

# **National long-term land transport demand model**

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# Abbreviations and acronyms

CPI	Consumers Price Index
ETS	Emissions Trading Scheme
GDP	gross domestic product
GUI	graphical user interface
HCV	heavy commercial vehicle
HH	household
LATR	living arrangement type rate
LCV	light commercial vehicle
LPV	light passenger-vehicle
NLTDM	National Long-term Land Transport Demand Model
NZTA	NZ Transport Agency
PT	public transport
RUC	road user charges
SNZ	Statistics New Zealand
VAR	vector autoregression
VKT	vehicle-kilometres travelled
NZIER	New Zealand Institute of Economic Research

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# Executive summary

The purpose of this research, which was conducted between October 2011 and November 2012, was to construct a National Long-term Land Transport Demand Model (NLTDM) that was capable of evaluating transport demand scenarios looking out 30 years, and taking account of mega-trends in:

- population growth dynamics
- spatial demographic trends
- technology trends
- income and economic growth
- industrial composition
- policy and prices, eg
  - environmental policy changes
  - fuel price escalation and volatility.

The intention was not to provide point estimates of future transport demand but rather to provide a tool for considering how transport might evolve over time.

The NLTDM features:

- top-down macro-forecasting methods with sufficient behavioural and spatial detail to account for structural change in transport demand
- a facility for users to input their own assumptions about controversial matters such as the long-run price of oil, or demand responsiveness to key variables such as price and income (ie elasticities)
- an easy-to-use interface with sufficient flexibility to accommodate scenario modelling by a range of users who are not modellers
- a reasonably high degree of regional disaggregation (12 regions) to capture trends in urbanisation, effects of density, and regional differences in economic growth prospects and industrial composition
- a stochastic mode that provides a sense of the degree of uncertainty that exists around how demand will evolve in coming decades.

The ultimate objective of the model was to project growth in household travel demands and freight demands. Projections were based on breaking these demands down into three different components:

- trends and patterns due to path dependencies; eg:
  - population growth, age structure and location
  - economic growth
  - vehicle fleet turnover

- deviations from trend path dependencies due to relative price and income effects; eg:
  - fuel price shocks
  - income effects
- temporal interdependencies; eg:
  - co-movement of industry growth
  - transmission of shocks over time.

The focus on long-term projections meant the first of these components was the most important.

A number of novel econometric models have been estimated to provide parameter values to underpin the key relationships in the model. The most notable of these is a model of household vehicle ownership, differentiated by household characteristics and region.

This version of the NLTDM is intended to be used as an input for strategic planning at the NZ Transport Agency (NZTA) and as a complement to qualitative scenarios about how transport demand is likely to develop in the long term. Given this purpose, the model has limited consideration of supply-side issues, so as not to confuse demand trends with supply-side responses that are, in part, determined by the NZTA.

The focus of the model on long-term demand scenarios means that it is not well equipped for dealing with short-term fluctuations in demand or drivers of transport demand. It is not a forecasting tool.

While the model has a very precise purpose and this means it has limitations, it could be extended to other purposes if further developed. We see four areas of particular potential value:

- *Revenue forecasting:* With some adjustments to account for short-term uncertainty, the model could be used to complement existing transport tax forecasting methods by providing a structural counterpart to existing (primarily econometric) models used to forecast National Land Transport Fund revenue or Accident Compensation Corporation (ACC) revenue.
- *Fiscal sustainability:* Greater consideration of supply-side elements (such as public transport subsidies) would allow the model to be used to assess the long-term fiscal sustainability of the transport sector.
- *Freight demand and impacts:* In the event that further research is conducted into detailed freight demands by origin and destination, the model could be adapted to map these demands to regional economic activity to provide a tool for predicting shorter-term demands and impacts on the transport network.
- *Supply-side constraints:* The model could be adapted to account for the effects of supply-side constraints, such as the impact of congestion on transport activity.



## **Abstract**

This report describes a National Long-term Land Transport Demand Model (NLTDM) for evaluating transport demand scenarios looking out 30 years and taking account of mega-trends in: population growth dynamics; spatial demographic trends; technology trends; income and economic growth; industrial composition; and policy.



# 1 Introduction

## 1.1 Purpose

The purpose of this report is to describe a National Long-term Land Transport Demand Model (NLTDM) for evaluating transport demand scenarios looking out 30 years and taking account of mega-trends in:

- population growth dynamics
- spatial demographic trends
- technology trends
- income and economic growth
- industrial composition
- policy and prices, eg:
  - environmental policy changes
  - fuel price escalation and volatility.

This list of trends has been laid out by the NZ Transport Agency (NZTA) because of their importance for internal strategic planning purposes. The NZTA uses qualitative scenarios about how these trends might evolve, and what this could mean for transport demand, to inform its internal functional strategies. The intention of our research was to produce a model that could provide a quantitative counterpart, a scenario-modelling tool, to complement this qualitative planning process.

The intended use of the model as a planning tool means that the model is not intended to project actual or realised transport activity over the long term. The model is intended to project underlying demand trends or demand drivers. Actual transport activity that takes place in the future will be a function of both demand trends and supply trends. To be useful as a strategic planning tool for the NZTA, the model has limited consideration of supply-side issues, so as not to confuse demand trends with supply-side responses that are, in part, determined by the NZTA.

This report provides a description of how the NLTDM model was constructed, the assumptions underpinning the model, the limitations of the model and the kinds of results the model produces.

## 1.2 Approach

Our approach to modelling transport demand over the long term with reference to the mega-trends of interest to the NZTA was one that combined top-down macro-forecasting methods with sufficient behavioural and spatial detail to account for structural change in transport demand.

Transport demand forecasting typically falls into three different categories:

- *Regional and local transport models* used for area strategy and project design and appraisal: These are best described as 'bottom-up' models, which tend to be fairly detailed, data intensive, and treat

many wider transport sector issues as a given. ('Four-stage' transport models are the most relevant in the context of this research project.)

- *Top-down regression models* used for forecasting demand based on high-level macroeconomic drivers and econometric relationships; eg the relationship between freight-kilometres travelled and gross domestic product (GDP), and a limited number of elasticities or behavioural parameters: These are simple but often not very informative.
- *Hybrid models*: These have a high-level simplified relationship between transport demand and macroeconomic aggregates, but combine top-down relationships with additional detail on behavioural parameters and often include reduced (ie simplified) forms of the conventional regional transport models.

Each of these has strengths and weaknesses (see table 1.1). In long-term projections, accurate data compilation and careful construction of relevant scenarios are more important to achieving forecasting objectives than complex models and methodology. Thus, this research demanded a fairly parsimonious modelling process. However, top-down regression models, while often parsimonious, are too limiting because they are calibrated to the past and do not necessarily offer sufficient flexibility to account for structural changes and major demand shifts. Four-stage modelling, while useful conceptually, would very quickly add to the complexity of the model and reduce its flexibility and intelligibility.

Our model takes a 'hybrid' approach. We believe this provides the right balance between sufficient detail for modelling a range of scenarios and too much detail, which would make the model unwieldy or imply a false level of precision.

Our approach was to build our model around major structural determinants of transport demand, such as population and income growth, and provide a facility for inputting assumptions about controversial matters such as the long-run price of oil, or demand-responsiveness to key variables such as price and income (ie elasticities). Chapter 2 provides further description of our meta-methods.

