are lower in Europe because of constraints on parking, better access to public transport etc. Car ownership in North America is typically higher, due to lower public transport use in many areas, longer distances travelled (due to urban sprawl), and the lower costs of car ownership. The propensity to own a car is context specific and difficult to translate to other situations.

The third approach that has been used historically is to examine the characteristics of licensed and unlicensed drivers. Often the behaviour of the car-owning population with relatively high incomes is examined and it is then assumed that these people have reached the saturation level of car ownership. This saturation level is assumed to be applicable to the remaining population as their real income levels increase over time. The saturation level of per person car ownership will also be influenced by the following factors:

- the proportion of the population who are permitted by law to drive a car
- the proportion of the potential car-owning population unable to drive because of physical or mental disability
- the proportion of the potential car-owning population who choose not to own a car.

The above factors can be estimated by various techniques and collected data.

6.2.2 Aggregate market model

Aggregate market models simulate supply and demand in the car market (although the focus is usually on the used car market). The key driver in these models is a scrappage model – the scrappage model predicts the rate at which cars are scrapped, based on age and the price of used cars. A used car market model is used to determine the price of used cars.

The key functionality of these models is that they can be used to predict the composition of the car fleet because they incorporate the scrapping of used cars. For example, these models are useful for predicting energy consumption and/or emissions and could be used to predict when a significant amount of energy inefficient vehicles are going to be retired.

The key output from these models is information about the vehicle fleet. As they use aggregate data they are unable to relate car purchases to household characteristics such as household structure.

These models require aggregate data on the car market, including the vehicle stock and/or imports, scrappage rate and used vehicle prices by vehicle type and perhaps by age.

6.2.3 Aggregate cohort model

The cohort approach involves segmenting the population by cohort (ie year of birth) and then making predictions for each individual cohort. These models forecast car ownership per cohort based on licence holding and income growth forecasts for each cohort.

Aggregate cohort models are similar to aggregate time series models in that they take aggregate data and (in effect) extrapolate it into the future.

Aggregate cohort models differ significantly from disaggregate models (eg static disaggregate models) because they produce data that is person based (rather than household based). Therefore, aggregate cohort models do not distinguish between first and second cars in the household.

The key functionality of aggregate cohort models is that they take into account inter-generational trends that can be anticipated. In particular, these models take cohorts into account.

The key outputs from aggregate cohort models are licence holding and the number of cars per person. Van den Broecke (1987) developed a cohort model that related car ownership in each cohort to licence holding and income growth in each cohort. A licence-holding model was used to predict licence holding in each cohort.

6.2.4 Heuristic simulation model

Heuristic simulation models predict car ownership by assuming that households have a budget they spend on cars. This budget is assumed to be a constant proportion of discretionary income.

The range of possible cars is categorised into car types. These types can be based on fuel type, weight and/or age of the car.

The households then choose a car type (or a set of car types) that fits within their budget. Households with high incomes will be able to afford the most expensive car types. Households with low incomes may not be able to afford any cars.

The key functionality of these models is that they can be used to predict car type choice, in addition to car ownership. However, the accuracy of the car type choice predictions is questionable because the model assumes that households choose the most expensive car possible within their budget, and this assumption is contrary to economic theory.

The key output from these models is car ownership data including data on both the number and types of cars owned.

6.2.5 Static disaggregate model

The static disaggregate approach makes forecasts using cross-sectional data (ie the car ownership patterns, income, household structures of a sample of households at a certain point in time).

Cross-sectional data is used to estimate how explanatory variables (such as income and household structure) influence the probability of households owning a car, or more than one car. The static disaggregate approach then makes inferences about how car ownership patterns will change in accordance with expected future changes in income, household structure, etc.

An early example of the static disaggregate approach was the Netherlands government transport forecasting model system (LMS), which was developed by Hague Consulting Group (1989). The LMS model predicts the number of cars owned by a household, given the number of licences in that household.

MVA Consultancy was commissioned by the UK Department of Transport in 1996 to report on an improved car ownership model. The NRTF car ownership model (DETR 1997a; 1997b) was consequently developed, which reflected the recommendations of the MVA report.

The 1997 NRTF model was similar to the LMS model. The NRTF model predicted whether a household owned at least one car, based on licences per adult, household structure, household income and area type. The model also predicted the probability of the household owning two or more cars (given that it owned at least one car). The UK Department of Transport acknowledged that an unresolved difficulty of the car ownership model was the omission of either car purchase prices or fuel prices as explanatory variables.

Whelan et al (2000) noted that the saturation levels ('S') in the 1997 NRTF were an input into the model. Saturation levels were determined by plotting cars per household against income within each household category – the levels of car ownership among the highest income groups were then examined.

Whelan et al (2000) noted that saturation levels could be estimated using the aggregate time series approach described in the preceding section. However, the authors concluded in favour of an approach that employed disaggregate data. This approach involved estimating the proportion of the population who were constrained not to own a car (see Whelan et al for more information).

Whelan (2001) audited the 1997 NRTF model and identified a number of possible improvements. The revised 2001 NRTF model incorporated an additional submodel, which predicted the probability of households having three or more cars (given that the household had two or more cars). In addition, the probability of owning two or more cars and the probability of owning three or more cars were both influenced by the number of company cars the household possessed.

The incorporation of company cars is similar to the approach adopted by the Hague Consulting Group (2001; 2002) when it developed the Sydney strategic transport model (STM) which explored a range of options for incorporating company cars:

- modelling private and company car ownership independently
- modelling private car ownership conditional on company car ownership
- modelling company car ownership conditional on private car ownership.

The Hague Consulting Group concluded that the best approach was to model private car ownership conditional on company car ownership.

6.2.6 Indirect utility model

Indirect utility models replicate household budget decisions. Households select both car ownership and car use based on household income, fixed car costs and variable car costs. Other explanatory variables include household size, age, gender and occupation of the head of the household.

The key functionality of these models is that they estimate both car ownership and car use. Furthermore, these are both estimated within the context of a single model. The key outputs of these models are predictions of car use and car ownership.

The other functionalities of these models include the fact that they enable estimation of the impact of household variables such as household income and household structure. In this regard, indirect utility models are similar to static disaggregate models.

Indirect utility models also have similar data requirements to static disaggregate models. Both models require disaggregate data on household car ownership and car use (the dependent variables) and explanatory variables, such as household income, household size and age. The main difference is that indirect utility models require information on both car ownership and car use.

Indirect utility models are also similar to static disaggregate models in other ways, in that both models predict car ownership and car use as a function of household explanatory variables. A key difference is that indirect utility models are constructed based on microeconomic theories about the maximisation of utility within budget constraints. In contrast, static disaggregate models are not as strongly founded on microeconomic theories.

6.2.7 Dynamic transaction model

Dynamic transaction models predict future 'transactions' (ie purchases and/or disposal of cars). If a household does not 'transact' then car ownership is assumed to be the same as the previous year. The time between transactions is determined using a duration model. The type of purchase is predicted using a type-choice model.

The key functionality of these models is that they predict both car ownership and car purchases. In addition, these models predict the type of purchase without assuming that households can choose a car instantaneously. The key outputs from these models are broader than most models; the outputs include both car ownership patterns and car purchases/disposals.

These models require disaggregate household data that relates vehicle purchases to explanatory variables (income, household structure, location, etc).

These models are similar to static disaggregate models because they use disaggregate data to predict car ownership. However, dynamic transaction models differ because they predict how car ownership changes through time (ie they are dynamic).

6.3 Features of key model types

There are three model types which, from our literature review, have been most widely adopted. Their technical attributes are discussed in this section.

- aggregate time series model
- static disaggregate model
- aggregate market model.

It is also noted that cohort approaches are often incorporated into static disaggregate models.

6.3.1 Aggregate time series model

6.3.1.1 Inputs

These models employ aggregate time series data on car ownership per capita and varying combinations of the following explanatory variables:

- GDP per capita
- motoring costs
- car prices
- population
- vehicle ownership.

Where possible, aggregate time series models should include car prices and GDP per capita, as excluding GDP can result in misleading forecasts. For example, the Bureau of Transport and Regional Economics (BTRE) obtained erroneous forecasts because they excluded car costs and GDP from earlier versions of their CARMOD model. The model failed to anticipate the impacts of recent GDP growth and, in particular, a recent decrease in real car prices.

Romilly et al (1998) looked at a range of explanatory variables and found that GDP per capita, motoring costs and bus fares were all significant. Their research is discussed in more detail in section 6.3.1.2.

6.3.1.2 Parameter valuations

Romilly et al (1998) provided the most econometrically robust estimates of parameter valuations for an aggregate time series model:

Table 6.2 Cointegration and error-correction model estimates, Romilly et al (1998)

Dependent variable: car ownership per capita		
	Short run	Long run
Time trend	0.09	-0.04
Real personal disposable income per capita	0.34	1.14
Real motoring cost index	-0.29	-2.19
Real bus fare	0.09	1.70

The estimates produced by Romilly et al showed the following:

- a 1.0% increase in income caused car ownership per capita to increase by 0.3% in the short-run (ie within a year) and 1.1% in the long-run
- a 1.0% increase in motoring costs caused car ownership per capita to decrease by 0.3% in the short-run and 2.2% in the long-run
- a 1.0% increase in real bus fares caused car ownership per capita to increase by 0.1% in the short-run and 1.7% in the long-run
- the estimates of long-run impacts were all larger than the estimates of short-run impacts – this finding is consistent with economic theory.

Romilly et al also estimated the impacts of unemployment rate, size of road network, real interest rate and age structure. But these variables were not statistically significant so they were excluded from the final model.

6.3.1.3 Outputs

The main output from an aggregate time series model is an estimate of car ownership per capita. An aggregate time series model can also produce an estimate of 'saturation' (ie long-run) car ownership per capita, but the accuracy of this is yet to be proved.

6.3.1.4 Model function

As discussed earlier, aggregate time series models generally fit an s-curve to time series data. This s-curve approach was pioneered by Tanner (1958; 1962). The Tanner approach assumed that car ownership could be predicted by the following equation:

$$C_t = \frac{S}{1 + ae^{-bt}} \quad \text{(Equation 6.1)}$$

where:

- C_t = cars per capita at time t
- t = time
- S = saturation
- a, b = constants

The equation above assumes that the growth rate diminishes as cars per capita grows. By fitting data to this curve, the country's position along that saturation curve can be estimated.

The approach above was modified by Tanner (1974) to accommodate causal variables of income and motoring costs. The model implied that a growth in income or decrease in motoring costs could 'speed up' the approach towards saturation. Tanner (1977; 1979) then revised this approach to incorporate a power function, so that saturation was approached more gradually:

$$C_t = \frac{S}{1 + (a + bt + c \ln(i) + d \ln(P))^{-n}} \quad \text{(Equation 6.2)}$$

where:

- C_t = cars per capita
- t = time
- i = per capita income
- P = real motoring costs
- a, b, c, d, n = constants

The Tanner approach has also been modified using a Gompertz curve. The general model form below was adopted by Van Der en Buningh (1978) and Dargay and Gately (1999):

$$C_t = Se^{-ae^{-bi}} \quad \text{(Equation 6.3)}$$

where:

- C_t = cars per capita
- t = time
- S = Saturation
- i = per capita income or other independent variable
- a, b = constants

(see Ogut 2004).

However, all of these s-curve approaches have the same basic shape with varying degrees of steepness at different points along the curve.

The s-curve approaches described above have the following functional limitations:

- In these models, the forecast level of saturation is assumed to be constant, regardless of changes in income, attitudes, car prices or fuel cost. Such variables may affect the speed at which the economy approaches saturation, but they do not affect the actual saturation level.
- These models do not provide information about the types of cars or the number of cars owned by households

6.3.1.5 National models

The BTRE has developed a car ownership/use model for Australia, using aggregate time series techniques.

The original model assumed that vehicle ownership followed a simple logistic function over time. This model failed to anticipate the recent surge in car ownership (which appears to have been driven by GDP growth and decreases in real vehicle prices). However, this model has been modified due to shortcomings in forecasting performance.

The modified model is unusual because it directly estimates VKT per capita without calculating cars per capita. VKT per capita is estimated using a logistic saturation curve. Interestingly, the trend in VKT per capita is consistent with a saturation curve. This model then derives VKT per car and cars per capita as an output of the VKT per capita forecasts described above. VKT per car is estimated as a function of GDP, trend in household ownership of cars and projected changes in the proportion of the population of working age.

6.3.2 Static disaggregate model

6.3.2.1 Inputs

Static disaggregate models estimate the impacts of household-based explanatory variables (household structure, household income etc) on household car-ownership patterns. Therefore, static disaggregate models require data for a sample of households – the data should show the number of cars the household owns and any explanatory variables of interest. The key inputs into static disaggregate models are household structure, household income and the licence-holding patterns within the household.

Unfortunately, static disaggregate models generally only use cross-sectional data – data from a sample of households at a point in time (or, at best, data from a sample of households at a few points in time). Therefore, incorporating variables that are constant across households (eg petrol prices, car prices) into static disaggregate models is problematic.

Static disaggregate models require other models as inputs. In particular, a model is required to forecast the number of households in each household structure category. In addition, a model is required to forecast income growth for each of the static disaggregate models sub-groups (eg area type, household structure type)

Static disaggregate models can be used to produce forecasts at sub-regional levels. For example, the UK NRTF model enables estimates of future car ownership to differ by area type. There are five area types in the NRTF model:

- Greater London
- metropolitan districts
- districts with density 10+ persons per hectare
- districts with density 2.0 to 10.0 persons per hectare
- districts with density 0.0 to 2.0 persons per hectare.

The NRTF model analysed some 130,000 households and extracted datasets on:

- gross household Income
- number of adults
- number of children
- total number employed
- number of retired adults
- area type (as above)
- number of cars and vans.

6.3.2.2 Outputs

Static disaggregate models produce outputs by breaking the population down into subgroups (eg region and household type) and then estimating the probability of a household in that subgroup owning a car. These probabilities are then combined with the number of people in that sub-group, producing the total number of households in that sub-group with at least one car. A similar process is used for estimating the number of households with two or more cars. Therefore, the static disaggregate model can be used to estimate of the number of households with zero, one, two or more cars. This output is a key advantage of static disaggregate models because it seems highly plausible that the number of kilometres driven by a household is influenced by the number of cars that the household owns. Static disaggregate models are often also used to predict company car ownership.

6.3.2.3 Model function

Probability models are used to predict whether a household owns zero, one, two or more vehicles based on household variables.

The NRTF model has the following structure:

There are three binary choice models that examine the household decision to own one or more vehicles (P1+), two or more vehicles conditional on the ownership of one or more vehicles (P2+1+), and three or more vehicles conditional on the ownership of two or more vehicles (P3+2+).

The mathematical equations are as follows:

$$P_{1+} = \frac{S_{1ah}}{[1 + e^{-U_{1+}}]} \quad \text{(Equation 6.4)}$$

$$P_{2+} = \frac{S_{2ah}}{[1 + e^{-U_{2+}}]}$$

$$P_{3+} = \frac{S_{3ah}}{[1 + e^{-U_{3+}}]}$$

Where:

S = saturation level by area (a) and household type (h)

U = the utility of ownership

The utility of ownership equations include the following variables:

- number of driving licences per adult for all of Great Britain
- household income
- household type
- area
- number of adults employed
- purchase cost index
- vehicle use cost index
- number of company cars in the household.

The Sydney STM consists of the following sub-models:

- a model to predict licence holding by household
- a model to predict car ownership, conditional on licence holding
- a model to predict the frequency of trips to work, by employed individuals.

Model for licence holding

In Sydney, between 1971 and 1998, licence holding increased from 62% to 81%. It was estimated that around 80% of this increase could be attributed to the 'catching up' of women's licence holding relative to men's licence holding. This occurred due to the replacement of older generations of women who had low licence holding by younger women, who had licence holding similar to men.

The report notes that many car ownership models include a 'trend' variable representing increasing car ownership that cannot be explained by income. This 'trend' can be attributed, at least in part, to a growth in licence holding. Therefore, it is important that projections into the future take into account the impact of licence holding.

The Sydney STM predicts the likelihood of households being in one the following four states:

- neither member of household has a licence
- head of household has a licence; partner does not have a licence
- head of household does not have a licence; partner does have a licence

- both head of household and partner have a licence.

Households are more likely to have licences as income increases, the number of children increases and with the presence of employment.

Households are less likely to have licences if the head of the household is female, the head of the household is under 25 or over 70 or if the household is large.

Model for car ownership

The Sydney STM company car ownership model predicts the probability of households having the following:

- no company cars
- 1 company car
- 2 company cars.