We set out to produce a model that could be manipulated by people with differing degrees of modelling expertise. We did this because transport models are inevitably controversial. Researchers and policy advisors often disagree on what the key drivers of transport demand are or quite how much they matter. Questions arise over just how responsive people are to price changes or income effects. Fundamental uncertainty exists around the extent to which transport demand trends from the past will persist and around how the economy and New Zealand's population are likely to evolve over time. We minimise these issues by putting major model assumptions in the hands of the model's users.

**Table 1.1 Summary of widely used transport demand forecasting and modelling approaches**

	<b>Conventional four-stage model</b>	<b>Simplified regression models</b>	<b>Hybrid model</b>
<b>Description</b>	<ul style="list-style-type: none"> <li>The four main stages required to build a four-stage transport demand model are trip generation, trip distribution, mode choice and route assignment.</li> </ul>	<ul style="list-style-type: none"> <li>Form varies depending on the level of simplicity.</li> <li>Most common ones include: choice models, elasticity/regression-based models and the highly simplified sketch models.</li> </ul>	<ul style="list-style-type: none"> <li>Conceptually a reduced form of the four-stage model, but simplified and highly aggregated.</li> <li>Usually estimates trips for passengers and freight separately.</li> </ul>
<b>Suitability for this purpose</b>	<ul style="list-style-type: none"> <li>Detailed programme investment and regional policy decisions, especially corridor infrastructure projects.</li> <li>Corridor or regional network forecasting.</li> </ul>	<ul style="list-style-type: none"> <li>Broad range of national policy and strategy option test purposes.</li> </ul>	<ul style="list-style-type: none"> <li>Nationwide transport forecasting.</li> <li>Strategic investment planning.</li> </ul>
<b>Strength</b>	<ul style="list-style-type: none"> <li>Able to provide forecasts at very disaggregated levels.</li> </ul>	<ul style="list-style-type: none"> <li>Rapid and cost effective to build.</li> <li>Transparent and easy to understand.</li> <li>Flexible in testing high-level policy options and scenarios.</li> </ul>	<ul style="list-style-type: none"> <li>Able to provide reasonably detailed information/forecasts.</li> <li>Allows changes in a broad range of assumptions and scenarios.</li> </ul>
<b>Limitations</b>	<ul style="list-style-type: none"> <li>Does not model the determinants of transport demand, such as economic activity, land use and population. Thus limited allowance of induced transport demand responses over time.</li> <li>Limited applicability for broader pricing and policy options.</li> <li>Not good at forecasting long-distance modes.</li> <li>Costly to build and can be hard to interpret due to complexity and scale of data output.</li> </ul>	<ul style="list-style-type: none"> <li>Cannot represent detailed networks or spatial areas and aggregates.</li> <li>Not suitable for detailed project appraisal.</li> <li>Limited capacity to incorporate the impacts of system effects such as inertia.</li> </ul>	<ul style="list-style-type: none"> <li>Not able to provide as detailed information/forecasts as the conventional model.</li> <li>Not as flexible or transparent as the simplified model.</li> </ul>
<b>Examples</b>	<ul style="list-style-type: none"> <li>Strategic Transport Demand Model – Australia (Sinclair Knight Merz 2009)</li> <li>The Waikato Region Transportation Model – NZ (Smith and Bevan 2010)</li> </ul>	<ul style="list-style-type: none"> <li>Strategic Transport Model – UK (Brand 2010)</li> <li>Strategy Review Model – NZ (Transport Futures Limited 2008)</li> </ul>	<ul style="list-style-type: none"> <li>Transport Demand Projection Model for AusLink Non-Urban Corridors – Australia (Department of Transport and Regional Services of Australia 2009)</li> <li>National Transport Model – UK (Department for Transport of the UK 2011)</li> </ul>

As this was a research project, the model and graphical user interface chosen were prototypes that could be extended or refined in the future to meet particular needs, whether in terms of tailored output or scenarios.

There are nine broad components or submodels that make up the overall model (see figure 1.2). These were constructed sequentially. We started with the most primitive components, population and regional population, and moved progressively towards greater degrees of detail, uncertainty and assumptions.

Chapters 3 to 10 describe the key equations and assumptions underpinning each of these components. The final chapter provides sample output from the model.

## 1.3 Limitations

The purpose of our research imposed limitations on the kinds of issues that could be addressed with the model. One is that the focus of the model on long-term demand scenarios means that it is not well equipped for dealing with short-term fluctuations in demand or drivers of transport demand. It is not a forecasting tool.

Another important limitation is that the model cannot be used to assess the impacts (costs and benefits) of specific transport network investments or other supply-side issues. It can be used to help assess high-level investment priorities or to provide context for investment-specific impact assessment. However, it does not have the necessary detail for judging the impacts of investment at the level of a particular network.

There are important spatial factors that drive demand growth but are not explicitly modelled. Limitations on land use and land development, for example, will doubtless have a major influence on how transport demand evolves in coming decades. In many respects these issues affect the core of underlying demand growth. However, we have treated them as supply issues because planning restrictions and supply-side transport planning are conducted in parallel and are not easily separated.

The approach we took does take account of major spatial changes in terms of regional differences in demand drivers and demand growth. The model uses regional differences as factors that affect national demand growth and the location of that growth. The model is, however, a national-level model and is not intended to provide a complete description of region-specific dimensions of transport activity.

We have assumed that road investment will be sufficient to prevent supply-side constraints and congestion impacting on transport demand. This is an artificial construct that is only used so we can parse out demand trends from supply decisions. For purposes other than strategic planning, the potential for capacity constraints (ie network congestion) would need to be modelled.

All of these issues could be dealt with by adapting the model and the modelling approach. However, models already exist for addressing these issues. The 'value add' in this research and in our approach was that it was filling a gap – it was a complement to existing models.