The predictions of the company car ownership model are influenced by (the log of) household income, the number of licences in the household, the ages of the household members and the presence of a female head of household.

Then, the Sydney STM total car ownership model predicts the probability of households having the following:

- 0 cars
- 1 cars
- 2 cars
- 3 or more cars.

The predictions of the total car ownership model are influenced by (the log of) household income, the number of licences in the household, the ages of the household members, the presence of company cars and the employment status (part-time, full-time) of the members of the household.

6.3.2.4 National models

The UK Department for Transport (DfT) has had a car ownership model for many years. The original NRTF model was based on an aggregate time series model and used s-shaped growth curves incorporating income, motoring costs and time as explanatory variables.

In the late 1990s the DfT moved to a disaggregate model. Since then the model has undergone updates to extend the car ownership choice levels (to three or more cars), include company cars, assess the impacts of employment levels and to include purchase and use costs.

6.3.3 Aggregate market model

6.3.3.1 Inputs

Aggregate market models simulate supply and demand in the car market. Their key driver is a scrappage model which predicts the rate at which cars are scrapped based on age and other factors. These models

require aggregate data on the car market, including the vehicle stock and/or imports, scrappage rate, and used vehicle prices by vehicle type and age.

6.3.3.2 Outputs

The key functionality of these models is that they can be used to predict the composition of the car fleet because they incorporate scrapping of used cars. For example, the scrappage model could be used to predict when a significant amount of energy inefficient vehicles are going to be retired. Therefore, these models are useful for predicting energy consumption and/or emissions.

The key output from these models is information about the vehicle fleet. As these models use aggregate data, they are unable to relate car purchases to household characteristics such as household structure.

6.3.3.3 Model function

The ALternative TRANSport systems (ALTRANS) model (see following section) has a car stock sub-model that consists of three different parts:

$$T_t = T_{t-1} + N_t - S_t \quad (\text{Equation 6.5})$$

Where:

T_{t-1} = existing stock of cars

N_t = acquisitions

S_t = scrapping

The scrappage model uses time series data and linear regression to produce scrappage equations for different categories of car (by fuel type, weight, age and at time t). The variables in these equations include price indices for fuel, repairing costs and income.

The transportation and environment strategy impact simulator (TRESIS) model (see following section) has automotive scrappage and price determination models. The base year has an observed set of used and new vehicle registrations in each class. For subsequent years, the number of vehicles in each class is estimated (as per the ALTRANS model). Demand for new vehicles in each forecast year uses a *vehicle price relativity approach*, where the supply of new vehicles is determined from the difference between the total household demand for vehicles and the supply of used vehicles after application of the scrappage model. Used vehicle prices are set as depreciated new vehicle prices. This approach ensures a predetermined relativity of prices of vehicles.

The scrappage model uses information about vehicle age, class and vehicle prices (to take into account the role that vehicle prices have on scrappage rates). The scrappage model is a set of empirical equations.

6.3.3.4 National models

The ALTRANS model was developed at the National Environmental Research Institute in Denmark for the purpose of forecasting energy consumption and emissions from personal transport.

The TRESIS model was developed to assist transport planners in making predictions about the impact of transport strategies. The TRESIS model is region specific and has been applied in South Australia.

6.3.4 Summary of key model types

Appendix D summarises the features of key model types.

6.4 Examples of international models

Table 6.3 summarises the following international car ownership models, based on published literature. These models were selected for review as information was readily available. These models have been adopted in various countries and applied at a national level, as discussed previously in this section:

- NRTF model – United Kingdom
- ALTRANS model – Denmark
- CARMOD model – Australia
- TRESIS model – Australia
- STM model – Australia
- FACTS models – Netherlands.

Appendix E provides more detail on each of these models.

Table 6.3 National models

Model	CARMOD	STM	TRESIS	NRFT		FACTS	ALTRANS
Country	Australia	Australia	Australia	UK	UK	The Netherlands	Denmark
Developer	Bureau of Transport and Regional Economics (BTRE)	Hague Consulting Group and the Institute of Transport Studies	See Hensher and Ton (2002)	Department of the Environment, Transport and the Regions	Department of the Environment, Transport and the Regions	The Transport Research Centre (AVV) of the Dutch Ministry of Transport	See Kveiborb (1999)
Year	2002	2001	2002	1997	1997	2002	1999
Objective	To forecast greenhouse gas emissions	To forecast travel patterns (including mode-choice and trip patterns) in the Greater Sydney Metropolitan Region	To forecast the impact of a wide range of policies (eg congestion pricing, new infrastructure, land-use change, and PT service changes) on variables of interest, including kilometres driven, energy use, emissions, and mode share.	To forecast national traffic levels	To forecast national traffic levels	To forecast emissions from the transport fleet	To forecast energy consumption and emissions from personal transport
Relevance to VKT and/or car ownership	End-model estimates fuel use. Sub-model estimates VKT per capita but this is only used to derive cars per capita	Car ownership model and work trip model	Car ownership model	Car ownership model	Car use model	Car ownership model and car use model	Car ownership model
General category of model (RAND)	<i>Aggregate time series</i> – ‘saturation’ curve for VKT per capita	<i>Static disaggregate ownership model</i>	<i>Aggregate car market model</i> of total demand, scrappage and new purchases.	<i>Static disaggregate ownership model</i>	<i>Static disaggregate use model</i> , combined with an <i>aggregate time series</i> model.	<i>Heuristic simulation model</i> , in which expenditure (on vehicle and kilometres driven) is a heuristic function of household budget.	<i>Aggregate car market model</i> of stocks, acquisitions and scrappage.

Development and application of a New Zealand car ownership and traffic forecasting model

Model	CARMOD	STM	TRESIS	NRFT	FACTS	ALTRANS	
General structure	<p>Fuel use is assumed to be a function of cars per capita, population, VKT per car and fuel efficiency.</p> <p>Cars per capita is derived from estimates for VKT per capita and VKT per car.</p> <p>VKT per capita is the 'driver' of the forecasts and this is related to GDP per capita using a logistic 'saturation' function.</p>	<p>A licence-holding model predicts the number of licences in each household, using explanatory variables such as age dummies and employment status of household members..</p> <p>A car ownership model predicts the number of cars owned by households – This stage consists first of a company car ownership model and second, a total car ownership model, conditional on company car ownership.</p> <p>A travel frequency model is also used to predict the number of work 'tours' made by each employed individual.</p>	<p>A scappage model determines scappage based on the age of used cars and used car prices. Used car prices are influenced by the exogenous price of new cars. New purchases are determined as the difference between total demand for cars and the supply of used cars (after scappage).</p>	<p>A household sub-model is used to estimate the number of households, by eight household types.</p> <p>Income is assumed to grow at 2.5% from 1996 to 2001 and 2.25% from 2001 to 2031.</p> <p>The probability of owning at least one car was estimated as a function of forecast income (modified by region & household type) and forecast licences per adult.</p> <p>The probability of owning two cars (if the household owns at least one car) was estimated as a function of forecast income (modified by region & household type) and forecast licences per adult.</p> <p>Licences per adult was forecast using cohort data.</p> <p>The probabilities are combined with the forecast number of household types, to produce forecasts for car ownership.</p>	<p>A cross-sectional model is used to calculate car use elasticities, broken down by household type and car ownership numbers – These are then used to produce initial car use forecasts.</p> <p>A fuel cost elasticity is estimated and this is used to modify car use forecasts.</p> <p>The car use forecasts are modified in the end by a company car adjustment.</p>	<p>A simulation model creates a number of households. Households are allocated a certain number of kilometres driven.</p> <p>Households then select the best car that they can, given the proportion of their budget allowed for expenditure on cars and kilometres driven. The household may not be able to afford a car; alternatively, the household may be able to afford multiple cars.</p>	<p>A 'scrapage model' is developed to predict car scappage (by fuel type, weight and age) and a 'behavioural model' predicts the car stock. The remainder is assumed to be vehicle acquisitions.</p>

Model	CARMOD	STM	TRESIS	NRFT		FACTS	ALTRANS
National regional applications	No regional components	The model is specifically designed for application to the Sydney region.	The model is integrated and is modified to take into account the details of each region	No regional forecasts, other than for area-types (ie Greater London, Metropolitan districts and three other categories with differing levels of population density).	No regional forecasts	No regional forecasts mentioned	No regional forecasts mentioned
Forecast time period	Forecasts to 2020	Forecast period not stated	Forecasts for 1998, 2003, 2008 and 2013	Forecasts to 2031	Forecasts to 2031	Forecasts period not stated	Forecasts are not discussed in detail
Variables involved in model (and sensitivity)	<ul style="list-style-type: none"> • GDP per capita • Fuel prices • Car prices • Proportion of population of working age • 'Trend in Household ownership of vehicles' 	<ul style="list-style-type: none"> • Employment status • Female head of household • Number of children • Income of head of household • Income of partner • Parking cost • Number of licences in household 	<ul style="list-style-type: none"> • Price of new cars • Age of existing fleet • Commuter mode choice <p>(note –variables not explicitly identified)</p>	<ul style="list-style-type: none"> • Numbers of people in each household type • GDP per capita (with income effect modified by region and household type) • Licence holding 	<ul style="list-style-type: none"> • Numbers of people in each household type and their location • Forecasts of car ownership by household type • GDP per capita (by household type) • Fuel cost (including fuel prices and fuel efficiency) 	<ul style="list-style-type: none"> • Income • Share of income spent on cars • Vehicle prices (perhaps) 	<ul style="list-style-type: none"> • Income • Fuel prices • Repair costs • Acquisition costs
Coverage (cars, all)	All cars – no distinction	All cars – no distinction	Cars distinguished by age, size and fuel-type	All cars – no distinction	All cars – no distinction	Cars distinguished by 18 car types (including fuel-type) and age (>5,≤5)	Cars distinguished by fuel-type, age and weight

Development and application of a New Zealand car ownership and traffic forecasting model

Model	CARMOD	STM	TRESIS	NRFT		FACTS	ALTRANS
Critique and commentary	The cars per capita variable does not appear to be an explanatory variable; rather, it appears to be the level of car ownership deduced given the forecasts for VKT per capita and VKT per car	The model is statistically robust because it uses cross-sectional data. The paper describes cohort analysis of licensing patterns but does not use the cohorts to predict future licensing The licencing and car ownership models use dummy variables for age, rather than continuous variables.	The paper/s do not discuss the details of the model. The model does not appear to incorporate common explanatory variables for car ownership, such as income, but this may be because these have not been stated. The scrappage model, which bases scrappage on age and used car prices, seems to be a useful model for development of car ownership model with details about the fleet. The model entails an assumption that used car prices are related to new car prices, which may or may not be correct.	The model is statistically robust because it uses cross-sectional data. The model is incoherent because licence holding feeds through both as a constraint – via ‘saturation’ levels – and as an explanatory variable via licences per adult.	The model is statistically robust because it uses cross-sectional data, but it has the added benefit of using time series data to produce fuel cost elasticities	The model is counter-intuitive because it assumes that people maximise expenditure on cars. In addition, the model only has a few explanatory variables (income, share of income spent on cars) and does not seem to account for other variables, such as fuel prices.	The impact of the explanatory variables is not discussed in detail. The model is very effective at describing the composition of the fleet, and hence emissions, but is less appropriate for predicting traffic
Key references	There are no key references	There are no key references	The paper refers to Hensher and Greene (2000) who use logit models and RP/SP data to develop a model of car choice. Variables that affected car choices included car price and running costs, engine size, acceleration and boot size.	There are no key references	There are no key references	There are no key references	The paper refers to an ‘acquisitions model’ developed by Cowi (1998)

7 Development of a recommended New Zealand modelling framework

7.1 Introduction

This section considers the development of a New Zealand modelling framework and methodology for car ownership and traffic forecasting. This has been based on the previous research that:

- examined New Zealand literature and current car ownership models
- reviewed New Zealand car ownership and use trends and data
- examined international car ownership models
- considered results from the 'needs survey' that was undertaken.

The methodology could be a new modelling suite, or an enhancement to an existing platform currently being used.

7.2 Potential model types

Section 5 reviewed the New Zealand models for car ownership while section 6 reviewed the types of models currently used internationally for car ownership and traffic forecasting.

There are three main types of car ownership models that are commonly used internationally as national car ownership car models. These are:

- aggregate time series models
- static disaggregate models
- aggregate car market model

The following section compares the three model types with the functional requirements detailed in section 4 that came out of the needs survey.

7.2.1 Aggregate time series models

New Zealand examples of the aggregate time series models are used in the MoT's VFEM and the Tauranga transport model. An aggregate time series model was also developed in this research (section 3). International examples include the Australian Bureau of Transport and Regional Economics (BTRE) CARMOD model.

Table 7.1 below compares the desired functionality with the general aggregate time series model.

Table 7.1 Aggregate time series model

Desired functionality	Meets requirements	Comment
Include segments of vehicles (eg private, company, LCVs)	XX	Not included in models
Ability to apply at national, regional and local contexts	√	The models provide a national forecast that can be applied to regional and local contexts
Focus on 25-year horizon	√	Models perform better in short-medium term
Include link between household structure and demographics	XX	Models do not specifically include link to household structure and demographics
Segments vehicles by fuel type/efficiency	-	Models do not include, but as with the MoT VFEM can be supplemented with an additional model
Sensitive to changes in income	√√	Models can include GDP/capita as an explanatory variable.
Sensitive to changes in fixed/variable vehicle costs	√√	Models can include car price index as an explanatory variable
Sensitive to the level of PT/TDM/land-use supply	XX	Not included in models
Outputs should include vehicle numbers, traffic forecasting and fuel consumption measures	-	Separate models are required for traffic forecasting and fuel consumption, as with the VFEM

Key: √√ meets requirements, √ somewhat meets requirements, - potential to meet requirements, X unlikely to meet requirements, XX does not meet requirements

It is clear that the aggregate model type, an example of which is reported in section 5 and is also used in a number of New Zealand models, is not able to provide all of the desired features specified in the needs survey. However, it is important to note that the data requirements for such models are relatively light and these types of models are currently used in New Zealand.

7.2.2 Static disaggregate models

A form of a static disaggregate car ownership model is used in the Auckland Regional Transport (ART2) model. An international example is the UK DfT (NRTE) model.

Table 7. compares the desired functionality with the general static disaggregate model.

Table 7.2 Static disaggregate model

Desired functionality	Meets requirements	Comment
Include segments of vehicles (eg private, company, LCVs)	√√	Models can include
Ability to apply to national, regional and local contexts	√√	Models can include area types
Focus on 25-year horizon	√√	Models perform well over the medium-long term
Include link between household structure and demographics	√√	Models are based on detailed household structure information
Segment vehicles by fuel type/efficiency	X	Vehicles are not segmented by type
Sensitive to changes in income	√√	Income is an explanatory variable
Sensitive to changes in fixed/variable vehicle costs	√√	Car purchase prices and use costs are explanatory variables
Sensitive to the level of PT/TDM/land-use supply	√	Area type can be used as a proxy for PT and accessibility
Outputs should include vehicle numbers, traffic forecasting and fuel consumption measures	√√	NRTF model provides these outputs

Key: √√ meets requirements, √ somewhat meets requirements, - potential to meet requirements, X unlikely to meet requirements, XX does not meet requirements

It is clear that static disaggregate model types are able to provide most of the features that are desired. However, it is important to note that the data requirements for these models are relatively significant.

7.2.3 Aggregate car market models

International examples of an aggregate car market model include the Denmark ALTRANS model and the Australian TRESIS model.

Table 7.3 below compares the desired functionality of a New Zealand car ownership model with the general aggregate car market model.

Table 7.3 Aggregate car market model

Desired functionality	Meets requirements	Comment
Include segments of vehicles (eg private, company, LCVs)	X	Car use is not an input into model
Ability to apply to national, regional and local contexts	√	The models provide a national forecast that can be applied to regional and local contexts
Focus on 25-year horizon	√√	
Include link between household structure and demographics	√	Household structure is an input into car acquisition behaviour
Segment vehicles by fuel type/efficiency	√√	The key component of the model is a car acquisition and scrappage model
Sensitive to changes in income	√√	Income is included in acquisitions model.
Sensitive to changes in fixed/variable vehicle costs	√√	Vehicle costs are on of the key inputs to model
Sensitive to the level of PT/TDM/land-use supply	XX	Not influencing variables
Outputs should include vehicle numbers, traffic forecasting and fuel consumption measures	-	Separate models are required – no traffic forecasting

Key: √√ meets requirements, √ somewhat meets requirements, - potential to meet requirements, X unlikely to meet requirements, XX does not meet requirements

Aggregate car market models provide the best representation of car fleet changes. However, as shown above, they cannot easily incorporate a number of other important functional requirements, such as sensitivity to the level of public transport and car use.

7.2.4 Recommendation

Based on the above, it is clear that a national **static disaggregate ownership model** would best provide the desired level of functionality. In particular, this type of model is able to test many policy variables (eg public transport provision) and there is a large international body of experience. The key disadvantage of this model type is that it has large data requirements.

The following section provides further details on what the structure of the static disaggregate ownership model could look like and what the data requirements are likely to be.

7.3 Recommended long-term future modelling methodology

As detailed above, the recommended long-term model methodology is a static disaggregate ownership model. The following provides further detail of how the model could be structured and the likely data requirements.

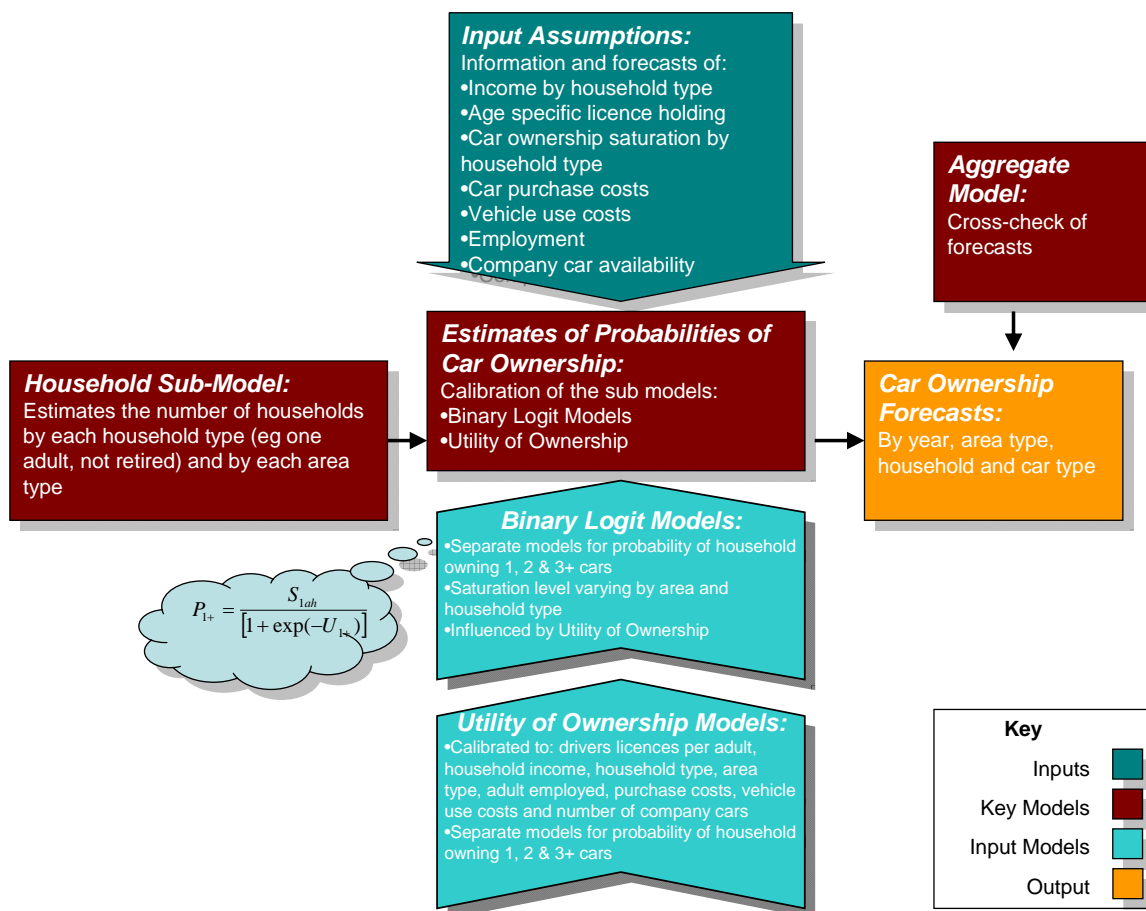
7.3.1 Overview and structure

The UK NRTF model has had considerable development over the last decade and has accessible documentation. The proposed structure and data requirements are based on the latest version of this model.

7.3.1.1 Car ownership model

Figure 7.1 shows the overall proposed structure of the car ownership model. Each of the key components of the model is described in further detail below. This structure is based on the latest updates to the UK car ownership model (DETR 2007 and Whelan 2001).

Figure 7.1 Car ownership model framework



Household sub-model

Future population forecasts are usually in the form age–sex distribution and total people. This data then needs to be converted into future household characteristics. The household sub-model uses the existing household survey to produce a sample of households that is internally consistent (the household survey is unlikely to be directly representative of the population) while also achieving consistency with aggregate statistics. The technique of ‘prototypical sample enumeration’ can be used, which utilises the existing sample in the base year while meeting the targets in the forecast years.

Binary logit models

The binary models assess household decisions to own zero, one, two or three vehicles. The form of the equations is as follows:

$$P_{1+} = \frac{S_{1ah}}{[1 + \exp(-U_{1+})]} \quad (\text{Equation 7.1})$$

$$P_{2+|1+} = \frac{S_{2ah}}{[1 + \exp(-U_{2+|1+})]}$$

$$P_{3+|2+} = \frac{S_{3ah}}{[1 + \exp(-U_{3+|2+})]}$$

Where:

P_{1+} is the probability of a household owning one or more vehicles

$P_{2+|1+}$ is the probability of a household owning two or more vehicles, conditional on the ownership of one or more vehicles

S is the saturation level by area (a), household type (h) and U is the utility of ownership (see below).

Utility of ownership models

The utility models are related to the socio-economic characteristics of the household, geographical-location, car purchase and use costs, and average licence holding. The models are in the form of:

$$U_{1+} = ASC_1 + b_1LPA + (c_1 + c_{h1}D_h + c_{a1}D_a)Y + d_1E + e_1O + f_1R \quad (\text{Equation 7.2})$$

$$U_{2+|1+} = ASC_2 + b_2LPA + (c_2 + c_{h2}D_h + c_{a2}D_a)Y + d_2E + e_2O + f_2R + g_{21}CC_1$$

$$U_{3+|2+} = ASC_3 + b_3LPA + (c_3 + c_{h3}D_h + c_{a3}D_a)Y + d_3E + e_3O + f_3R + g_{31}CC_1 + g_{32}CC_2$$

Where:

LPA is the number of driver licences per adult in NZ

Y is the household income

D_h is a vector of household type dummy variables

D_a is a vector of area type dummy variables

E is the number of adults employed

O is an index of purchase costs

R is an index of vehicle use costs

CC_1 is a dummy variable if there is one company car in the household

CC_2 is a dummy variable if there are two company cars in the household

ASC is a vector of alternative specific constants
b,c,d,e,f and g are parameter vectors (estimated)

Aggregate model

An aggregate model, as developed in section 3 of this report, could provide a cross-check on the sum of the disaggregate model forecast.

Process of applying model

The models, detailed above, can be used to develop ownership forecasts for particular zones (eg census zones). A six-stage process is used to apply the models:

1 Base sample definition

The base sample of the population households is defined from survey information.

2 Target area definition

The second stage is to define the geographical 'target' areas for which the forecasts are required (eg census zone areas or larger areas).

3 Forecasting period definition

Forecasts are required at five-yearly internals for the forecast period.

4 Target variable definition

In this stage the aggregate socio-demographic characteristics of each target area in each time interval are described in terms of the target variables (see below). A sampling method is used to generate artificial disaggregate samples that when aggregated, match the totals of the target variables and also maintain the detailed relationships in the base-year data.

Target variables could include:

- the number of people who live in the zone
- the number of children aged between 0 and 15 in the zone
- the number of males in the zone, aged between 16–64 in fulltime employment
- the number of males in the zone, aged between 16–64 in part-time employment
- the number of males in the zone, aged between 16–64 who are students
- the number of males in the zone, aged between 16–64 who are neither students nor employed
- the number of males in the zone who are 65 or more years old
- as above for females
- the total number of people in the zone in employment
- the number of single person households in the zone
- the number of households in the zone with more than one person

- the number of company cars in the zone.

While household income is not included in the above target variables, the variation in income levels across zones is achieved by factoring income levels in each zone.

5 Household category

Households are grouped into pre-defined categories that cover the key dimensions of the sample.

6 Adjusting constraints

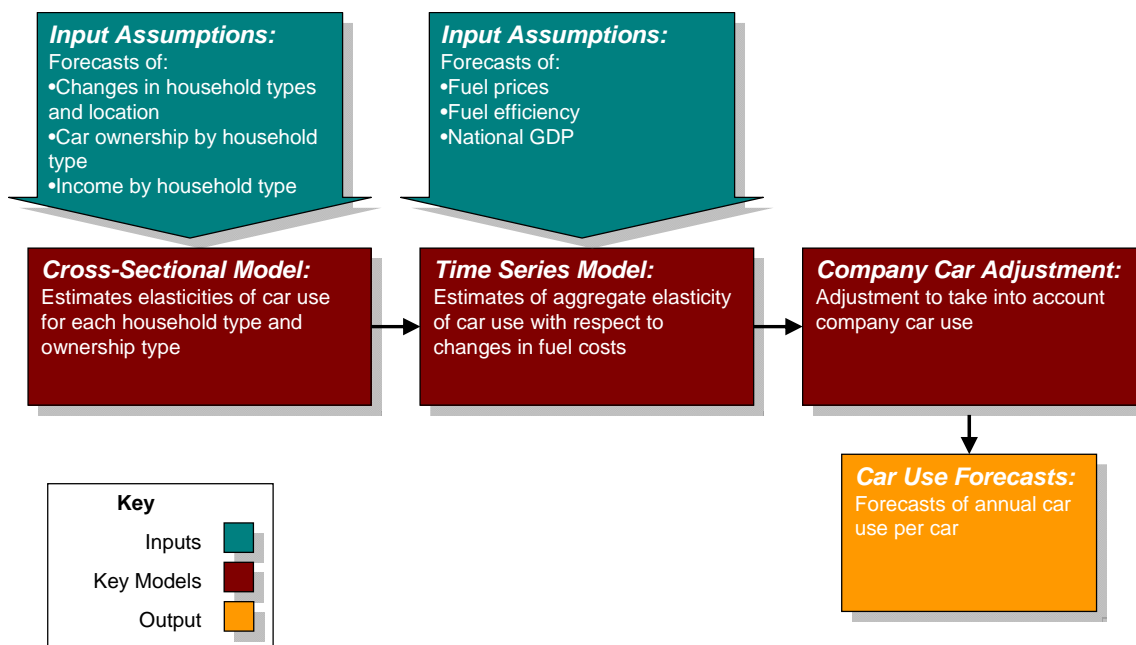
To ensure that the model is able to replicate the base ownership probability for each zone, the model constants (ASCs) are adjusted so that the forecast matches the actual ownership levels from the base year census information.

The outputs from the car ownership forecasts (by year, area type, household and car type) can then be applied at a regional/local level. This would be done by applying the forecasts to the regional/local estimate of area types and household types.

7.3.1.2 Traffic forecasting (car use) model

Figure 7.2 below shows the overall proposed structure of the traffic forecasting model. Each of the key components of the model are described in further detail below. This structure has been based on the UK car use model (DETR 1997a; 1997b).

Figure 7.2 Traffic forecasting model



Cross-sectional model

In order to be compatible with the car ownership model, traffic forecasting should also use the same household types. In the cross-sectional model the 'first' car is defined as the car with the highest use (ie kilometres travelled) and the 'second' car includes the use of any additional cars.

The model could be based on a national travel survey with the following explanatory variables:

- real gross annual household income
- number of employed people per household
- proximity of bus services
- proximity to rail services
- a variable to indicate whether the head of the household is disabled
- a variable indicating the location of the household (eg if there are five generic locations then there will be five variable values)
- a variable to indicate whether the head of the household is a full-time student
- a variable indicated whether the car modelled is a company car.

The form of the cross-sectional model is as follows:

$$\log(\text{car use}) = \text{function} \left(\begin{array}{l} \log(\text{income}), \text{employment}, \text{bus services}, \text{rail services}, \\ \text{disabilities}, \text{household area type}, \text{student}, \text{company car status} \end{array} \right) \quad (\text{Equation 7.3})$$

All variables, except income, are discrete dummy variables (either a value of 0 or 1). For example, if there is one or more persons employed in the household the employment variable is 1, otherwise it is 0. The log form of car use and income means that the estimated income elasticities are constant across all income levels within each household type.

Using regression analysis, the elasticities of car use by household type and car type (eg first or second car) are determined.

Time series model

The above cross-sectional model does not incorporate time dependent determinants of traffic forecasting. The key influencing variable of car use is fuel cost. The elasticity of traffic forecasting with respect to fuel costs over time is influenced by:

- fuel costs themselves (including tax changes over time)
- personal or household income
- fuel efficiency of vehicles.

Using regression analysis, elasticities for car use with respect to fuel can be derived. In order to provide a time series model, assumptions will need to be made on how the above variables will change with time.

Company car adjustment

Company car use is generally higher than private-ownership car use as the fuel costs and other running costs are paid for (or contributed to) by a company. An exaggeration of traffic forecasting could occur if it is assumed that as a household moves from a one-car to a multi-car household they adopt the same company car rate as existing multi-car households. To avoid potential overestimation of traffic

forecasting, in the future it can be assumed that the overall proportion of company cars in each household type remains unchanged and an adjustment factor calculated.

7.3.2 Data requirements

The data requirements have been based on the above proposed structure (UK models). The data requirements have then been compared with the currently available New Zealand data to identify gaps where additional data would need to be collected.

7.3.2.1 Car ownership model

The UK car ownership models are based on data from:

- the Expenditure and Food Survey (formally Family Expenditure Survey) and the National Travel Survey to form household car ownership data
- constructed indices for car ownership costs, car running costs, general prices (CPI) and historical trends on the average number of driving licences per adult.

Household car ownership data

Household datasets (for multiple years, last 20–30 years) is required including:

- gross household income
- number of adults
- number of children
- total number employed
- number of retired adults
- area type
- number of cars and vans (separated by company and private).

The UK dataset had 7000–15,000 observations in each dataset. Datasets were collected every five years from 1971 to 1996, and then yearly from 1997.

The New Zealand five-yearly census could provide a dataset that is broadly similar to that used in the UK. Discussions with Statistics NZ have identified that census data back to 1981 can be interrogated and should be able to provide a suitable dataset. There would be limitations with the data as the questions vary from one census to another and most data has been put into bands. Certain information, such as company cars, is not available from earlier years. Considerable processing of the census data would be required and one of its most significant limitations would appear to be the five-year interval between data points.

Another source of the data would be the MoT New Zealand Household Travel Survey. This survey collects information on sample households travel behaviour, including household characteristics (eg income, employment status). Processing of the data would be required to determine area type. However, the survey has only been undertaken in 1997/98, 1989/90 and yearly from 2003 and would not give sufficient time series of data on its own to provide the required data for the model.

Based on the high-level review, it would appear that there is not one data set on its own that could currently provide the required data to construct a static disaggregate model. However a combination of census and household travel survey data might be able to provide the required data, especially if the latter is undertaken regularly in the future.

Indices

Historical indices are required for licences per adult, car purchase and running costs, and CPI.

- Licences per adult can be obtained from the MoT.
- A car purchase index has already been developed by Statistics NZ.
- An index of real running costs (fuel, maintenance, tax and insurance) would need to be developed.
- Historical CPI data is readily available from Statistics NZ.

Future forecasts

In order to use these models to forecast future car ownership, projections are required to be developed at five-yearly intervals for the extent of the forecast (eg 30 years into the future), including:

- population demographic by area
- GDP
- changes in car running and purchase costs
- inputs from various organisations would be required to obtain robust future forecasts.

7.3.2.2 Traffic forecasting model

The UK model uses data from the National Travel Survey. Key data requirements for the cross-sectional estimation of income elasticities by household type are:

- car use (kilometres travelled)/car type (eg first, second car)/household type (eg one adult, retired)
- annual household income
- number of employed people per household
- proximity to bus services
- proximity to rail services
- variable indicating whether the head of the household is disabled
- variable indicating the type of location of the household
- variable indicated whether the household head is a fulltime student
- variable indication whether the car modelling is company owned.

The New Zealand Household Travel Survey collects information on car use. The survey collects most of the information detailed above. The travel survey does not collect information on disabilities and proximity to bus/rail services may have to be derived.