Figure 1.1 Model graphical user interface - example

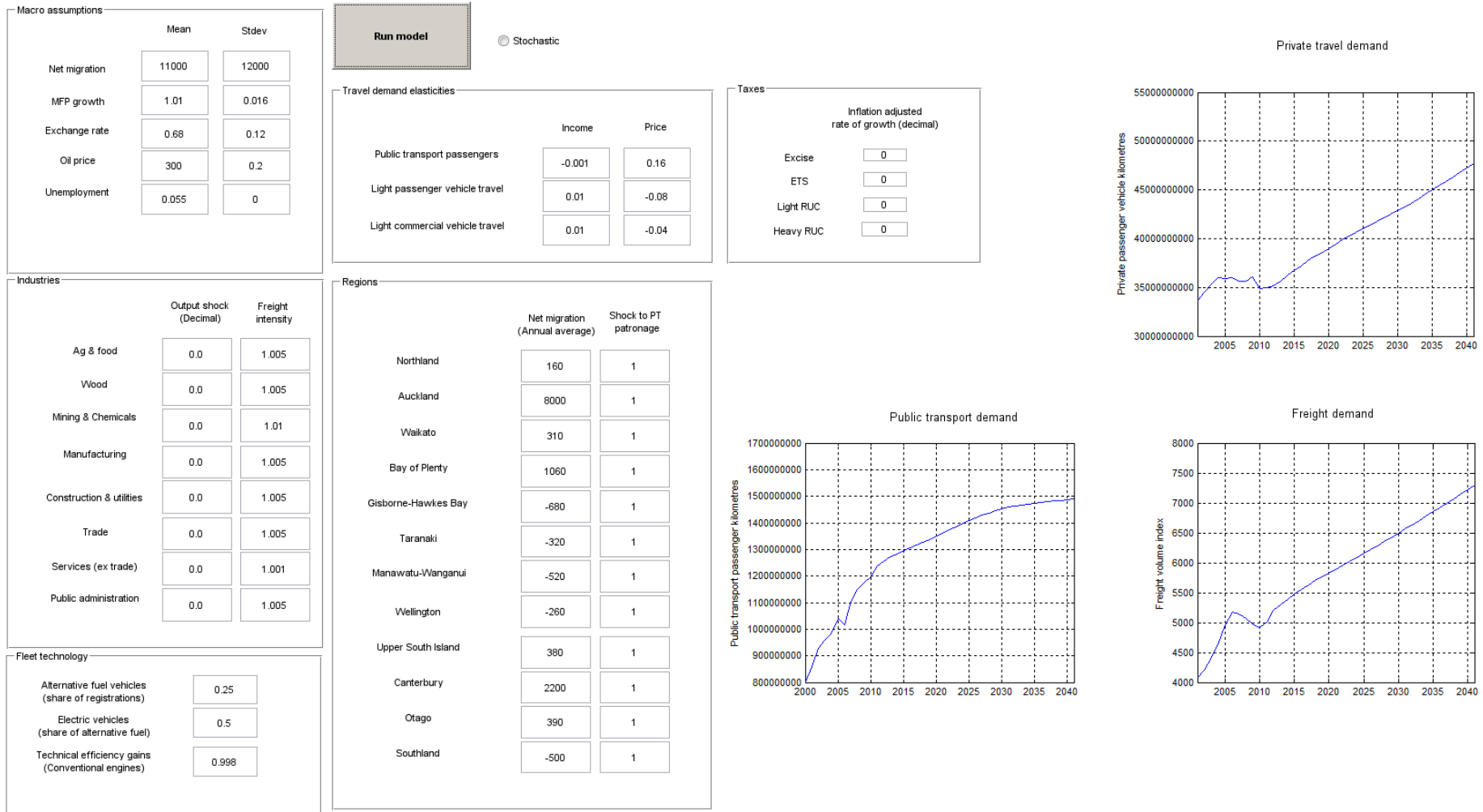


Figure 1.2 Model dimensions

Population	Regional population	Growth and incomes	HH vehicle demand	Freight demand	Prices	Vehicle fleet	VKT and cost	HH travel
<p><b>Outputs</b> Population by age and sex Households, by type Average age of households Number of people per household Labour force Long-run employment</p> <p><b>Scope</b> Ages 0 to 90 years 6 Household types: alone, one parent, two parent, couple, multi-person, multi-family 12 regions: Northland, Auckland, Waikato, Bay of Plenty, Gisborne-Hawke's Bay, Taranaki, Manawatu-Wanganui, Wellington, Upper South Island, Canterbury, Otago, Southland</p> <p><b>Input assumptions and key statistical models</b> Net migration (ARIMA(1,0,1)) Age-specific mortality and fertility Living arrangement type rates (LATRs) Labour force participation rates Long-run unemployment rates</p>	<p><b>Outputs</b> GDP by industry and region HH incomes by type and region</p> <p><b>Scope</b> As for population plus 8 industries: agriculture and food; forestry and wood manufacturing; mining and chemicals; other manufacturing; construction and utilities; trade and transport; other services; public administration</p> <p><b>Input assumptions and key statistical models</b> National and industry multifactor productivity growth Trend growth in industry GDP Historical covariance between industries in economic activity (VAR model) Relationship between GDP per capita and HH incomes</p>	<p><b>Outputs</b> Vehicles per household by region and HH type</p> <p><b>Scope</b> As for population plus forecast probability a HH will own 0, 1, 2, 3 or more vehicles</p> <p><b>Input assumptions and key statistical models</b> Generalised linear model (logistic) of conditional probabilities (by HH type) of vehicle ownership based on income, average age, population density and a Wellington dummy</p>	<p><b>Outputs</b> Freight volumes by mode, industry, and region Road freight tonne-kilometres</p> <p><b>Scope</b> 8 industries and 12 regions and three modes: rail, sea, road</p> <p><b>Input assumptions and key statistical models</b> Trends in freight intensity (value of freight input per unit of GDP by industry) Regional industrial comparative advantage based on historical employment shares Freight mode share by industry by region</p>	<p><b>Outputs</b> Taxes Fuel price at pump Vehicle price trends</p> <p><b>Scope</b> NZ</p> <p><b>Input assumptions</b> Long-run exchange rate Inflation (CPI) ETS costs Oil prices</p>	<p><b>Outputs</b> Number of vehicles by age, type, technology, and size</p> <p><b>Scope</b> Ages 0 to 30 Types: light passenger, light commercial, motorcycle, heavy commercial, bus Technology: Petrol, diesel, hybrid, electric, and plug-in hybrid Sizes based on engine cc rating: 5 light sizes, 2 motorcycle sizes, 9 heavy sizes and 3 bus sizes</p> <p><b>Input assumptions and key statistical models</b> Fuel efficiency Age of import Registrations of alternative fuel vehicles Number of registrations that are new vehicles Scrapage rates</p>	<p><b>Outputs</b> VKT by non-private passenger vehicles by vehicle type and age Emissions by vehicle type and age Cost per kilometre of travel, by vehicle type Tax revenue from transport</p> <p><b>Scope</b> As for vehicle fleet</p> <p><b>Input assumptions and key statistical models</b> VKT by vehicle age Travel behaviour and congestion impacts on fuel consumption Emissions factors</p>	<p><b>Outputs</b> Passenger kilometres by public transport and private passenger vehicle Passenger vehicle VKT</p> <p><b>Scope</b> Regions Passenger transport mode</p> <p><b>Input assumptions and key statistical models</b> Regional distributions of VKT Regional vehicle occupancy trends Age distributions in propensity to use public transport VKT cost and income elasticities PT fuel price and income elasticities</p>	



## 2 Meta-method

The ultimate objective of the model was to project growth in household travel demands and freight demands. We broke these demands down into three different components:

- trends and patterns due to path dependencies; eg:
  - population growth, age structure and location
  - economic growth
  - vehicle fleet turnover
- deviations from trend path dependencies due to relative price and income effects; eg:
  - fuel price shocks
  - income effects
- temporal interdependencies; eg:
  - co-movement of industry growth
  - transmission of shocks over time.

The focus on long-term projections meant the first of these components was the most important. Compositional effects included slow-moving influences such as population age structure or vehicle fleet turnover. Detailed descriptions of these processes and influences on transport demand underpin the usefulness of this model as a scenario-modelling tool.

It is instructive to consider how these would be dealt with differently if the objective of the modelling exercise was different. For shorter-term projections or forecasts, for example, the order of importance of these three components of demand would be reversed. The focus would begin with a careful description of the time-series data-generation process, including underlying trends and the extent to which demands co-evolve. Once the data-generation process was accurately described, one would then proceed to try and understand how prices and income effects were likely to influence the evolution of demand over time. Finally, there could be some consideration of the impacts of primitive compositional issues; eg what if there was a shift towards rail freight due to a major investment in rail capacity? However, the focus on existing data and shorter-term dynamics would mean that the analyst could only ever have fairly limited confidence that the model could account for these things. In effect, the underlying structure of the economy would be held constant.