In addition to the above household data, forecasts of fuel prices, fuel efficiency and national GDP are required. These would need to be derived with input from various stakeholder groups and with key assumptions documented.

7.3.2.3 Recommendations

Based on the above high-level review, it appears that the New Zealand Household Travel Survey collects most of the data ideally required to build a static disaggregate car ownership and use model. The key limiting factor is the relatively short length of time of data collection. Continuing to undertake the travel survey annually should provide a solid base in the future in which a static disaggregate model could be constructed.

It is recommended that the MoT seek a detailed review of the New Zealand Household Travel Survey to ensure the survey would be capable of providing a suitable data set should a static disaggregate model be constructed for New Zealand.

As previously identified, there are different definitions used for car ownership levels. For example census data is not directly comparable with TRC figures due to the different definitions. It would be beneficial if these definitions could be brought into line.

7.3.3 Model development and data collection process

Assuming that the recommended model approach is adopted, the following further key steps are recommended to progress the model development and data collection:

- Seek proposals from suitably qualified consultants or organisations to develop the model.
- Confirm methodology and undertake detailed investigation into the data availability and cost of processing or collected further data (if necessary). Adjust methodology accordingly.
- Collect further survey data (if required)
- Develop the model
- Peer review the model.

It is noted that the development of a new model and the associated data processing and collection would require a considerable effort, is likely to be relatively expensive and could take a number of years. The model will also require regular updating. Therefore the decision to proceed with a new model requires careful consideration, against other options (see section 7.4).

7.3.4 Use of the model

Should a static disaggregate ownership model be developed, it is expected the model could be used and applied as follows;

- The transport sector agencies could use the model to study changes in car ownership as a result of various factors, including changes to:
 - household structure and demographics
 - income

- public transport supply, travel demand management measures and land use supply
- emissions from the vehicle fleet
- The transport sector, particularly the NZTA, could use the traffic forecasting part of the model to provide guidance on future traffic growth rates (by area) for evaluation of transport projects.
- As the model is sensitive to the factors including household structure and public transport supply, which vary from region to region, it could also be used to predict regional car ownership.

7.4 Short- to medium-term modelling methodology

It is recognised that developing a static disaggregate car ownership model for New Zealand is a substantial undertaking and the development costs are likely to be significant. It would probably take a number of years to develop the model as the data required to construct the model is not readily available and would need to be collected and processed.

As developing a national static disaggregate car ownership model could be a long-term undertaking, there is merit in exploring a short-to medium-term modelling framework. This could be viewed as an intermediate step in working towards the desired end point (ie a national static disaggregate model).

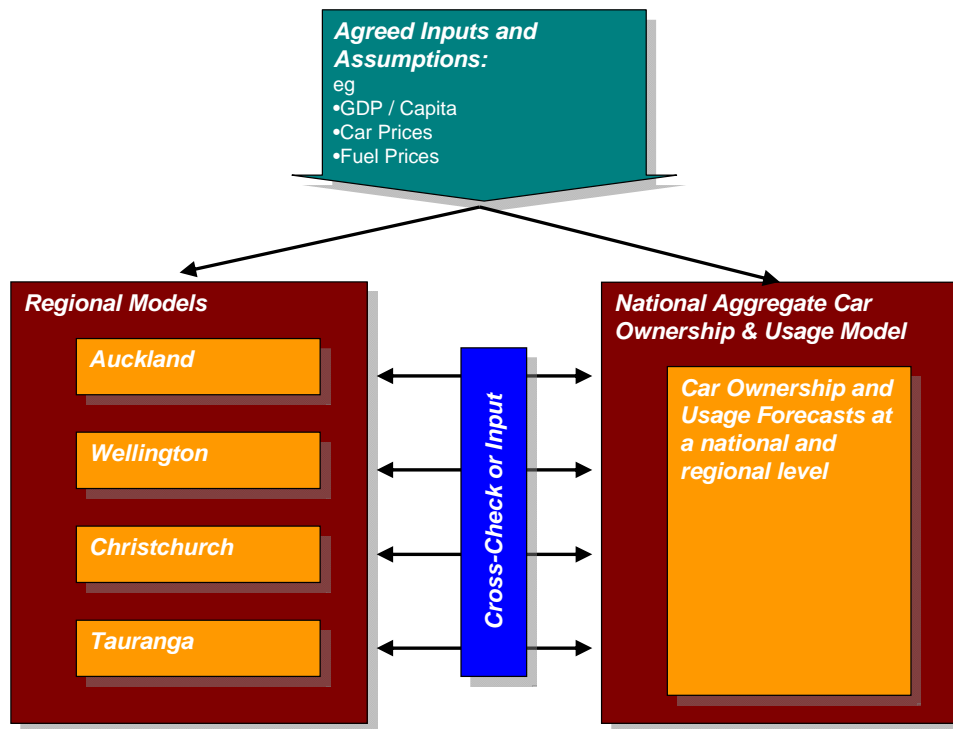
7.4.1 Short- to medium-term framework

Currently the MoT VFEM provides the only accepted national car ownership model. Each region appears to have different methodologies for car ownership forecasting. What appears to be missing is a hierarchy of models where a national model can provide an input into regional models or national and regional models can be checked against each other to ensure consistency.

Figure 7.3 shows a proposed framework that could be implemented in the short to medium term. This framework could be used as a basis to work towards a national disaggregate ownership and use model.

At the highest level in the framework is an agreed set of inputs and assumptions that are used for all car ownership forecasting (this is discussed further below). These assumptions feed into both the regional models and national model. The national model outputs could provide an input into regional models (eg Wellington, Christchurch), depending on the regional car ownership modelling methodology adopted or the national/regional models could provide a cross-check to ensure consistency.

Figure 7.3 Short- to medium-term framework



7.4.2 National aggregate model: MoT VFEM

A key part of the proposed short- to medium-term framework is a national aggregate model. The MoT VFEM would be the appropriate basis for such a model for the following key reasons:

- Central government (eg the MoT) is an appropriate place to have stewardship over a national model.
- The VFEM aggregate time series model is already well understood and the MoT is continuing its development.

The work undertaken in this research by Booz Allen Hamilton (2000) and by Beca (2003) also highlights that enhancements to the VFEM should be considered. A particular limitation with the VFEM car ownership model is that it only includes time as an explanatory variable. However, the above research work has identified that both GDP per capita and car prices are important explanatory variables in car ownership.

As such it is recommended that this research and the role proposed for the VFEM model in the national framework be taken into account in the ongoing development of the VFEM.

7.4.3 Agreed set of inputs and assumptions

From the review of New Zealand practices, it is apparent that the developers of regional models do not have an agreed set of consistent inputs and assumptions to draw upon (eg future car prices). This has the potential to result in different assumptions between models and therefore a different basis for car ownership forecasts across New Zealand. Developing an agreed set of inputs, assumptions and forecasts for key inputs should be a relatively easy way to overcome this.

7.5 Summary

The development of a static disaggregate model is the recommended car ownership and use modelling methodology. This is because it provides the desired level of functionality identified in the needs survey completed in this research. In particular a static disaggregate ownership model is able to test many policy variables (eg public transport provision) and there is a large international body of experience to draw upon.

However it is recognised that developing a static disaggregate car ownership model for New Zealand is a substantial undertaking and the development costs are likely to be significant. Consequently, there is merit in exploring a short- to medium-term modelling framework. This framework would look to build upon the MoT VFEM aggregate model to provide the basis for car ownership and use forecasts and to ensure national consistency.

8 Conclusions and recommendations

8.1 Conclusions

Examination of New Zealand car ownership and use data shows the following:

- Car ownership in New Zealand has continued to increase. In 1970 car ownership was 0.310 cars per person, by 2005 it had risen to 0.574 cars per person.
- There appears to be a relationship between times of increasing GDP/person and decreasing car prices corresponding to increased car ownership per person.
- New Zealand continues to have one of the highest rates of car ownership in the world.
- Information on vehicle kilometres travelled has been collected since 2001, using odometer readings taken during the vehicle WoF inspections. This data shows that light vehicle travel per person increased between 2001 and 2005, but decreased in 2006. Average annual travel per vehicle has been decreasing since 2002.
- Previous research has shows that increased petrol prices result in less fuel consumption per person.

An aggregate car model, previously developed by Booz Allen Hamilton (2000) has been updated as part of this research. The following key conclusions have been made from its results:

- The current level of car ownership in New Zealand, approximately 0.58 cars per capita, is below the estimated saturation level of car ownership. The current saturation levels are estimated to be in the range 0.67 cars per capita (lower) to 0.75 cars/capita (upper). By year 2041 the saturation level is predicted to increase, due to changes in age distribution, to 0.71 cars per capita (lower) and 0.79 cars per capita (upper).
- Elasticities of GDP per capita and car price index can be used to predict future changes in car ownership, particularly in the short to medium term. These appear to be a strong set of relationships.
- There is considerable uncertainty over factors that could have a significant impact on car ownership. For example it is unlikely that the real downward trend in the car price index will continue. The ability to forecast future car ownership is dependent on the ability to accurately forecast changes in GDP and car prices.
- Economic conditions and car prices are predicted to have a significant impact on future car ownership.
- Using the Booz aggregate model under the 'high' scenario, car ownership could reach the lower estimate of saturation by approximately 2021.
- The Booz aggregate model appears to perform better than the other examined New Zealand aggregate models in the short-term (< 10 years). Over the medium term (10–20 years) the three models perform in a similar manner.

A car ownership and use modelling 'needs survey' was conducted with transport practitioners in New Zealand. The purpose of this survey was to examine the needs of users of car ownership and use data. Conclusions drawn from this survey were used as an input to the development of a New Zealand car

ownership and use modelling framework. They indicated that a modelling methodology for car ownership and use should ideally:

- be segmented by private vehicles (private and company ownership) and LCVs
- be applied to national, regional, and local contexts
- focus on forecasting within a 25-year horizon
- segment vehicles by fuel type/efficiency and split between private and business
- be sensitive to changes in fixed/variable costs, and in particular changes in fuel taxes and road user charges, changes in income and the level of PT supply
- have outputs that include vehicle numbers, usage, emissions and fuel consumption measures and to a lesser extent, government revenue.

This review of New Zealand modelling practices and literature has identified the lack of a consistent approach to forecasting car ownership in New Zealand. While some of the regional models are regulated by national forecasts for car ownership, they are not the same forecasts. There does not appear to be a consistent set of key input assumptions for these model forecasts (eg future GDP or income, car prices). As these regional models are used to predict future transport requirements, the outputs forming an input to project prioritisation, it would be highly desirable if the forecasting of car ownership was undertaken on a consistent basis. As such, what appears to be lacking in New Zealand is an integrated framework for forecasting car ownership.

The development of a national *static disaggregate model* is the recommended car ownership and use modelling methodology. This is because it provides the desired level of functionality as identified in the needs survey. In particular a static disaggregate ownership model is able to test many policy variables (eg public transport provision).

However it is recognised that developing a static disaggregate car ownership model for New Zealand is a substantial undertaking and the development costs are likely to be significant. Consequently, there is merit in exploring a short- to medium-term modelling framework. This framework would look to build upon the MoT VFEM aggregate model to provide the basis for forecasting car ownership and use, and ensure national consistency.

8.2 Recommendations

The following actions are recommended for the transport sector:

- To undertake a detailed review of the New Zealand Household Travel Survey and census data to ensure these would meet the future requirements of a static disaggregate car ownership model. The travel survey might need to be modified and should be undertaken on an annual basis.
- To review definitions of vehicle ownership and classification used in census data, the household travel survey and motor vehicle registration records with a view to achieving consistency throughout.
- To implement a short- to medium-term framework for car ownership and use by:
 - continuing development of the VFEM to strengthen it as a national car ownership and use model

- developing a nationally consistent set of inputs, assumptions and forecasts for use in car ownership at both the national and regional level
- encouraging developers and users of regional models to use the national car ownership model as an input or cross-check of regional models (as appropriate).
- To develop a static disaggregate car ownership and use model.
- To review national guidelines for transport professionals to take into account changes in car ownership and use when evaluating projects. Ideally these guidelines should be linked to the national car ownership and use model.

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Appendix A: New Zealand vehicle ownership data

Table A.1 New Zealand vehicle ownership data (000)

NZ Yearbook licensed motor vehicles as at 31 March						NZ Statistics licensed motor vehicles – Sept quarter					MoT
Year	Cars	Motorcycles	Goods	Other	Total	Cars	Mcyys	Goods	Buses	Total	Lic veh to 31/12
1951	252.5	21.0	84.9	6.9	365.4						447.1
1952	282.0	26.7	95.2	7.0	410.9						494.2
1953	307.3	29.2	101.0	7.2	444.7						513.7
1954	325.3	29.7	103.0	7.3	465.3						553.5
1955	358.1	30.4	107.3	7.5	503.2						601.1
1956	395.5	28.8	115.2	7.7	547.1						638.3
1957	427.0	31.2	121.5	7.8	587.4						672.6
1958	464.6	33.9	115.3	7.8	621.7						702.9
1959	482.6	36.2	117.7	7.3	643.8						728.2
1960	504.8	36.8	119.4	7.2	668.3						762.7
1961	526.3	39.3	124.4	7.2	697.2						806.3
1962	555.8	44.4	130.2	7.5	737.8						844.1
1963	586.8	45.7	133.0	7.9	773.3						899.4
1964	633.3	46.9	138.3	7.6	826.1						963.9
1965	691.5	50.1	153.8	8.8	904.2						1013.8
1966	727.7	49.7	163.4	8.2	949.0						1060.2
1967	784.1	49.6	163.0	7.7	1004.5						1087.6
1968	810.9	48.4	164.7	7.7	1031.7						1114.7
1969	836.6	47.9	167.0	7.9	1059.3						1148.7
1970	865.2	48.0	171.5	7.8	1092.4	874.1	40.3	169.4	3.1	1086.8	1208.7
1971	911.9	53.1	181.8	7.4	1154.1	913.3	47.7	175.8	3.0	1139.9	1272.4
1972	959.5	62.9	190.6	7.3	1220.3	968.0	55.8	180.3	3.0	1207.0	1349.1
1973	1,025.0	72.4	194.7	7.3	1299.4	1029.5	63.6	187.3	3.0	1283.4	1438.8
1974	1,083.8	87.1	200.1	7.3	1378.4	1092.1	76.3	192.9	3.0	1364.4	1515.3
1975	1,134.9	93.7	206.8	7.6	1442.9	1134.0	83.4	194.6	3.1	1415.2	1574.5
1976	1,177.4	103.0	211.2	7.6	1499.2	1159.6	88.0	216.4	3.1	1467.2	1631.3
1977	1,205.9	107.0	232.2	7.7	1552.8	1181.9	85.5	221.3	3.2	1491.9	1642.8
1978	1,221.2	105.8	236.7	7.7	1571.3	1203.5	82.7	230.4	3.2	1519.9	1675.1
1979	1,250.2	106.5	247.9	7.7	1612.3	1239.9	95.8	235.6	3.2	1574.5	1732.9
1980	1,289.6	125.1	253.6	7.9	1676.2	1273.0	108.1	245.1	3.4	1629.6	1789.4
1981	1,325.4	138.5	264.5	8.0	1736.4	1308.5	113.5	257.3	3.3	1682.6	1846.1
1982	1,366.7	145.9	281.2	7.9	1801.8	1347.1	114.3	262.4	3.7	1727.4	1896.3
1983	1,401.2	145.4	288.0	7.5	1842.2	1378.3	112.6	270.9	4.0	1765.9	1921.5

Table A.1 New Zealand vehicle ownership data (000)

NZ Yearbook licensed motor vehicles as at 31 March						NZ Statistics licensed motor vehicles-Sept quarter					MoT
Year	Cars	Motorcycles	Goods	Other	Total	Cars	Mcyys	Goods	Buses	Total	Lic veh to 31/12
1984	1439.2	142.5	294.0	7.9	1883.6	1427.1	108.0	275.1	4.5	1814.8	1969.3
1985	1491.9	138.9	299.8	7.6	1938.2	1454.8	105.2	283.5	4.9	1848.4	1995.0
1986	1523.2	134.8	306.0	8.1	1972.1						2010.1
1987											2030.6
1988	1382.3	98.3	289.2	11.0	1780.8	1404.3	91.8	292.5	8.1	1796.8	2045.4
1989	1438.7	90.7	289.2	11.1	1829.7	1464.8	82.4	295.3	8.4	1850.9	2108.4
1990	1497.7	82.3	295.3	11.2	1886.5	1511.3	72.1	300.5	7.8	1891.8	2197.7
1991	1548.1	74.8	301.2	10.8	1934.8	1549.9	69.0	312.1	7.2	1938.2	2220.1
1992	1551.4	66.7	309.3	10.9	1938.2	1524.4	55.5	313.4	7.8	1901.0	2227.1
1993	1571.8	61.2	322.4	12.0	1967.4	1562.8	52.9	334.3	8.3	1958.4	2243.8
1994	1611.8	59.1	340.3	12.7	2023.9	1626.9	52.0	353.9	8.8	2041.7	2289.3
1995	1660.5	55.9	355.8	13.6	2085.8	1662.3	46.7	359.6	9.1	2077.8	2354.6
1996	1650.1	49.3	342.2	15.0	2056.6	1698.4	43.5	357.7	9.7	2109.3	2379.8
1997	1691.0	46.7	346.5	16.1	2100.4	1757.3	43.3	352.9	10.4	2163.9	2392.7
1998	1776.0	46.2	359.4	17.5	2199.1	1795.7	43.8	357.2	11.1	2207.8	2440.4
1999	1883.4	48.2	371.4	19.0	2322.0	1888.4	45.5	367.3	11.9	2313.2	2512.3
2000	1905.0	45.0	368.6	20.0	2338.7	1913.1	42.8	363.4	12.4	2331.7	2601.7
2001	1933.9	43.3	363.2	19.8	2360.1	1947.4	42.3	361.1	12.9	2363.6	2633.2
2002	1988.5	43.4	366.9	20.9	2419.8	1999.4	42.1	365.2	13.6	2420.2	2709.5
2003	2056.6	41.5	374.4	21.9	2494.3	2091.0	41.3	376.2	14.3	2522.8	2801.0
2004	2140.4	43.5	386.3	23.0	2593.2	2172.2	44.0	389.2	15.1	2620.5	2920.7
2005	2211.8	48.0	399.8	23.8	2683.5	2242.5	51.5	402.8	15.8	2712.5	3030.4
2006						2280.5	60.2	409.7	16.7	2767.1	3124.3

Table A.2 Estimates of NZ motor vehicle ownership 1970–2006 (000)

Year	Licensed vehicles 1 Sept quarter	Adjustment factor	Booz & Company estimate
1970	1086.8	0.99	1075.9
1971	1139.9	0.99	1128.5
1972	1207.0	0.99	1195.0
1973	1283.4	0.99	1270.6
1974	1364.4	0.99	1350.7
1975	1415.2	0.99	1401.0
1976	1467.2	0.99	1452.5
1977	1491.9	0.99	1476.9
1978	1519.9	0.99	1504.7
1979	1574.5	0.99	1558.7
1980	1629.6	0.99	1613.3
1981	1682.6	0.99	1665.8
1982	1727.4	0.99	1710.1
1983	1765.9	0.99	1748.2
1984	1814.8	0.99	1796.6
1985	1848.4	0.99	1829.9
1986	1859.3	0.99	1840.7
1987	1891.4	0.99	1872.5
1988	1796.8	1.05	1886.7
1989	1850.9	1.05	1943.4
1990	1891.8	1.05	1986.3
1991	1938.2	1.05	2035.1
1992	1901.0	1.05	1996.1
1993	1958.4	1.05	2056.3
1994	2041.7	1.05	2143.8
1995	2077.8	1.05	2181.6
1996	2109.3	1.05	2214.8
1997	2163.9	1.05	2272.1
1998	2207.8	1.05	2318.2
1999	2313.2	1.05	2428.8
2000	2331.7	1.05	2448.3
2001	2363.6	1.05	2481.8
2002	2420.2	1.05	2541.2
2003	2522.8	1.05	2648.9
2004	2620.5	1.05	2751.5
2005	2712.5	1.05	2848.1
2006	2767.1	1.05	2905.4

Notes:

(1) NZ Statistics September quarter (Table D.1)

(2) Figures for 1986 and 1987 estimated

Table A.3: New Zealand motor vehicle ownership 1970–2006

Year	Cars (000)	Motorcycles (000)	Goods (000)	Buses (000)	Total (000)	Population mean (000)	Cars per person	Motor-cycles per head
1970	865.3	39.9	167.7	3.0	1075.9	2788.9	0.310	0.014
1971	904.1	47.2	174.1	3.0	1128.5	2831.2	0.319	0.017
1972	958.3	55.2	178.5	3.0	1195.0	2876.0	0.333	0.019
1973	1019.2	63.0	185.4	2.9	1270.6	2931.3	0.348	0.021
1974	1081.2	75.6	190.9	3.0	1350.7	2993.6	0.361	0.025
1975	1122.7	82.6	192.7	3.1	1401.0	3057.8	0.367	0.027
1976	1148.0	87.1	214.2	3.1	1452.5	3111.3	0.369	0.028
1977	1170.1	84.7	219.1	3.1	1476.9	3136.2	0.373	0.027
1978	1191.5	81.9	228.1	3.2	1504.7	3143.5	0.379	0.026
1979	1227.5	94.8	233.2	3.2	1558.7	3143.1	0.391	0.030
1980	1260.3	107.0	242.6	3.4	1613.3	3138.0	0.402	0.034
1981	1295.4	112.3	254.8	3.3	1665.8	3146.7	0.412	0.036
1982	1333.6	113.1	259.8	3.7	1710.1	3161.2	0.422	0.036
1983	1364.6	111.4	268.2	4.0	1748.2	3189.5	0.428	0.035
1984	1412.8	107.0	272.4	4.5	1796.6	3230.6	0.437	0.033
1985	1440.3	104.1	280.6	4.9	1829.9	3259.3	0.442	0.032
1986	1451.7	105.2	278.1	5.8	1840.7	3273.3	0.444	0.032
1987	1478.4	102.7	285.3	6.1	1872.5	3281.6	0.451	0.031
1988	1474.6	96.4	307.2	8.5	1886.7	3310.2	0.445	0.029
1989	1538.0	86.5	310.1	8.8	1943.4	3318.3	0.463	0.026
1990	1586.8	75.7	315.5	8.2	1986.3	3336.5	0.476	0.023
1991	1627.4	72.5	327.7	7.5	2035.1	3373.1	0.482	0.021
1992	1600.6	58.2	329.1	8.2	1996.1	3415.8	0.469	0.017
1993	1641.0	55.6	351.0	8.7	2056.3	3452.0	0.475	0.016
1994	1708.3	54.6	371.6	9.2	2143.8	3491.1	0.489	0.016
1995	1745.5	49.0	377.6	9.6	2181.6	3539.3	0.493	0.014
1996	1783.3	45.6	375.6	10.1	2214.8	3618.3	0.493	0.013
1997	1845.2	45.4	370.6	10.9	2272.1	3747.3	0.492	0.012
1998	1885.5	46.0	375.1	11.6	2318.2	3792.2	0.497	0.012
1999	1982.8	47.8	385.7	12.5	2428.8	3821.9	0.519	0.013
2000	2008.7	44.9	381.6	13.0	2448.3	3842.9	0.523	0.012
2001	2044.7	44.5	379.1	13.5	2481.8	3867.5	0.529	0.011
2002	2099.3	44.2	383.4	14.3	2541.2	3899.6	0.538	0.011
2003	2195.6	43.4	395.0	15.0	2648.9	3970.0	0.553	0.011
2004	2280.8	46.2	408.7	15.8	2751.5	4044.9	0.564	0.011
2005	2354.6	54.1	422.9	16.6	2848.1	4101.3	0.574	0.013
2006	2394.5	63.2	430.2	17.5	2905.4	4148.0	0.577	0.015

Note: Figures for 1986 and 1987 estimated

Appendix B: Components of general model archetypes

Table B.1 General model types

	MACRO Aggregate (saturation) time series models	Aggregate market models	Heuristic simulation models	MICRO Static disaggregate ownership models	Indirect utility models	COHORT Cohort models or panel models	Dynamic transaction models
General model structure	<p>The earliest models Tanner (1958, 1962) fitted an 'S-curve' as a function of time: car ownership per capita grew rapidly a moderate levels of car ownership but tapered off as car ownership approached saturation.</p> <p>Later models such as Tanner (1974) were modified to incorporate other explanatory variables such as per capita income and motoring costs. These models implied that a growth in income or motoring costs could 'speed up' the approach towards saturation.</p> <p>However, it is important to note that the eventual 'saturation level' of car ownership is not affected by income or motoring costs – These variables only influence the speed at which saturation is</p>	<p>These models simulate supply and demand in the car market (although the focus is usually on the used car market).</p> <p>The key driver these models is the scrappage model – The scrappage model predicts the rate at which cars are scrapped, based on age and the price of used cars.</p> <p>The used car market model is used to determine the price of used cars.</p> <p>Other models are used to predict either the desired stock of cars or new car purchases.</p>	<p>These models predict car ownership, based on heuristic assumptions about the proportion of net income (after expenses) that is spent on cars.</p> <p>In the FACTS model, households are assigned desired kilometres and they then choose cars so as to use up the proportion of net income available for expenditure on cars.</p> <p>Low income households may be unable to afford any cars, while high income</p>	<p>These models estimate the probability of a household owning at least one car. This estimate is influence by characteristics of the household, including income and household structure.</p> <p>They models also estimate the probability of a household owning more than one car, given than that own at least one car.</p> <p>The estimations are produced using limited dependent variable regression models and cross-sectional data.</p>	<p>These models allow households to choose the combination of car ownership and car use that maximises their utility</p>	<p>These models generally group and average households into age-based cohorts. Each cohort is treated as an observation through time</p> <p>Some models use longitudinal data of individuals throughout time.</p> <p>These models generally estimate car ownership forecasts for each cohort</p>	<p>These models predict future 'transactions' (ie purchases and/or disposal of cars)</p> <p>These models begin with current car ownership patterns.</p> <p>A duration model is used to predict the time (eg years) until a household next 'transacts'.</p> <p>If a household does not 'transact' then car ownership is assumed to be the same as it was last year.</p> <p>If a household does 'transact' then a type-choice model will be used to predict the type of car purchased.</p>

	MACRO Aggregate (saturation) time series models	Aggregate market models	Heuristic simulation models	MICRO Static disaggregate ownership models	Indirect utility models	COHORT Cohort models or panel models	Dynamic transaction models
	<p>approached.</p> <p>The earliest models fitted s-curves based on a logistic function. However, other researchers have employed power function curves and Gompertz curves.</p>		<p>households may be able to afford two cars.</p>				
Attributes of model	<p>Aggregate time series models may be useful for long-term predictions because they focus on 'saturation'.</p> <p>However, these models assume that the 'end-state' is the same, regardless of intervening events (eg people will eventually want two cars per household, regardless of what happens to population density). This assumption may not be accurate.</p> <p>In addition, these models appear to implicitly assume that the impact of explanatory variables (such as GDP per capita) diminishes as households get closer to saturation. This appears to be a reasonable approximation</p>	<p>Aggregate market models are useful for predicting the composition of the future car fleet because they incorporate scrapping of used cars</p> <p>Therefore, these models are useful for predicting energy consumption and//ore emissions.</p>	<p>Heuristic simulation models exploit the observed consistency of the proportion of net income spent on cars and car travel</p>	<p>Static disaggregate models have two main advantages:</p> <ol style="list-style-type: none"> 1. These models use cross-sectional data, which avoids issues with time series data 2. These models incorporate characteristics (such as household structure) that are likely to influence car ownership and use in the future. 			<p>Dynamic transaction models are the 'dynamic' version of static disaggregate models – They enable the use of disaggregate models in predicting type-choice, without assuming that households can choose a new car instantaneously.</p>

	MACRO Aggregate (saturation) time series models	Aggregate market models	Heuristic simulation models	MICRO Static disaggregate ownership models	Indirect utility models	COHORT Cohort models or panel models	Dynamic transaction models
	but, nevertheless, this assumption should be considered in assessment of models.						
Inputs required by the model	<p>Aggregate time series data:</p> <ul style="list-style-type: none"> • average car ownership rates • GDP per capita • other. <p>Assumptions about the appropriate functional form</p>	<p>Aggregate data:</p> <ul style="list-style-type: none"> • scrappage by age and vehicle type • used vehicle prices by vehicle type and perhaps by age • imports and/or vehicle stock by vehicle type. • other. 	<p>Aggregate data:</p> <ul style="list-style-type: none"> • household expenditure on cars and car travel • vehicle prices. 	<p>Disaggregate car ownership models require cross-sectional data on household car ownership and explanatory variables:</p> <ul style="list-style-type: none"> • income • household structure • location • other. <p>Disaggregate car type ownership models require disaggregate data collected from SP and/or RP surveys.</p>	<p>Disaggregate data collected from SP surveys</p>	<p>Longitudinal data and/or household data that can be aggregated into cohorts</p>	<p>Disaggregate data relating to household vehicle choice data:</p> <ul style="list-style-type: none"> • income • household structure • location • other.

Appendix C: Model archetypes influencing factors

Economic growth

Static disaggregate models generally incorporate economic growth in the most sophisticated manner. For example, the national road traffic forecasts (NRTF) model uses forecasts of income by household-type and area to predict the probability of a household (in a particular household-type-area segment) owning a car.

Aggregate time series models incorporate economic growth into their models but only in a simple manner: one of the key explanatory variables is forecast GDP per capita.

Heuristic simulation models also incorporate economic growth by making heuristic assumptions about the relationship between net income and car purchases. However, the validity of these assumptions seems questionable, especially for long-term forecasts, because the relationships between net income and car purchases may change in the future.

Indirect utility models and dynamic transaction models also incorporate economic growth by incorporating income as an explanatory variable. Cohort models and aggregate market models are designed to focus on other aspects of car ownership.

Population and household size

Static disaggregate times series models and dynamic transaction models allow transport planners to incorporate expected changes in household structure into forecast car ownership. This is a key advantage of these models because household structure is likely to have an important influence on future car ownership (eg future households are likely to have less children and more single-person households). Furthermore, household structure is relatively easy to forecast so it is important that forecasts utilise this information. Household structure can potentially also be incorporated into heuristic simulation models, indirect utility models and cohort models.

However, models that use aggregate data, such as aggregate time series models and aggregate market models cannot incorporate disaggregate data like household structure. This is a major disadvantage of these models.

Age distribution and cohort effects

Cohort models are the only models that incorporate the impacts of generational trends in a comprehensive manner. A key generational trend is the increased incidence of licence-holding amongst young females – this will have implications for future car ownership.

These generational trends would appear to be an important influence on car ownership. Therefore, the long-term forecasting ability of a car ownership model may be undermined if it does not incorporate a licence-holding cohort model as an input into the main model. For this reason, the NRTF static disaggregate ownership models uses a licence-holding cohort models as an input. The authors of the Sydney STM static disaggregate ownership model mention that a licence-holding cohort model could be developed as an input.

The remaining models are more limited in their incorporation of age or ageing effects. In particular, models that use aggregate data, such as aggregate time series models and aggregate market models cannot incorporate disaggregate data like age.

Lag effects

The concept of lag effects is only applicable to aggregate time series models. Models with lag effects are designed to reflect the time taken for changes in explanatory variables (eg petrol price changes, car price changes) to feed through into car ownership patterns. Romilly et al (1998) found that the incorporation of lag effects improved the forecasting performance of aggregate time series models considerably (see Forecasting Performance for more information).

Saturation effects

Both the aggregate time series models and the static disaggregate models incorporate the concept of 'saturation'.

However, the concept of 'saturation' underlying an aggregate time series model is quite different from the concept of 'saturation' underlying a static disaggregate model. These differences are illustrated in the table below:

Table C.1 Differences in concept of 'saturation'

	Saturation in aggregate time series models	Saturation in disaggregate models (eg NRTF)
Dependent variable	Aggregate car ownership	Proportion of households that own a car
Main explanatory variable	Time	Income
Other key explanatory variables	GDP per capita	Household structure Licence holding
Incorporation of saturation level into model	The model assumes that there is a saturation level for car ownership.	The model assumes that the proportion of households that own a car is between zero and the saturation level (eg 80%)
Incorporation of saturation curve into model	As time increases car ownership follows a s-curve: early in an economy's development car ownership grows rapidly, then it diminishes towards saturation	As income increases, the probability of owning a car follows an s-curve: at low levels of income increases in income have a big impact on the probability of owning a car, but this effect diminishes as income grows.

The table shows that the 'saturation' concept for aggregate time series models relates to car ownership per capita, while the 'saturation' concept for static disaggregate models relates to the probability of a household owning a car. Obviously, there are interlinkages between the two different concepts.