Projections are based on three approaches:

- trend extrapolation, which:
  - relates fundamental population and economic characteristics to demand growth
  - is generally a deterministic process
  - typically relates to the path-dependent elements of demand

- reliance on scenarios in relation to assumptions about the range parameter values that should apply, such as for demand response to variables that policy seeks to affect, and also those variables for which historical relationships are unlikely to hold in the future
- stochastic dimensions, which are econometric and statistical models that describe temporal interdependencies – errors of these models are used to describe and generate results that reflect ‘uncertainty’ around projections.

## 2.1 Literature review

As a first step towards specifying our model parameters, we looked to the literature on transport demand to determine which demand relationships mattered and the size of key relationships.

The kinds of transport demands we were interested in included:

- freight demand (in tonne-kilometres)
- vehicle ownership and vehicle-kilometres travelled
- public transport patronage.

The relationships or demand drivers we were accounting for, and for which we needed empirical estimates of the strength of relationships, included:

- the effects of income growth on travel and freight demand
- the relationship between industry composition and freight demand
- the sensitivity of all transport demands to prices, including:
  - fuel prices
  - tax rates
  - vehicle prices
  - freight costs
- the role of population characteristics in explaining demand, including:
  - population age structure
  - household formation trends
- the effects of population location, reflecting significant variations in:
  - transport demand across regions and urban areas
  - incomes, age groups and other household characteristics
- inertia in the vehicle fleet and future vehicle-technology trends.

We were primarily interested in estimates produced using New Zealand data, although we also reviewed the international literature.

When evaluating estimates in the literature, we focused on the following three issues:

- How widely studied are these determinants of transport demand?
- How useful are existing studies? Do they, for example, address transport demand at a level of aggregation that is useful for our purposes?
- How much confidence do we have in the estimates we have found?

Our literature search was conducted with the objective of producing a database on empirical estimates of drivers of transport demand from which to draw the 'priors' for our modeling work.

When searching for literature, we looked primarily at sources that were published by authoritative sources and frequently referenced. This improved the reliability of the estimates collected. The search proceeded as follows:

- We began with the New Zealand literature and worked outwards to the international by tracing references cited in the New Zealand sources.
- We focused on literature published in the last 10 years, because the drivers of transport demand as well as their interactions have changed in that time, and therefore the estimates generated prior to this could be of less value to this project.
- In the case of the New Zealand literature, both regional and national-level estimates were taken into account.
- We focused, where possible, on literature from overseas countries that shared some similar characteristics to New Zealand. This included, in the first instance, developed country members of the Organisation for Economic Cooperation and Development (OECD). We would have liked to restrict our review to countries with similar spatial features and levels of incomes, but there did not appear to be any.
- Countries that we drew on included the US, UK, Australia, France, Germany, the Netherlands and Canada.
- Sources that we relied on included:
  - online journal databases and websites, such as Econlit, and JSTOR
  - official transport authorities' websites for selected countries (eg Department for Transport for the UK)
  - official international transport databases (eg Transportation Research Board database, and the UK's Transport Conference database)
  - published journal articles and authoritative publications that estimated (through development of a certain model) or provided (through summary articles or meta-analysis) the elasticities for transport demand.

The references canvassed in our literature review are included in the bibliography at the end of the report.

## 2.2 Limited use of existing studies

We were surprised by the number of limitations in existing studies – this shaped our overall approach to focus on:

- a) scenarios
- b) structural determinants of demand, such as population composition
- c) variable relationships/parameters.

We initially anticipated populating much of the model with parameter values from pre-existing studies. However, we found that there were some large gaps in the literature for which we had to make assumptions, calibrate our model, and conduct our own estimates.

We found that even where there were many existing studies, there were major limitations in using them for our purposes. A key limitation was that many studies estimated individual demand relationships, such as demand for vehicle-kilometres and its relationship to fuel prices, without accounting for the alternative demands, such as relative price of, and demand for, public transport. This meant we could not be sure of the extent to which estimated relationships reflected substitution effects and therefore the effects that were being captured by the parameters we were looking at. This was problematic for a model of system-wide demand, as it could lead to double counting of effects.

Limitations were strongest in the case of studies of transport demand in New Zealand. The wide range of different and sometimes erroneous methods used to estimate transport demand drivers, as well as the wide range of results that they produced, gave little certainty regarding which were the right parameter values to use.

Fully resolving these issues was outside the scope of this research. Furthermore, the parameter estimates we found and the studies from which they came still provided a useful reference point (ie priors) for our own work, even if we could not take estimates and assessments at face value.

### 2.2.1 Key gaps in the literature

The key gaps in the literature, from our perspective, were empirical estimates of relationships between:

- household characteristics and household transport demand, including both travel demand and mode choice
- regional characteristics and household transport demand
- industrial composition (both nationally and regionally) and freight tonne-kilometres, whether by road or other modes
- income and prices, and vehicle technology trends.

The lack of information on relationships between household characteristics and transport demand was quite surprising to us. Such information was only available at an extremely disaggregated level for use in region-specific traffic flow and land-use interaction models. Higher-level information necessary for a national scenario model such as ours was limited to descriptive two-dimensional statistical relationships.

Table 2.1 Availability of estimates of drivers of transport demand

Impact of ...	On ...	Availability
<b>1 Population growth dynamics</b>		
Household size	Car ownership	√ <sup>a</sup>
Household size	Mode choice	√
Household size	Vehicle-kilometres travelled	√
Population age structure	Car ownership	√
Population age structure	Mode choice	√
Population age structure	Vehicle-kilometres travelled	√
<b>2 Economic growth and industrial composition</b>		
Economic growth	Freight tonne-kilometres	√√√
Industry composition	Freight tonne-kilometres	× <sup>b</sup>
Income growth <sup>c</sup>	Vehicle-kilometres travelled	√√√
Income growth	Car ownership	√√√
Income growth	Mode shares	√
Income growth	Vehicle technology	×
<b>3 Spatial demographic and economic trends</b>		
Industry growth	Freight tonne-kilometres	×
Density	Car ownership	√
Density	Mode choice	√
Density	Vehicle-kilometres travelled	√
<b>4 Fleet technology trends</b>		
Fuel prices	Vehicle technology	√
Fuel prices	Scrappage rates	×
Income growth	Scrappage rates	×
<b>5 Travel costs</b>		
Fuel prices	Vehicle-kilometres travelled	√√√
Fuel prices	Vehicle purchase	√√√
Fuel prices	Public transport demand	√√

a) The number of '√' indicates the extent to which information is available. For example, '√' indicates there is some literature, while '√√√' indicates a large amount of literature.

b) '×' indicates no estimates available.

c) Income growth here includes household income, as well as other proxies such as GDP per capita.

The literature is not devoid of information on these issues. For example, the *New Zealand household travel survey* (MoT2012) and a number of NZTA studies using that data have provided information on travel behaviour of households (eg Abley et al 2008; Milne et al 2011).<sup>1</sup> However, information from such sources is limited to simple descriptive statistics that are often snapshots in time. Formal statistical

<sup>1</sup> The census also holds similar information.

models are needed to turn existing descriptive information into underlying relationships. These are needed because they control for competing influences on transport demand.

Similarly, while the National Freight Demands Study (Paling 2008) provided useful information on commodities moved around New Zealand in 2006/07, it did not provide a basis for understanding how demand evolves over time according to the industrial composition of the economy.

In some cases the lack of empirical studies was a function of limited data. This was particularly so in the case of trends in freight tonne-kilometres by industry and at a regional level.

Indeed, even where estimates did exist, we found that there were some fundamental data limitations that meant estimated relationships were not always what they purported to be. Consequently, for practical purposes, there were gaps – for example, information about the price sensitivity of public transport users in New Zealand.

The most problematic gap we observed was for freight demand. While estimates of relationship were available from overseas studies, the range of estimates was so wide and clearly dependent on infrastructure availability (such as road versus rail), and industrial composition that it was not possible to glean valid insights. In New Zealand, published empirical studies of freight demand drivers do not go beyond the relationship of freight demand to GDP.

**Table 2.2 Freight demand drivers – estimated impacts on demands (% change) of a 1% increase in drivers**

Demands	Drivers				
	GDP	Transit time	Industrial production	Reliability	Cost of freight
Road freight	1.0-1.40	n/a	0.09-3.39	n/a	n/a
Rail freight: short run	n/a	-0.4	n/a	0.6	-1.1
Rail freight: long run	n/a	-0.3	n/a	0.6	-1.1

Existing studies of transport demand drivers had much more limited usefulness than we expected. It was extremely difficult to draw broad comparisons of demand drivers across the literature. For those parts of transport demand where empirical estimates were widely studied, the variation in findings was considerable; for example, over the long term, the findings regarding the speed of growth of private vehicle passenger demand (ie car travel) relative to income growth varied from between one to one-and-a-half times as fast.

A major reason for the wide range of results was the different types of travel demands being estimated. The fact that transport is a derived demand (for travel) means it can be represented in a variety of ways.

Although the figures in table 2.3 are normalised, to the extent possible for presentation and summary purposes, these figures do in fact represent a mixture of different demand definitions. Some definitions included both trips and trip length. Others measured passenger-kilometres and aggregate kilometres travelled. In the case of public transport, the most common definition of demand was boardings or trips.

**Table 2.3 Passenger travel demand relationships – cells describe the range of estimated (% change) impacts on demands of a 1% increase in drivers<sup>a</sup>**

Demands	Timing	Drivers							
		Income	Transit fare	Bus fare	Rail fare	Auto operating costs	Petrol price	GDP	Car ownership
Car travel	SR <sup>b</sup>	0.3	0.03 to 0.1	0.18	n/a	-0.3 to -0.44	-0.02 to -0.44	n/a	0.94
	LR <sup>b</sup>	0.47 to 1.05	0.15 to 0.3	0.01 to 0.34	0.03 to 0.15	-0.34 to -1	-0.07 to -0.40	n/a	0.81
Bus travel	SR	0.14 to 0.2	n/a	-0.2 to -0.83	n/a	n/a	0.20 to 0.28	n/a	-1.96
	LR	0.15 to 0.7	n/a	-0.28 to -1.02	0.13 to 0.56	0.06 to 0.47	0.32 to 0.37	n/a	-0.73 to -3.1
Rail travel	SR	0.4 to 0.61	n/a	n/a	-0.20 to -0.97	n/a	0.13	n/a	-1.04
	LR	1.0 to 2.36	n/a	0.01 to 0.44	-0.49 to -1.68	0.19 to 0.79	0.42	0.40 to 3.48	n/a
Public transport	SR	-0.05 to -0.67	-0.13 to -0.51	n/a	n/a	0.05 to 0.15	0.06 to 0.48	n/a	n/a
	LR	-0.09 to -0.9	-0.4 to -1.0	n/a	n/a	0.2 to 0.4	0.03 to 0.37	n/a	n/a
Total travel	SR	0.2	n/a	n/a	n/a	n/a	-0.1 to -0.20	n/a	n/a
	LR	0.5	n/a	n/a	n/a	n/a	-0.25 to -0.31	0.21 to 0.55	n/a

a) Demands here have been converted into a common basis, such as vehicle- or passenger-kilometres travelled, where possible.

b) SR = short run, LR = long run.

Definition differences also arose in relation to the short-run and long-run effects of demand drivers. Some studies included structural inertia (such as lags in the turnover of the vehicle fleet), and had a fairly precise interpretation of the long run as being the measured time it takes for a change in demand driver to reach full effect. Other methods, including much of the econometric literature, implicitly defined the long run as some underlying or trend relationship, rather than some actual time period.<sup>2</sup>

Furthermore, in other cases there remained considerable uncertainty over whether commonly used empirical estimates were valid. We have already mentioned issues around empirical estimates of the price sensitivity of public transport, and a number of other issues bear mentioning.

The one area of transport demand that has been well canvassed in the literature, including by New Zealand-specific empirical studies, is vehicle ownership and vehicle-kilometres travelled. This may be due to the comparative wealth of data available.

<sup>2</sup> These methods are those that rely on 'co-integration' and 'error correction' as a method for determining long-run trends.

Conder (2009) provides a particularly useful discussion of the history of vehicle demand modelling in New Zealand and elsewhere. It also usefully points out the limitations of existing approaches, although those limitations are less applicable to an aggregate modelling exercise such as ours.

**Table 2.4 Car ownership demand drivers – cells describe the range of estimated (% change) impacts on demands of a 1% increase in drivers**

Demand	Timing	Drivers					
		GDP per capita	Car price index	Fuel price	Income	Disposal income per capita	Bus fare
Vehicle ownership	Short run	0.52 <sup>a</sup>	-0.18 <sup>b</sup>	-0.1	0.37 to 0.4	0.34	0.09 to 0.19
	Long run	-	-	-0.25	0.56 to 1.0	1.14	0.42 to 1.7

a) Average of short and long run.

b) NZIER data.

The only point of contention we have with Conder (2009) is the extent to which there are saturation effects in vehicle ownership, and the rates of ownership at which these effects take place. Conder's saturation values for New Zealand range from 0.65 to 0.95 cars per capita, whereas observed ownership rates elsewhere in the world reach levels slightly above one car per capita in some places. Most New Zealand estimates of the level of car ownership at which saturation occurs appear to be by assumption, rather than being empirically determined.

The only major gaps remaining in terms of the determinants of vehicle travel were estimates of the variability in demand across regions and household types, as discussed earlier.

One of the most widely studied issues in transport demand is the response of consumers to changes in trip and travel prices. Unfortunately, we found that New Zealand-specific studies were, in two important cases, beset by data problems that limited the usefulness of their findings.

The first example was in terms of fuel price impacts on vehicle-kilometres travelled and related measures of private-vehicle transport demand. Currently, the most widely cited and used study on fuel price in New Zealand is that of Kennedy and Wallis (2007). However, the estimates in that study overstated price responsiveness. The estimates were biased upwards because the data series the researchers used to characterise fuel consumption was fuel deliveries by fuel companies. That data was affected by supply-side purchasing and stock control strategies, as well as by consumption.

As the price of fuel increases, one can observe that fuel companies meet consumer demand by running down stocks of petrol.<sup>3</sup> This happened in New Zealand between 2002 and 2007 (see figure 2.1) and meant lower fuel deliveries but not a commensurate reduction in fuel consumption. Thus the use of fuel deliveries as a measure of fuel consumption meant that the Kennedy and Wallis (2007) study overestimated the responsiveness of petrol consumption to changes in petrol prices.