Factors influencing distance travelled

The following factors that affect car use were identified by the UK Department of Transport:

- household income
- composition of household and their location
- changes in the level of car ownership including the proportions of single and multi car-owning households
- changes in fuel prices
- change in fuel economy/efficiency.

The key determinants in car use were found to be income, the location and composition of households, and the costs of motoring.

Car prices and fuel price changes

Disaggregate car ownership models do not generally incorporate car prices and fuel prices because they are based on cross sectional data (ie a sample of people at a point in time). The UK Department for Transport acknowledged that this was an unresolved difficulty of the 1997 NRTF model. In contrast, aggregate time series models can incorporate car prices and fuel prices because they are based on time series data (ie observations throughout time).

Some of the other models incorporate car prices (and sometimes also fuel prices): aggregate market models and heuristic simulation models both have a strong focus on modelling the impact of car prices on car purchases. Car prices could also be potentially incorporated into indirect utility models and dynamic transaction models.

PT service and accessibility levels

Very few models incorporate PT service and accessibility levels. In particular, aggregate time series models do not incorporate PT service or accessibility levels because they only use aggregate data.

There are a few exceptions. One exception is a static disaggregate model – the NRTF model – that produces forecasts for different area-types (ie Greater London, Metropolitan districts and three other categories with differing levels of population density) – This serves as a proxy for public transport accessibility.

Data inputs

Aggregate time series models have the least demanding data input requirements. All these models require is aggregate data on car ownership, GDP per capita, petrol prices, car prices, etc. Aggregate market models and heuristic simulation models also have relatively low data requirements because they also use aggregate data.

Static disaggregate models and dynamic transaction models require more detailed data. These models require a sample of households, along with data about each of these households including the number of cars in the household, the number of licences, household income, etc.

Cohort models have one of the most demanding data input requirements. These models require longitudinal data on individuals and/or household data that can be aggregated into cohorts.

Indirect utility models have to be estimated using disaggregate data collected from stated preference surveys. The quality of this data is less than ideal because it is based on stated rather than revealed preferences.

Model outputs

Aggregate time series models only produce estimates of car ownership per capita.

Cohort models predict single variables, such as car ownership per capita or incidence of licence holding, amongst specific cohorts.

Dynamic transaction models and aggregate market models focus on the car stock as the key output. Both of these models forecast based on the number of cars in use, the number purchased and the number disposed.

Static disaggregate models and heuristic simulation models produce a richer set of predictions. These models predict the number of households with no cars, one car and multiple cars. This information can be used to forecast car use, using the number of vehicles in a household as an explanatory variable.

Forecasting performance

Research by Romilly et al (1998) explored the forecasting performance of a range of car ownership models. The researchers compared the UK Department of Transport's forecasts, which are based on a static disaggregate model, with their own forecasts, which were based on a simple linear aggregate time series model. The researchers found that the forecasts using the aggregate time series model were superior.

References

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Appendix D: Summary of key model types

	Aggregate (saturation) time series models	Static disaggregate ownership models	Aggregate market models
General model structure	<p>The earliest models Tanner (1962) fitted an 'S-curve' as a function of time: car ownership per capita grew rapidly a moderate levels of car ownership but tapered off as car ownership approached saturation.</p> <p>Later models such as Tanner (1974) were modified to incorporate other explanatory variables such as per capita income and motoring costs. These models implied that a growth in income or motoring costs could 'speed up' the approach towards saturation.</p> <p>However, it is important to note that the eventual 'saturation level' of car ownership is not affected by income or motoring costs – These variables only influence the speed at which saturation is approached.</p> <p>The earliest models fitted s-curves based on a logistic function. However, other researchers have employed power function curves and Gompertz curves.</p>	<p>These models estimate the probability of a household owning at least one car. This estimate is influence by characteristics of the household, including income and household structure.</p> <p>These models also estimate the probability of a household owning more than one car, given than that own at least one car.</p> <p>The estimations are produced using limited dependent variable regression models and cross-sectional data.</p>	<p>Aggregate market models simulate supply and demand in the car market (although the focus is usually on the used car market). The key driver in these models is a scrappage model – the scrappage model predicts the rate at which cars are scrapped, based on age and the price of used cars. A used car market model is used to determine the price of used cars.</p> <p>The key functionality of these models is that they can be used to predict the composition of the car fleet because they incorporate scrapping of used cars. For example, the scrappage model could be used to predict when a significant amount of energy inefficient vehicles are going to be retired. Therefore, these models are useful for predicting energy consumption and/or emissions.</p>
Variants/ supplementary models	<p>Dargay and Gately (1999) estimated Gompertz functions using partial adjustment models. These partial adjustment models enabled estimation of short-run and long-run dynamics.</p>	<p>The car type choice model estimates the impact of explanatory variables on the type of vehicle purchased.</p> <p>These models predict the type of vehicle purchased as a function of explanatory variables, such as household income, vehicle prices, number of children and fuel costs.</p> <p>These models are estimated using data from SP and RP surveys.</p>	<p>There is variation in how vehicle scappage and acquisition is modelled.</p>

	Aggregate (saturation) time series models	Static disaggregate ownership models	Aggregate market models
National models reviewed	CARMOD NRTF	NRTF STM	ALTRANS TRESIS
Other national models		LMS VMM (car-type choice) for the UK	TREMOVE
Inputs required by the model	<p>Aggregate time series data:</p> <ul style="list-style-type: none"> • Average car ownership rates • GDP per capita • other influencing factors (eg car prices). <p>Assumptions about the appropriate functional form</p>	<p>Disaggregate car ownership models require cross-sectional data on household car ownership and explanatory variables:</p> <ul style="list-style-type: none"> • income • household structure • location • other. <p>Often data is collected from stated preference (SP) and/or revealed preference (RP) surveys.</p>	<p>These models require aggregate data on the car market, including the vehicle stock and/or imports, scrappage rate and used vehicle prices by vehicle type and perhaps by age.</p>
(Dis)advantages	<ul style="list-style-type: none"> + limited data requirements + dynamic • no or limited vehicle type distinctions • no or limited number of policy variables and demographic distinctions • no car use. 	<ul style="list-style-type: none"> + behavioural foundation + many car types possible + many policy variables possible • large data requirements (but data on a household level is often available) • no car use (but can be included) • problems with shorter-time periods. 	<ul style="list-style-type: none"> + limited data requirements + both supply and demand side represented • static model • limited vehicle type distinctions • limited number of policy variables • no car use.

	Aggregate (saturation) time series models	Static disaggregate ownership models	Aggregate market models
Outputs/ functionalities	<p>Aggregate saturation models use time series data to produce a forecast of a possible long-run saturation level for car ownership per capita.</p> <p>The models are limited in the sense that the long-run saturation level is assumed independent of income, fuel costs, etc. In particular, these models assume that policy variables have no permanent impact on 'long-run' car ownership. Saturation models also produce forecasts for future progression towards the saturation level.</p> <p>The rate of progression towards the saturation level is influenced by explanatory variables such as income, etc.</p> <p>The model is of limited use for traffic forecasting because it only forecasts car ownership per capita – The model does not distinguish between the number of first, second and third cars, whereas this distinction is important for forecasts of future traffic levels.</p>	<p>Disaggregate ownership models predict the number of households that own no cars, one car, two cars, etc.</p> <p>A key functionality across all of the main disaggregate ownership models is that they enable estimation of the impact of income growth on car ownership. They do this by looking at car ownership patterns across different income groups, and then using that information to extrapolate the impacts of income growth.</p> <p>All of the main disaggregate ownership models also enable estimation of the impact of household structure on car ownership. However, different models represent household structure in different ways</p> <p>The Sydney STM also incorporates licence holding as an explanatory variable. In addition the STM estimates company car ownership separately.</p> <p>None of the disaggregate ownership models reviewed incorporate the impact of variables such fuel prices into forecasts because they depend on the use of cross-sectional data, rather than time series data.</p> <p>Disaggregate car type models employ SP/RP data relating to new vehicles cars purchased. Therefore, the main functionality of car type models is in forecasting the market share of each car type in new vehicle forecasts.</p> <p>Disaggregate car type models do not generally generate the total number of new vehicles purchased so a separate model is required to meet this functional need.</p>	<p>The key output from these models is information about the vehicle fleet. These models use aggregate data so they are unable to relate car purchases to household characteristics such as household structure.</p>

	Aggregate (saturation) time series models	Static disaggregate ownership models	Aggregate market models
Outputs/ accuracy of forecasts	<p>The model's forecasts will be relatively less accurate because the forecasts use time series data – Econometric analysis using time series data is often less accurate than analysis using cross sectional data, due to small sample size and autocorrelation.</p> <p>In addition, the amount of confidence one can have in 'saturation' levels is debated in the literature.</p> <p>The model might produce accurate long-term forecasts if one has confidence in the long-run 'saturation' level that is estimated.</p> <p>The model may not be very effective at producing short-term forecasts because it is so strongly based around a long-term curve tracing toward saturation.</p>	<p>The forecasts from a disaggregate car ownership model can be quite accurate because cross sectional data is employed. This provides for a high sample size and econometric issues with time series are avoided because of random sample independence between observations.</p> <p>The disaggregate models produce insightful long-term forecasts because they incorporate long-run drivers of car ownership, such as income and household structure.</p> <p>One possible weakness of disaggregate models (in terms of long-term forecasts) is that they do not generally take into account drivers that can only be measured with time series data, such as fuel costs.</p> <p>Another possible weakness of disaggregate models is that they make inferences about the effect of income on car ownership by comparing car ownership across income groups. However, some of the differences in car ownership across income groups may be due to factors other than just income (eg differences in attitudes).</p> <p>The disaggregate models are relatively less effective at short-term forecasts because the explanatory variables, such as household structure, do not explain much of short-term volatility in car ownership. Short-term volatility in car ownership is caused primarily by variables that are excluded from these models (car prices, exchange rates, petrol prices, public transport prices).</p> <p>The forecasts for car-type market share from disaggregate car-type models are dependent on the quality of SP/RP data. Research by Brownstone, Bunch and Train (2000) suggests plausible forecasts require RP data in addition to SP data.</p>	<p>The aggregate market models are particularly useful in providing emissions forecasts as they are able predict vehicle types (including age, class, fuel) and vehicle use.</p> <p>The weakness of this model type is that it is effectively a static model. For example the TREMOVE model is described as scenario explorer as the equations used are specifically designed to analyse changes in behaviour as a result of changes in economic conditions.</p>

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Appendix E: Review of international models

MODEL: Various

Reference

De Jong, G, J Fox, A Daly, M Pieters and Smit, R (2004) Comparison of car ownership models. *Transport Reviews* 24, no.4: 379–408.

General forecasting model structure

The paper reviews nine types of car ownership models:

- aggregate time series models
- aggregate cohort models
- aggregate car market models
- heuristic simulation methods
- static disaggregate car ownership models
- indirect utility car ownership and use models
- static disaggregate car-type choice models
- (pseuo)-panel methods
- dynamic car transactions models with vehicle type condition on transaction.

Aggregate time series models usually contain a sigmoid-type function of GDP per capita. The function that increases slowly at low levels of GDP per capita, then rises steeply, then ends approaching a saturation level. These models can be modified to incorporate fuel price levels, population density, road network density, rail network density and time trends.

Aggregate cohort models segregate the current population into groups with the same birth year, and then car ownership patterns for each of these cohorts. Certain cohorts have certain characteristics. For example, the older generations grew up when a car-ownership lifestyle had not yet become firmly established; therefore, this group retained relatively low rates of motorisation. In contrast, younger generations have grown up during the 'car era' and can have more cars and can be expected to keep cars for longer.

Aggregate car market models distinguish between the demand and supply of cars in the car market. The second-hand car-price is determined endogenously. The supply of new cars is generally assumed to be perfectly elastic.

The REMOVE model, as developed by KU Leuven and Standard & Poor's DRI (1999) is an aggregate car market model with three key components:

- The first component determines transport flows by mode choice.

- The second component describes how transport flows by mode choice, scrapping rates and car prices affect car ownership by car-type.
- The third component calculates emissions based on the number of kilometres driven by each vehicle.

The paper also discusses the ALTRANS model, which was described by Kveiborg (1999) and the TRESIS model, developed by Hensher and Ton (2002) for Australian cities.

Heuristic simulation methods assume that households spend a constant proportion of net income on transport. A discussion on evidence on these assumptions is provided in Schafer (2000).

The FACTS model, which was developed for the Netherlands, is provided as an example of a heuristic simulation method. The model allocates business cars to households. The model then has households picking car categories based on their household incomes. Households choose the most expensive car that they can given their household incomes; the author points out that this is cost-maximising behaviour, which is inconsistent with economic theory.

Static disaggregate car ownership models predict the number of cars owned by each household, generally using binary logit models or similar empirical techniques.

The Dutch national model system (LMS), which is discussed by the Hague Consulting Group (1989) is an early example of a static disaggregate car ownership model. This model first predicts licence holding, also using disaggregate modelling. The model then uses licence holding to predict car ownership:

- households with no licence will have no cars
- household with one licence will choose between zero cars or one or more cars
- households with two or more licences will choose between one car or two or more cars.

The decisions about number of cars owned in the LMS model are influenced by net monthly income (i.e. income less expenditure on food, clothing and housing); therefore, if monthly income rises the probability of car ownership increases. There is a fixed cost associated with car ownership; therefore, if fixed car costs rise the probability of car ownership decreases.

The Sydney strategic transport model (STM), as described by the Hague Consulting Group (2000) incorporates company car ownership into a static disaggregate car ownership model. In the Sydney STM, the company car ownership model uses explanatory variables to predict the number of company cars owned. It then uses a total car ownership model to predict the total number of cars in each household, conditional on the number of company cars owned.

The UK Department for Transport modified its NRTF model to incorporate car ownership using a static disaggregate car ownership model. First, the model predicts whether households have at least one car. Then, if the model has at least one car, it predicts whether the household has two or more cars. The model is influenced by a saturation level and licences per adult, household income and area type.

The NRTF model was later revised, based on an audit by Whelan (2001). An additional model was added that estimated the probability of households having three or more cars. In addition, the model was modified to allow single-person households to own more than one car; however, additional cars do not impact on traffic forecasts because one person can only drive one car at a time.

Indirect utility car ownership and use models integrate both car ownership and car use into an integrated micro-economic framework.

De Jong (1989) developed two models that integrate car ownership and car use:

- The first model – the ‘statistical model’ – assumes that a household has a structural desired annual kilometrage, which depends on household income, household size, age, gender and occupation of the head of the household. The household will own a car if the desired annual kilometrage exceeds a certain threshold.
- The second model – the ‘indirect utility model’ – allows households to compare combinations of car ownership and car use and allows them to choose the combination with the highest utility. This decision is influenced by both fixed car cost and variable car cost.
- ‘Indirect utility models’ were also developed by Train (1986), Hensher et al (1992) and for Norway’s national model.

Norway’s national model is similar to the De Jong (1989) model, except that it has two components:

- one component decides if the household has at least one car
- another component decides if the household has one car or two cars (conditional on it having at least one car).

The following variables were found to have a statistically significant impact on the number of cars chosen in Norway’s national model: log of remaining household income, the variable cost of driving, the log of household size and percentage urbanisation. The presence of a female head of household had a significant impact on the first-car decision. The age of head of household (over 45 years, over 65 years) also had an impact on the second-car decision.

Static disaggregate car-type choice models are similar to the models above, except that they also address the choice of car-type in the household, given car ownership. These models are not discussed in detail in the review of this paper because the research project is less concerned with car-type ownership.

(Pseudo) panel methods involve creating an artificial panel based on (cohort) averages of repeated cross-sections. However, the averaging process means that information about individuals is lost because it is captured in cohort means. The paper notes that, when defining cohorts, one should pursue homogeneity within the cohorts and heterogeneity between the cohorts.

The research by Dargay and Vythoukas (1995) is an example of pseudo panel methods. The researchers broke the data down by five-year cohorts and by year between 1983–93, creating 165 pseudo-cohorts. The dependent variable in the Dargay and Vythoukas (1995) is the average number of vehicles per cohort, while the explanatory variables included a lagged dependent variable, car purchase costs, car running costs, public transport fares, income, the number of adults, the number of children, metropolitan and rural areas and a generation effect for the head of the household. The only insignificant variables were public transport fares and the number of children.

Dynamic car transactions models with vehicle type conditional on transaction model car purchase decisions. For example, the Hocherman, Prashker and Ben-Akiva (1983) model allows a zero-car household to choose to either purchase a new car or to do nothing. For a one-car household, the options are replacement or do nothing.