Another issue, and a perennial problem for researchers, is the absence of consistent and well-defined data on prices and travel volumes for public transport. While there have been various attempts to estimate the

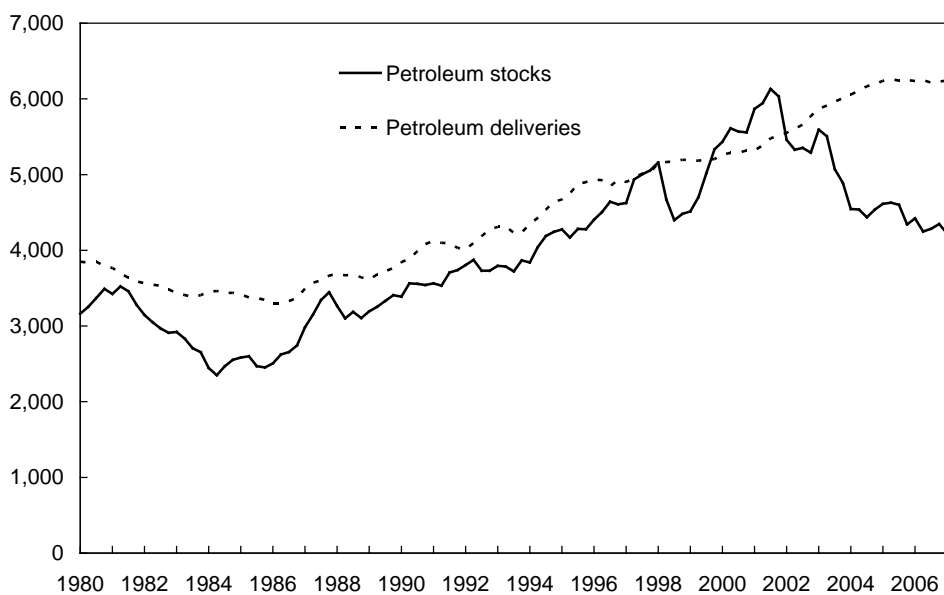
<sup>3</sup> One should expect that as the fuel price rises, the money or value that is tied up in stocks increases and the physical volume of stocks is adjusted to reflect a desirable value of stocks or working capital.



drivers of public transport demand in the New Zealand context, the responsiveness of public transport use to changes in prices (ie fares) has not been accurately estimated.<sup>4</sup>

In the absence of robust price indices or fare information, studies draw on proxy measures such as revenue per boarding as a measure of price (eg Wang 2011). These revenue figures are not prices. They hold information about both price and composition of demand, and are thus not representative of the incremental charges facing marginal public transport users. They cannot, therefore, accurately reflect price sensitivity of public transport demand. Unlike the case for private vehicle demand, there is little we can do to address this problem.

**Figure 2.1 Petroleum stocks and deliveries – kilo-tonnes, time period used in Kennedy and Wallis (2007)**  
(Source: Statistics New Zealand – SNZ)



Empirical transport demand studies often include careful detail around specifying drivers of demand, from trip choice to distance travelled, but very few premise their studies on detailed consideration of the form and function of demand and supply systems. As a result, they are not always well specified from an economic or statistical perspective.

Note that it is not necessarily the case that estimates are ‘wrong’, as much as that they do not accommodate issues of importance in the context of a multimodal long-run transport model.

We observed three such issues in the literature:

- partial estimation of individual transport demands
- focusing on percentage changes and thus overlooking data levels and not adequately accounting for structural changes
- conflating demand and supply effects.

<sup>4</sup> The most recent and robust nationwide (ie for more than one major centre) estimates for studies appear to be Booz Allen Hamilton (2001) and Wang (2011).

### 3 Population

The most important structural aspect of the model developed in this research was a projection of underlying population growth, age and household composition, and household location. Key outputs of this part of the model are:

- national and regional populations, by age and sex
- numbers of households, by household type
- the average age of households
- the number of people per household
- the labour force
- long-run employment.

This part of the model included significant detail in order to accommodate a wide range of possible scenarios about demographics and living arrangements.

#### 3.1 Trend growth and population age composition

We used a ‘modified cohort component method’, where population was broken down by size and age, and evolved according to a transition matrix  $T$  plus net migration ( $i-m$ ):

$$p_t = T \cdot p_{t-1} + i_t - m_t$$

$$T = \begin{bmatrix} F_1 & \dots & F_i & \dots & F_k \\ P_1 & 0 & 0 & \dots & 0 \\ 0 & \ddots & 0 & \dots & 0 \\ 0 & 0 & P_i & \dots & 0 \\ 0 & 0 & 0 & P_{k-1} & 0 \end{bmatrix}$$

(Equation 3.1)

where:

$F$  is age-specific fertility rates

$P$  is the probability of a person shifting from one age group at time  $t$  to the next age group at time  $t+1$

$T$  evolves with time with:

- changes in age-specific fertility rates, based on autoregressive time series forecasts
- changes in age-specific mortality rates, based on SNZ’s 2009 base-year medium scenarios.

The model was limited to ages 0–90, to focus on the ages most relevant to transport demand.

Net migration was initially held constant, using SNZ’s population projection assumptions, but was subject to both scenarios and stochastic dimensions, as explained next.

The stochastic dimension of the population model was applied at a fairly aggregated level (following the approach of Dunstan 2011<sup>5</sup>) to net migration, which underpins most of the uncertainty in population growth amongst the age groups of particular interest to us.

Net migration was modelled as an ARIMA(1,0,1) process:

$$N_t = \rho \cdot N_{t-1} + \theta \cdot \varepsilon_{t-1} + \varepsilon_t + \mu \cdot N_t \quad (\text{Equation 3.2})$$

For the purposes of stochastic projections the error ( $\varepsilon$ ) was sampled randomly from a normal distribution (with standard errors from historical estimation).

We assumed that the age profile of migrants was the same as the average over the previous 10 years.

## 3.2 Household numbers and household composition

Population projections were converted to household projections by using age- and sex-specific living arrangement type rates (LATRs). LATRs describe the probability that a person of a given age and sex will live in a particular family and household type. These probabilities are determined by census data information.

Rates of change in LATRs over the past decade were projected linearly (based on observed trends between 1996 and 2006) over the next 10 years and assumed to remain constant thereafter. Thus, we assumed no structural change in LATRs, by default.

Household types included in the model were:

- people living alone
- couple households (no children)
- one-parent households
- two-parent households
- multiperson households (not related)
- multifamily households.

We assumed that the proportions of one-parent and two-parent families in multifamily households remained constant over time.

We also modelled the proportion of the population not covered in the above categories (ie living in non-private households), but these were not represented elsewhere in the model.

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<sup>5</sup> Dunstan, K (2011) 'Experimental stochastic projections for New Zealand: 2009(base)-2111', *Statistics New Zealand Working Paper No 11-01*. We note that since our model was constructed, SNZ has begun publishing official stochastic population projections.

### 3.3 Employment and labour force

The working-age population (over 15 years old) was used to determine the size of the labour force by applying labour force participation rates based on historical age-group and sex-specific constants (by default) based on the SNZ Household Labour Force Survey.

Employment growth was modelled as a function of growth in the working-age population, age- and sex-specific labour force participation rates, and the unemployment rate. The unemployment rate ( $UR$ ) was assumed to follow a smooth adjustment towards the long-run rate ( $UR^*$ ) over a period approximating  $s$  years:

$$UR_t = UR_{t-1} + (UR^* - UR_{t-1})/s \quad (\text{Equation 3.3})$$

### 3.4 Regional populations and regional migration

Regions in the model were:

- Northland
- Auckland
- Waikato
- Bay of Plenty
- Gisborne–Hawke’s Bay
- Taranaki
- Manawatu–Wanganui
- Wellington
- Upper South Island (Tasman, Nelson, Marlborough, West Coast)
- Canterbury
- Otago
- Southland.

Regional populations followed the same cohort component approach as for the national population, with regional growth constrained to add up to the national population.

Much like national net migration, regional migration was based initially on historical averages. However, regional net migration was used to describe the distribution of net migration flows across regions so that the sum of regional movements added to the national (external) migration figures:

$$Netm(r,t) = Ave(Netm(r,0)) + stdev(Netm(r,0)) \times abs[(Ave(Netm(r,0))/stdev(Netm(r,0))) \times Netm(NZ,t)/12]$$

(Equation 3.4)

where  $Netm(r,t)$  is net migration in region  $r$  at time  $t$ . This ensured that user-inputted scenarios would be internally consistent and stochastic shocks (imposed on national net migration) would be transmitted to the regions in a consistent fashion.

## 4 Economic growth and incomes

The ‘Growth and incomes’ submodel provides projected growth in GDP, industry shares of GDP, regional GDP, and household income growth, by region.

### 4.1 GDP growth

The framework we used to project *trend* growth was a growth-accounting model based on a conventional Cobb-Douglas production function which, when transformed by logs, implied that long-run growth potential ( $Y$ ) was a function of growth in multifactor productivity ( $A$ ), the capital stock ( $K$ ) and employment ( $L$ ):

$$Y_t = A_t \cdot K_t^\alpha \cdot L_t^{1-\alpha}$$

$$\ln(y_t) = \ln(A_t) + \alpha \cdot \ln(K_t) + (1-\alpha) \cdot \ln(L_t) \quad (\text{Equation 4.1})$$

Incomes shares of labour and capital were described by the parameter  $\alpha$ , which was assumed to remain constant over time. Employment growth rates were taken from the ‘National population’ submodel.

We assumed that the capital stock evolved at a constant rate equivalent to growth in employment. These assumptions about labour force rates, growth in the capital stock, and our approach to modelling the unemployment rate, were adopted so as to avoid modelling business cycles explicitly and to limit sources of uncertainty in economic growth to a single factor – ie multifactor productivity – which would make uncertainty easier to evaluate and would allow users to easily control the evolution of growth when running scenarios.

These assumptions meant that the growth-forecasting equation was reduced to a function of population growth, employment and multifactor productivity – the same approach as used by the Treasury for its Long Term Fiscal Model.

Uncertainty in long-term growth is modelled as shocks ( $\varepsilon$ ) around trends in multifactor productivity growth ( $\mu$ ):

$$A_t = \mu \cdot A_{t-1} + \varepsilon_t; \text{ with } \varepsilon \sim N(0, \sigma) \quad (\text{Equation 4.2})$$

### 4.2 Regional GDP growth

Industry-specific GDP forecasts were used to derive region-specific economic growth based on historical trends in employment, by industry, by region. If, for example, agriculture grew its share of GDP then regions with traditionally high shares of employment in the agriculture and food-manufacturing sector would enjoy deterministically higher economic growth; ie

$$Y_{r,t} = \sum[(\text{EMP}_{i,r} / \text{EMP}_i) \times \text{GDP}_{i,t}] \quad (\text{Equation 4.3})$$

where:

EMP is employment counts

the subscript  $r$  denotes regions

subscript  $i$  denotes industries

the sigma term denotes the sum over all industries.

The model also calculated region-specific productivity growth based on historical trends in productivity growth, by industry. These figures were used to gauge the extent to which productivity growth would reduce demand for labour and lead to a gap in labour demand; ie between top-down population-based employment measures and bottom-up labour demand measures.

This calculated gap between labour demand and deterministic population-based employment was not used in the current version of the model, but could be used as an input for richer modelling of regional-specific variables such as region-specific estimates of labour input for calculating regional GDP, or economic determinants of wage rates, or inter-regional migration flows. We decided not to include these in this model because the purpose of the model was to assess national impacts and this additional detail was deemed too complicated for a national model.

### 4.3 Industry share of GDP

The industries that entered the model were based on a bespoke aggregation of the usual industry groups published in National Accounts aggregates by SNZ. The reason for using this bespoke aggregation was to ensure that we had industry groupings that were reasonably highly aggregated (to enable ease of user inputs and scenario modelling) but had aggregations that would be meaningful for freight demand. The industries were:

- agriculture and food manufacturing (AG)
- forestry, logging and wood-processing industry (FOREST)
- mining, petroleum and chemicals industry (MINING)
- manufacturing industry (excluding wood and food manufacturing) (OTHM)
- construction and utilities (water, gas and electricity) industry (CONS)
- wholesale, retail, food and beverages, and accommodation services industry (TRADE)
- communications, finance, real estate and professional services industry (OTHS)
- central and local government administration industry (PUB).

The AG, FOREST, and TRADE categories covered the lion's share of freight demand. By convention, forestry was aggregated with agriculture but this did not make sense for running scenarios of freight demand, given the freight intensity of both sectors and the fact that they are, to some extent, competing land uses. We combined agriculture with food and beverage manufacturing, given the close relationship between the two industries and the extent to which freight demand in each industry typically reflects movements between the two industries. Other sectors, where freight is less important, were aggregated based on their connection to different macroeconomic demand drivers, rather than in terms of their freight demand drivers *per se*; eg construction and utilities are both connected to domestic demand.

We modelled industry contributions to GDP by extrapolating trends in industry GDP. These trends were modelled within a simple vector autoregressive (VAR) model of industry GDP in order to accommodate user-defined shocks to industry GDP. This was done to ensure an internally consistent set of adding up constraints that would also capture covariance of industry output when a sector is shocked (ie which sectors would expand or contract). Such shocks to industry output were constrained so that they would only affect industry composition (GDP shares) and not national potential or trend economic growth.

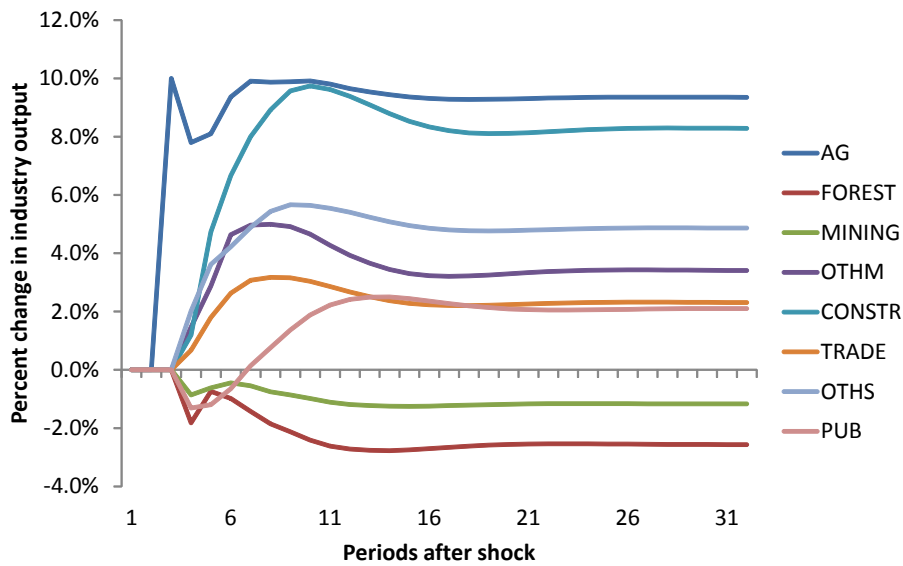
**Table 4.1 Matrix of coefficients in VAR model of industry shares of GDP**