Another example of a dynamic transaction model is the DVTM model developed by the Hague Consulting Group (1993; 1995). The DVTM model also makes transaction decisions, which involve expanding or replacing household vehicles. However, transactions are only made occasionally, and the time between transactions is determined by a hazard-based duration model.

Table E.1 Summary table

	Aggregate time series models	Aggregate 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
General structure	Most models use a sigmoid-shaped 'saturation' function to predict car ownership	These models generally estimate car ownership forecasts for each cohort	These models simulate the supply and demand for cars	These models assume that a certain proportion of net income (after some expenses eg food, rent) is spent on cars. Households on very low incomes will be unable to afford any cars	These models first estimate impacts on the decision to have at least one car, then they estimate the number of cars owned. At least one model incorporates company car ownership	These models allow households to choose the combination of car ownership and car use that maximises their utility	These models address the choice of car type of the household, given car ownership	These models use longitudinal data of individuals throughout time	These models group and average households into age-based cohorts. Each cohort is treated as an observation through time	These models predict 'transactions' (ie purchases and/or disposal of cars)
Underlying theory	'Saturation' based on product life-cycle and diffusion theories	Car ownership is driven by forecast licence-holding within each cohort	The supply of existing cars (along with cost and price information) influences new sales of cars	The model is heuristic because it lacks underlying theory and predicts cost-maximisation behaviour (which contradicts economic theory)	The model assumes that explanatory variables affect the decisions about car ownership	The model assumes that households maximise their utility	The model assumes that households maximise their utility	The number of cars per household is assumed to change over time, as explanatory variables change	The number of cars per household is assumed to change over time, as explanatory variables change	
Car types	No	No	Yes	Yes	No	No	Yes	No	No	Sometimes
Dependent variable	Car ownership per capita	Car ownership per capita (for each cohort)	The number of vehicles of each type in the vehicle stock	The number of vehicles in each household, broken down by vehicle-type	The probability of owning a car at each stage of the decision-making process	Unestablished	Unestablished	The number of cars per household	The number of cars per household	
Explanatory variables	The main explanatory	The main explanatory	Inputs to the simulation model	Inputs to the simulation model	The explanatory variables are net	The explanatory variables considered	The explanatory variables	The explanatory	The explanatory	

Table E.1 Summary table

	Aggregate time series models	Aggregate 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
	variable is GDP per capita, but other variables (population density, fuel prices) can also be incorporated	variable is the predicted number of licences in each cohort. Other explanatory variables include income growth per cohort	can include demand for transport across modes, the prices of vehicles, and scrapping rates.	only include income, annual kilometrage (see below) and the costs (fixed & variable) associated with each vehicle-type	income (income less expenditure on food, housing and clothing), fixed car costs, age, gender, household size, number of workers in household, and region-specific variables.	include fixed car cost, variable car cost, remaining household income, household size and level of urbanisation. The gender and age of the head of the household also had an effect on decisions	considered include vehicle attributes (price, engine size, fuel type, etc) and household attributes (gender of head of household, number of children, etc)	variables can include socio-economic characteristics of the household (income, number of adults, number of children, etc)	variables can include socio-economic characteristics of the household (income, number of adults, number of children, etc)	
Cohort effects	No	Yes	No	No	No, but age is an explanatory variable	No	No	Yes	Yes	No
Lag effects	Yes	?	No	No	Possible with time series data	No	No	Yes	Yes	No
Saturation levels	Yes	Yes	No	No	No	No	No	No	No	No
Links to traffic modelling	None	None	The TREMOVE model calculates transport flows and modal choice, and then uses this information to predict demand in the car market.	The FACTS model draws annual kilometrage at random from a distribution and uses this as an input into the model		These models calculate both car ownership and car use simultaneously; therefore, the car use outputs can be incorporated into traffic modelling	These models are used to describe the composition of the vehicle fleet and are less applicable to traffic modelling	These models can also predict car usage, but only if data on km driven is available	These models can also predict car usage, but only if data on km driven is available	
Empirical techniques	Time series analysis (eg artial	Unestablished	Simulation model	Simulation model	Binary or multinomial logit	Unestablished	Binary or multinomial logit	Panel data analysis	Panel data analysis	Logistic models are

Table E.1 Summary table

	Aggregate time series models	Aggregate 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
used	adjustment model)				models The data can be modelled using ordered or unordered response choice mechanisms Bhat and Pulugurta (1998) recommend unordered response choice mechanisms		models are used to predict vehicle choices, using both SP and RP data			used to predict 'transactions' Hazard-based simulation models predict the time between transactions
Features	These models are particularly attractive for application to development countries because income is considered to be the driving influence behind car ownership (and data requirements are low)	These models are useful for predicting the impact of population changes on car ownership	These models are useful for estimating impacts of car types and, hence, emissions	These models have the limitation that vehicle choice is affected only by the fixed and variable costs associated with each vehicle category		These models have the advantage that they explain both car ownership and car use within the same integrated framework	These models are primarily used to predict the composition of the vehicle fleet			
Examples			TREMOVE model	FACTS model	UK NRTF model					

MODEL: National road traffic forecasts (NRTF) – car ownership

References

Department of the Environment, Transport and Regions (1997) Car ownership: modelling and forecasting. *National road traffic forecasts (Great Britain) 1997 working paper no.1*. 46pp.

Department of the Environment, Transport and Regions (2001) *Updating car ownership forecasts*. Final report. Institute for Transport Studies.

Department of the Environment, Transport and Regions (2007) *Updating national car ownership model*. MVA Consultancy.

General forecasting model structure

The UK Department of the Environment, Transport and Regions (DETR) developed both a car ownership model and a car use model, which are then combined to create traffic forecasts.

There is, in effect, a car ownership model for each of the following household types:

- one adult, not retired
- one adult, retired
- one adult, with children
- two adults, retired
- two adults, no children
- two adults, with children
- three-plus adults, no children
- three-plus adults, with children.

DETR created 'saturation' levels for each of these household types. These 'saturation' levels were influenced by both reasoning and analysis of licence data. For example, the model assumes that single adult households will never own more than one car.

DETR used a three-step method to predict car ownership for each of the household types:

- First, as noted above, the department created 'saturation' curves for each of the household types. These 'saturation' curves predict the maximum proportion of households that own at least one car.⁵ It then uses a logistic model to predict (in effect) where each household type is along their 'saturation' curve. Each household type's position along their 'saturation' curve is affected by a utility of ownership, based on explanatory variables (which is discussed below).

⁵ For example, the maximum proportion of one adult retired households that own at least one car is assumed to be 0.7

- Second, DETR created additional ‘saturation’ curves for the proportion of households owning two or more cars, given that the household owns at least one car. Again, the household type’s position along their ‘saturation’ curve is affected by a linear predictor of explanatory variables.
- Third, DETR created additional ‘saturation’ curves for the proportion of households owning three or more cars, given that the household owns at least two cars. Again, the household type’s position along their ‘saturation’ curve is affected by a linear predictor of explanatory variables.

Forecasting model variables and their incorporation into model

The utility of ownership equations incorporate the following explanatory variables:

- household income (by household type and area type)
- number of adults employed
- licences per adult
- index of purchase costs
- index of vehicle use costs
- company cars.

The models are estimated using data from the Expenditure and Food Survey and the National Travel Survey and relate the number of cars owned to:

- socio-economic characteristics of the household
- its geographical location
- purchase and use costs
- licence holding.

These explanatory variables are combined with car ownership ‘saturation’ assumptions and used to create forecasts of car ownership by household types. The number of households within each household type is also forecast (using demographic forecasts). These are combined with the forecasts of car ownership by household types – the resulting forecasts reflect a prediction of car ownership in the future.

Table E.2 Forecasting model variables and their incorporation into model

Component	Content
Economic growth or income growth	The GDP or ‘income’ is included as an explanatory variable (and is modified by household-type and area) The report notes that distribution of ‘income’ is also important, but is assumed to be unchanged into the future, for the purposes of forecasting.
Population and household size	The number of households (broken down by household type) is forecast using demographic forecasts.
Cohort effects	The car ownership model does not directly include cohort effects. However, the saturation levels are set with regard to cohorts. Also, the forecasts for future licences per adult were based on analysis of cohorts.
Time trend effects	There are no explicit time trend variables but a method was adopted which forecasts ‘year specific constants’ into the future, by relating them to the

Component	Content
	projected growth in licence holding.
Lag effects	There are no lag effects
Saturation effects	There are saturation effects in this model – the assumed ‘saturation’ rates constrain the forecast car ownerships. For example, single-adult households are assumed to only have either no car or one car; similarly, only 70% of single-adult retired households are assumed to ever have a car.
Car price and fuel price effects	Car purchase prices and use costs are explanatory variables.
PT service and accessibility effects	There are no explicit allowances for PT. However, the area type discussed below may serve as a proxy for accessibility to PT services because the area types reflect differing population densities.
Region effects	The model allows the impact of ‘income’ on car ownership to differ by area type. Five area types are incorporated: <ul style="list-style-type: none"> • Greater London • Metropolitan districts • districts with density 10+ persons per hec. • districts with density 2 to 10 persons per hec. • districts with density 0 to 2 persons per hec.
Trends in distance travelled per car	Car use is discussed in working paper 2.

Linkages between car ownership model and traffic models

Forecasts for car ownership and forecasts for car use (ie kilometres per car) are combined together to create traffic forecasts.

Approaches to forecasting at national, regional and sub-regional/local levels

The model is capable of producing forecasts for each of the five area-types discussed earlier.

Application of the model

The model is implemented and is used for the NRTF.

MODEL: NRTF – car use

Reference

Department of the Environment, Transport and Regions (1997) Car use: modelling and forecasting. *National road traffic forecasts (Great Britain) 1997 working paper no.2.* 49pp.

General forecasting model structure

This model focuses on forecasting car use (defined as the average annual distance travelled per car).

The forecasting process consists of three stages:

- Stage 1 – incorporate elasticities of car use with respect to income, broken down by household type and car ownership patterns
- Stage 2 – incorporate an aggregate elasticity of car use with respect to changes in fuel costs
- Stage 3 – refine model using company car adjustment

During stage 1, DETR estimated the elasticities of car use with respect to income using cross-sectional data from the 1991/93 National Travel Survey. However, the car use forecasts produced using stage 1 had no regard to the impact of fuel costs (fuel prices and fuel efficiency) on car use. Therefore, during stage 2, DETR estimated fuel cost elasticities using an error correction model. DETR then used the error correction model to project two series for car use forecasts: one series included assumptions about future fuel costs; the other series assumed that fuel costs stayed constant. The difference between these two series was used to adjust the forecasts from stage 1. During stage 3, the forecasts from stage 2 were modified using a company car adjustment. This adjustment was made to ensure that the proportion of company cars in the car stock (and the consequent effects on kilometres driven) did not increase disproportionately as the number of multi-car-owning households increased.

The general form of the resulting equation is:

(Equation E.1)

$$\left(\sum_i^{\text{each household type}} \right) \left(\sum_j^{\text{number of car sin household}} \right) \left[\left(\frac{\text{base year milage}}{\text{fuel cos t effect}} \right) \times \left(\frac{\text{forecast yearhouseh oldincome}}{\text{baseyearho useholdinc ome}} \right)^{\text{Income density}} \times \left(\frac{\text{forecast year}}{\text{number of car owning households}} \right) \right] \times \left(\frac{\text{company car adjustment}}{\text{car adjustment}} \right)$$

Table E.3 Forecasting model variables and their incorporation into model

Component	Comment
Economic growth or Income growth	The cross sectional car use model (from stage 1) uses forecast income, by household type and car ownership, as an input into the model. The paper notes that there is a clear relationship between income and car-use – the relationship is almost linear – there is no evidence of a ‘saturation’ effect, as there is with car ownership.
Population and household size	The cross sectional car use model incorporates forecasts for numbers of people in each household type. For example, the number of one adult, retired households was forecast to rise by 135% from 1996 to 2031.
Cohort effects	The car use models do not explicitly incorporate cohort effects but they use forecasts of numbers of people in each household type, which may be based on cohort analyses.
Time trend effects	There are no time trend effects.
Lag effects	There are no lag effects
Saturation effects	There are no saturation effects
Car price and fuel price effects	The time series model (from stage 2) estimates the impact of fuel cost (fuel price and fuel efficiency) on car use.
PT service and accessibility effects	Proximity to bus services and proximity to rail services were included in cross-sectional analyses of 1991–93 National Travel Survey data. However, these variables were not used in the final cross sectional model. The reasons for this are not stated, but the empirical output shows that the

Component	Comment
	coefficients on these variables were often counter-intuitive.
Region effects	The paper claims on paragraph 8 that location is incorporated into the car use model, but there is no evidence elsewhere of this, including in the empirical output.
Trends in distance travelled per car	The paper notes that car use has generally growth. However, there have been periods of decline (1973–79, 1990 onwards) which can generally be associated with shocks to the price of fuel, and lower growth in GDP.

Linkages between car ownership model and traffic models

The car use forecasts are combined with the car ownership forecasts to produce forecasts for total traffic.

Estimates of parameters produced

Car use in Great Britain, measured in annual kilometres per car, has grown from an average of 13,860km in 1951 to 15,970km in 1996. It was also identified that in the 20 years up to 1996, there was an increased in the proportion of shorter journeys and the average car trip length increased.

The following table provides the household elasticities from the model:

Figure E.1 Household elasticities of car use with respect to income, and average kilometres per car

Household Type		Income elasticity	Average kms per annum (1991/3)	Number of observations
One adult, not retired	Only car	0.36***	15,744	664
	First car ¹	0.27**	7,606	296
One adult, retired	Only car	0.25**	12,666	153
	First car ¹	0.32***	9,906	848
One adult, with children	Only car	0.32***	n/a	n/a
	First car ¹	0.27	n/a	n/a
Two adults, retired	Only car	0.16	n/a	n/a
	First car ¹	0.29***	16,494	1,079
Two adults, no children	Only car	0.29***	24,497	583
	First car	0.16**	9,779	1,125
Two adults, with children	Only car	0.29***	16,365	1,185
	First car	0.15***	25,370	542
All three-plus adults	Only car	0.16**	9,779	1,125
	First car	0.25***	14,631	637
All three-plus adults	First car	0.20***	23,556	801
	Second car ²	0.27***	11,529	801

Significance levels: *** = 1%, ** = 5%, * = 10%

¹ Elasticities proxied by two adult, no children household estimate.

² Estimated using *all* two adult household types.

Approaches to forecasting at national, regional and sub-regional/local levels

The method does not appear to vary by region.

Application of the model

The model is implemented and is used for the NRTF.

Model: CARMOD

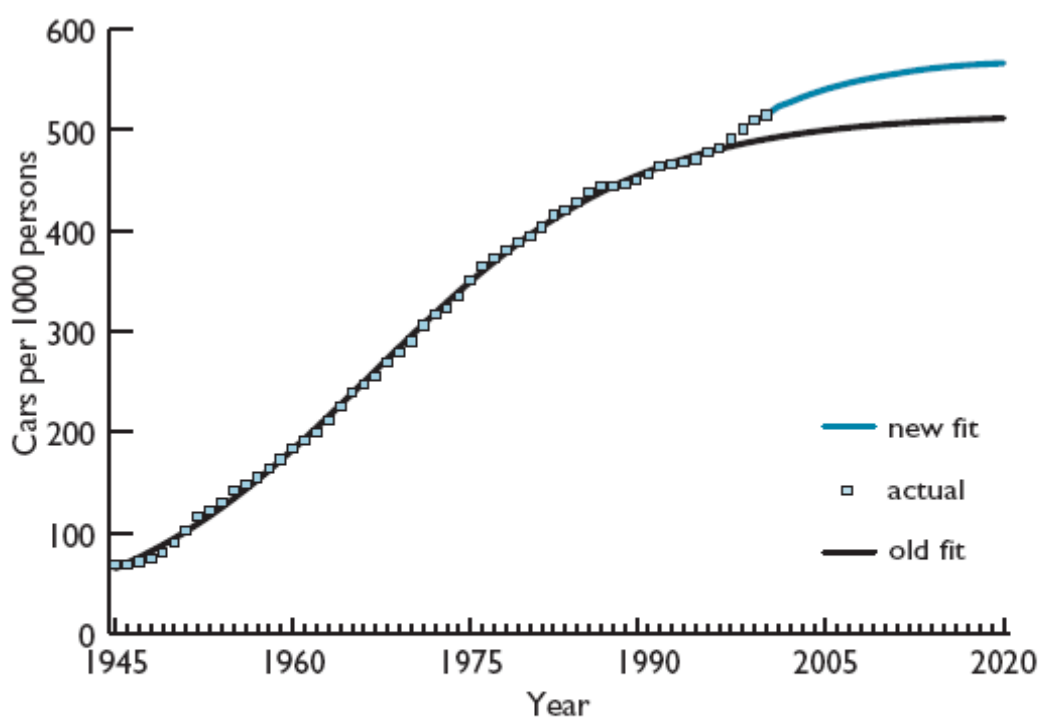
Reference

Bureau of Transport and Regional Economics (BTRE) (2002) Greenhouse gas emissions from transport, Australian trends to 2020. *Bureau of Transport and Regional Economics report 107*,

General forecasting model structure

The Bureau of Transport and Regional Economics (BTRE) developed the CARMOD model for the purpose of forecasting car fuel use. Previous versions of CARMOD calculated total vehicle numbers as the product of population and vehicle ownership – vehicle ownership was assumed to follow a simple logistic function over time. However, GDP growth and decreases in real vehicle prices have encouraged higher car ownership levels than that implied by the older model, as depicted in the following figure.

Figure E.2 Projected car ownership in Australia



Notes: 'Old fit' refers to projected values used in BTCE Report 94 (BTCE 1996b). 'New fit' refers to revised estimates allowing for price and income effects (including the recent surge in vehicle sales).

Sources: BTRE estimates, ABS (2000b).

Notes: 'Old fit' refers to projected values used in BTCE Report 94 (BTCE 1996b).

'New fit' refers to revised estimates allowing for price and income effects (including the recent surge in vehicle sales).

CARMOD has been revised to take into account the surge in vehicle ownership experienced over the past five years. It is now based on a function that relates total private vehicle travel to real income growth. Car ownership rates are then derived using forecast VKT per person and forecast VKT per car.

The recently modified version of CARMOD model is relatively simple:

$$\text{Car fuel use} = \text{cars per capita} \times \text{population} \times \text{VKT per vehicle} \\ \times \text{average fuel intensity}$$

The process of predicting vehicles per capita consists of the following steps:

- 1 Estimate VKT per capita, using a logistic (saturation curve) that relates VKT per capita to real GDP per person.
- 2 Estimate VKT per car, using the trend in annual GDP change (with an elasticity of 0.12), the trend in household ownership of vehicles (with an elasticity of -0.4) and projected changes in the proportion of the population of working age⁶ (with an elasticity of -0.75).
- 3 Derive cars per capita, using the two series above. The car ownership per capita series is modified for changes in vehicle prices over time (with an elasticity of -0.1).

Population was forecast based on projections from the Australian Bureau of Statistics.

VKT per car was estimated at a rate of 15,500 kilometres per year per car – this estimate is derived from aggregate petrol sales, the total number of vehicles on the road and the average rate of fuel consumption⁷.

VKT per car is assumed to be constant looking into the future. There are a variety of factors that would tend to increase VKT over time (such as increasing income levels). But there are also factors that would tend to decrease average VKT per car (such as the aging population, increasing traffic congestion and more multi-car households).

The average fuel intensity of cars is not known with accuracy. It is estimated to be between 11 to 12 litres per 100 kilometres, and is assumed to be constant into the future. The paper suggests that technological progress toward more efficient engines will be counter-balanced by a tendency for consumers to choose larger, more powerful engines.

Table E.4 Forecasting model variables and their incorporation into the model

Component	Content
Economic growth or Income growth	GDP per capita is used to predict VKT per capita, using a logistic 'saturation' curve. GDP per capita is also used to predict VKT per car, by assuming an elasticity of 0.12. Both VKT per capita and VKT per car are then used to predict cars per capita.
Population and household size	Population is incorporated into the model; car fuel use is assumed to be linearly related to population.
Cohort effects	There are no cohort effects.

⁶ The proportion of the population of working age is used as a proxy for a variety of demographic factors that tend to reduce average VKT as the average age of the population increases.

⁷ The BTRE produced estimates using aggregate gasoline sales because the data available on kilometres travelled in Australia tends to be inconsistent and difficult to reconcile.

Component	Content
Time trend effects	There was a time-trend effect in the previous version of CARMOD, but this has been abandoned in favour of a model that is related more to GDP per capita.
Lag effects	There are no lag effects.
Saturation effects	A saturation effect is assumed for the relationship between VKT per capita and GDP per capita; therefore, a logistic 'saturation' model is used to model this relationship.
Car price and fuel price effects	Car price is incorporated into the model because the forecasts for cars per capita was modified based on forecasts for car prices and an assumed elasticity of -0.1.
PT service and accessibility effects	There are no PT service effects.
Region effects	There are no region effects.
Trends in distance travelled per car	The paper does point out the surprising surge in car ownership for the five years leading up to 2000. This was attributed to GDP growth and decreases in real vehicle prices.

Linkages between the car ownership model and traffic models

In a sense, the CARMOD model begins with traffic model variables (VKT per capita, VKT per car) and it uses these to derive car ownership (ie cars per capita). The cars per capita variable is then used, in conjunction with other variables, to predict total fuel use. This approach is confusing, especially since VKT per capita is already calculated and seems to remove any need to estimate cars per capita.

Empirical/MR techniques for estimating parameters

The logistic relationship between VKT per capita and GDP per capita was estimated using Australian data. The elasticities for the forecasts of other variables were estimated, where possible, using regression analyses on BTRE long-term data sets for Australian vehicle characteristics. Where this was not possible, elasticities were based on the literature.

Estimates of parameters produced

VKT per car with respect to GDP: 0.12

VKT per car with respect to 'the trend in household ownership of vehicles': -0.4

VKT per car with respect to the proportion of population of working age: 0.75

VKT per car with respect to fuel price changes: -0.1

Cars per capita with respect to vehicle prices: -0.1

Approaches to forecasting at national, regional and sub-regional/local levels

The model is national.

Application of the model

The model has been implemented and is used for predicting future emissions from the transport sector.

Critique and commentary

The BTRE initially estimated the relationship between VKT per capita and GDP per capita.

The most efficient method of calculating total fuel use would be to combine VKT per capita, total population and fuel efficiency.

However, the BTRE appears to use a less efficient method:

- VKT per car is also estimated
- VKT per car and VKT per capita are used to estimate cars per capita
- Cars per capita, VKT per car, population and fuel efficiency are all used to estimate total fuel use.

Model: ALTRANS

Reference

Kveiborg, O (1999) Forecasting developments of the car fleet in the Altrans model. *Paper presented at the conference Trafikdage på AUC*. August 30-31st 1999.

General forecasting model structure

The Altrans (ALternative TRANSport systems) model was developed at the National Environmental Research Institute (DMU) in Denmark for the purpose of forecasting energy consumption and emissions from personal transport. The Altrans model has a car stock sub-model that consists of three different parts:

$$T_t = T_{t-1} + N_t - S_t$$

Where: T_t = existing stock of cars

N_t = acquisitions

S_t = scrapping.

The car stock sub-model uses existing information on the stock of cars from Statistics Denmark. This information is also used to calculate estimates for scrapping. The level of scrapping is calculated for cars broken down by fuel-type, weight and age. These breakdowns are all considered important because these attributes all influence emissions. A 'scrapping model' is used to estimate the level of scrapping in the future (S_t). Scrapping is assumed to be a function of various exogenous variables, including income and price indices for fuel, acquisitions and repairing costs.

The acquisitions of new cars (N_t) is assumed to be the difference remaining after the stocks and scrappings above are estimated.

Table E.5 Forecasting model variables and their incorporation into model

Component	Content
Economic growth or Income growth	Income is an explanatory variable
Population & household size	Population is not an explanatory variable
Cohort effects	No cohort effects
Time trend effects	No time trend effects
Lag effects	No lag effects, but predictions of future stocks are based around current stock levels
Saturation effects	No saturation effects
Car price and fuel price effects	The price of fuel and acquisitions (of cars) are both included in the model as explanatory variables
PT service and accessibility effects	Not included
Region effects	Not discussed
Trends in distance travelled per car	Not discussed

Linkages between car ownership model and traffic models

The models described above are used to estimate future vehicle stocks.

The 'behavioural model' is also used to estimate the absolute level of driven kilometres. This absolute level of driven kilometres is then apportioned out to the vehicle stock, using information on the average distance driven by cars of certain ages.

Empirical/MR techniques for estimating parameters

Maximum likelihood is used to predict the impact of fuel type, weight and age on scrapping in each of the 120 categories.

Estimates of parameters produced

The paper does not discuss parameter estimates.

Approaches to forecasting at national, regional and sub-regional/local levels

The paper indicates that the model is only used for national forecasting

Application of the model

The model has been implemented and is used to prediction national emissions.

Model: TRESIS

Reference

Hensher, DA and T Ton (2002) TRESIS: A transportation, land use and environmental strategy impact simulator for urban areas. *Transportation 29, no.4: 439-457*.

With supporting evidence from:

Stopher, P (2005) Challenges to using an integrated land-use transport model in Australia. Presentation at the *Oregon Integrated Models Symposium*, November 2005.

General forecasting model structure

The transportation and environment strategy impact simulator (TRESIS) was developed to assist transport planners in making predictions about the impact of transport strategies.

TRESIS contains a number of discrete choice models:

- household location and type of dwelling
- work locations for household workers
- number and type of vehicles owned by the household
- levels of use of vehicles by trip purpose
- means of travel by departure time.

This review focuses on the discrete choice models for the number and type of vehicles owned by the household. There are 10 size classes for conventional fuel vehicles (micro, small, medium, upper medium 1, upper medium 2, large, luxury, light commercial, four wheel drive and light trucks). There is also capacity for including vehicles based on alternative fuels. Vehicles are also distinguished by age.

TRESIS predicts automobile fleet size and vehicle type mix choice conditional on commuter mode, departure time choice and residential locations. More information on these models can be found in Hensher and Ton (2002).

TRESIS can model vehicle ownership using two alternative methods:

The vehicle price relativity approach:

In the vehicle price relativity approach, new vehicle prices are exogenous. Used vehicle prices are predicted based on new vehicle prices, using a non-linear empirical equation. This approach ensures a relativity between new vehicle prices and used vehicle prices. The scrappage rate is predicted as a function of vehicle age and used vehicle prices.

The supply of new vehicles is determined as the difference between total household demand for new vehicles and the supply of used vehicles (which is affected by scrappage).

The equilibration approach

In the equilibration approach, new vehicle prices are also exogenous. However, used vehicle prices are determined by equilibrium. As with the vehicle price relativity approach, the scrappage rate is a function of age and value.

Total demand for vehicles (by class) is determined by vehicle choice and fleet size models. The difference between demand and scrappage gives the number of new vehicles by class.

Table E.6 Forecasting model variables and their incorporation into model

Component	Content
Economic growth or Income growth	Income is not explicitly mentioned as an explanatory variable
Population and household size	Population and household size are not explicitly mentioned as an explanatory variable. However, the impact of residential density on household behaviour, such as kilometres driven, can be estimated.
Cohort effects	Cohort effects are not discussed.
Time trend effects	Time trend effects are not discussed
Lag effects	Lag effects are not discussed
Saturation effects	Saturation effects are not discussed, but the behavioural models that determine car choice possibly incorporate plausible assumptions about the number of cars owned by households.
Car price and fuel price effects	Vehicle prices are exogenous explanatory variables in the model so the impact of vehicle price changes on the vehicle fleet could be explored. Fuel prices are not discussed as an explanatory variable for car ownership, but they are an explanatory variable in the wider TRESIS model.
PT service and accessibility effects	PT service and accessibility are not explicitly mentioned as an explanatory variables for car ownership. However, modal share is an output variable in the TRESIS model – so PT service is incorporated into the TRESIS model in some manner.
Region effects	The TRESIS prototype was developed to be applicable to the Sydney Metropolitan Area. It was also been applied in South Australia and the paper notes that it can be applied to six urban areas.
Trends in distance travelled per car	These are not discussed.

Linkages between car ownership model and traffic models

The TRESIS model is integrated so it incorporates both car ownership and travel demand.

Empirical/MR techniques for estimating parameters

This is not discussed.

Estimates of parameters produced

This is not discussed.

Approaches to forecasting at national, regional and sub-regional/local levels

The TRESIS model is region-specific. It contains a lot of detail that appears to be specific to the region of interest.

Application of the model

The model has been developed and applied in South Australia.

Model: STM

Reference

Hague Consulting Group and the Institute of Transport Studies (2001) *Sydney strategic travel model: stage 1 estimation: estimation summary report*. Report for New South Wales Department of Transport.

Hague Consulting Group and the Institute of Transport Studies (2002) *Sydney strategic travel model: stage 1 estimation: further model estimation report*. Report for New South Wales Department of Transport.

General forecasting model structure

The Sydney strategic travel model (STM) consists of the following sub-models:

- 1 A model to predict licence holding by household
- 2 A model to predict car ownership, conditional on licence-holding
- 3 A model to predict the frequency of trips to work, by employed individuals

Model for licence holding

In Sydney, from 1971 to 1998, licence holding increased from 62% to 81%.

About four fifths of this increase in licence holding can be attributed to a 'catching up' of women's licence holding relative to men's licence holding. This occurred because of a gradual replacement of generations of women who had low licence holding by younger women whose licence holding has always been very similar to men's. This 'catching up' effect has been the main driver of changes in licence holding over the last 20 years. The effect will probably continue to be a major driver of licence over the next 20 years. However it may be dampened by immigration from countries where women's licence holding is generally low.

Many car ownership models include a 'trend' variable representing increasing car ownership that cannot be explained by income. This 'trend' can be attributed, at least in part, to a growth in licence holding. Therefore, it is important that projections into the future take into account the impact of licence holding. Cohort analysis could be used to forecast licence holding for the future, but it is not in the Sydney STM. However, the accuracy of those forecasts will depend on information on immigration from South American, African and Asian countries.

The Sydney STM predicts the likelihood of households being in one the following four states:

- neither member of household has a licence

- head of household has a licence; partner does not have a licence
- head of household does not have a licence; partner does have a licence
- both head of household and partner have a licence

Households are more likely to have licences as income increases, the number of children increases and with the presence of employment. Households are less likely to have licences if the head of the household is female, the head of the household is under 25 or over 70 or if the household is large.

Model for car ownership:

First, the Sydney STM *company car* ownership model predicts the probability of households having the following:

- no company cars
- 1 company car
- 2 company cars.

The predictions of the company car ownership model are influenced by (the log of) household income, the number of licences in the household, the ages of the household members and the presence of a female head of household.

The Sydney STM *total car* ownership model then predicts the probability of households having the following:

- 0 cars
- 1 cars
- 2 cars
- 3 or more cars

The predictions of the total car ownership model are influenced by (the log of) household income, the number of licences in the household, the ages of the household members, the presence of company cars, and the employment status (part-time, full-time) of the members of the household. Interestingly, in the total car model, the income term is reduced by the average car ownership for the cars owned by the household.

Model for travel frequency

The Sydney STM for travel frequency predicts the number of trips to work for employed individuals. The first stage of the travel frequency model predicts whether any work 'tours' will be made. The second stage of the model predicts whether more than one 'tour' will be made each day due to, for example, a second job. The travel frequency model is influenced by age dummies, gender, the presence of a licence, income, manufacturing employment and employment status (eg full-time, part-time, casual).

Table E.7 Forecasting model variables and their incorporation into model

Component	Content
Economic growth or Income growth	Household income is an explanatory variable in the car ownership models and in the travel frequency model.
Population and household size	Prototypical sampling was employed – The sample was ‘re-weighted’ to reflect future populations.
Cohort effects	Cohort effects were discussed and presented in graphs, but were not incorporated into the model.
Time trend effects	These were not employed, and the use of time trends in other car ownership models was criticised.
Lag effects	These were not discussed.
Saturation effects	There was no saturation function, but the models used to predict car ownership only allow up to three cars. Furthermore, the number of cars is influenced by licence-holding.
Car price and fuel price effects	Car prices and fuel prices do not affect the number of cars owned in the model.
PT service and accessibility effects	PT service accessibility does not affect the number of cars owned in the model.
Region effects	The model is designed to be applicable to the Sydney region.
Trends in distance travelled per car	These are not discussed in detail.

Linkages between car ownership model and traffic models

The initial models predict car ownership and this is used as an input for predicting the frequency of travel to work and the times of the day in which travel to work occurs.

Empirical/MR techniques for estimating parameters

The models were all estimated using cross sectional data.

Estimates of parameters produced

The parameter estimates are provided in appendices A, B and C of the Hague Consulting Group and the Institute of Transport Studies (2002) report.

Approaches to forecasting at national, regional and sub-regional/local levels

The model is designed to be applicable to the Sydney region.

Application of the model

The model is implemented.

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