		Dependent variable = log differenced (industry GDP)							
		AG	FOREST	MINING	OTHM	CONS	TRADE	OTHS	PUB
Coefficient on log difference GDP lagged one year:	AG	-0.21	-0.19	-0.09	0.15	0.13	0.07	0.21	-0.14
	FOREST	0.39	0.16	0.43	0.43	-0.14	-0.00	-0.26	0.12
	MINING	-0.23	-0.74	-0.44	-0.53	-0.58	-0.35	-0.12	-0.28
	OTHM	0.45	0.08	0.31	-0.04	0.34	0.05	-0.11	0.54
	CONSTR	0.26	-0.11	-0.28	0.12	-0.09	0.16	-0.22	-0.03
	TRADE	-0.37	0.36	-0.09	0.27	0.26	0.32	0.87	-0.56
	OTHS	-0.16	-0.17	0.29	0.48	1.08	-0.03	0.52	0.27
	PUB	0.03	-0.36	0.12	-0.59	-0.16	-0.39	-0.14	0.83
Constant trend		0.03	0.04	0.00	-0.02	-0.02	0.03	0.01	0.01
<b>Model fit statistics:</b>									
R-squared		0.47	0.63	0.18	0.37	0.52	0.38	0.75	0.76
Std error, equation		0.04	0.03	0.05	0.06	0.05	0.04	0.02	0.02
F-statistic		1.31	2.53	0.34	0.87	1.62	0.92	4.46	4.67
Log likelihood		45.10	46.81	37.37	34.38	38.28	45.42	61.15	58.03
Std deviation, dependent		0.04	0.04	0.05	0.06	0.06	0.04	0.03	0.03

A sample VAR result is shown in figure 4.1 for a 10% shock to output in the agriculture and food-manufacturing industry.



Figure 4.1 Response of industry output to a shock (percent change in output following a 10% shock to AG)



## 4.4 Household incomes

The equation we used to project household income was:

$$INC(i,j,t) = INC(i,j,t-1) \times (1 + (\alpha(i) \cdot \Delta GDP(j,t)) + (\beta \cdot \Delta AGE(i,j,t))) \quad (\text{Equation 4.3})$$

where:

$i$  denotes household type

$j$  denotes region

$t$  is the time subscript.

Household incomes ( $INC$ ) were assumed to roughly follow growth in GDP per working-age person ( $\Delta GDP$ ). However, we tempered this relationship to take account of the fact that some household types experience slower income growth than others, due to life-cycle effects as in the case of multiperson households (which are overwhelmingly young people), or where there is a higher propensity for benefits being a major source of income.

We also introduced average age of households ( $\Delta AGE$ ) as a predictor of income growth, in order to capture some of the impact of shifts in the age composition on household income that had not been captured by 'household living arrangement'.

The coefficients used in the above equation are shown in table 4.2. They came from a panel regression of household income, using Household Labour Force Survey data (results can be found in appendix A).

**Table 4.2 Household income equation coefficients**

<b>Variable</b>	<b>Coefficient</b>
Average age of household	1.0346
Growth in GDP per working-age person for people living alone	1.1644
Growth in GDP per working-age person for couple households	1.3486
Growth in GDP per working-age person for multiperson households	0.8329
Growth in GDP per working-age person for multifamily households	0.7493
Growth in GDP per working-age person for one-parent households	0.8746
Growth in GDP per working-age person for two-parent households	1.0961

## 5 Household vehicle demand

The purpose of this submodel is to project growth in vehicle demand, by household type and region. The results are then used:

- as a *first-round* input into determining growth in regional vehicle-kilometres travelled (in the VKT and cost submodel) by multiplying the number of vehicles in a region by regional estimated vehicle-kilometres travelled per vehicle
- as growth rates, on top of existing vehicle fleet numbers (in the 'Vehicle fleet' model) to determine growth in demand for passenger vehicles.

Demand for vehicles was modelled at the household and region level using a generalised linear model (GLM) employing a logit link function (ie a logit model). We used census data on vehicle holdings by household, by region, for 1996, 2001 and 2006 to estimate the probability that a household would own one, two, or three or more vehicles.

In the general terms the model was:

$$P_{hh}(VEH = x | VEH = y < x) = \exp(\beta x) / \exp(1 - \beta x)$$

$$\beta x = f(\text{INC}, \text{DENS}, \text{AGE}, \text{WEL\_DUM}) \quad (\text{Equation 5.1})$$

The probability that a household of a given kind owns 'x' vehicles, conditional on owning 'y' vehicles, was a function of real household income (INC), the density of the region in which the household was resident (DENS), the average age in the household (AGE), and whether or not the household was in Wellington (WEL\_DUM).<sup>6</sup>

For each kind of household the model was estimated sequentially for x=1, 2, and 3 or more. For some types of households explanatory variables were dropped because they were insignificant. Full estimation results are provided in appendix A.

Vehicle ownership was modelled separately for the following types of household:

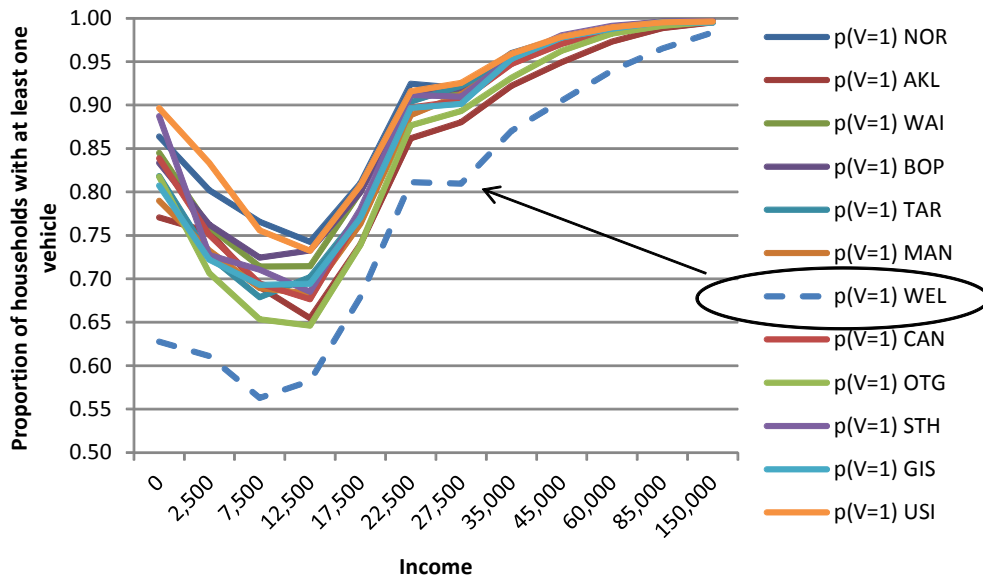
- individuals living alone
- couples
- one-parent families
- two-parent families
- multifamily households
- multiperson households.

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<sup>6</sup> We included household income bands across all levels of income. However, this did admit low reported incomes for which there were potential empirical problems associated with, for example, one-off impacts or under-reporting of income. Full investigation of this issue was outside scope of this work but could be a topic for future research.

The Wellington effect (or dummy) was necessary to capture the very large difference between Wellington and all other regions in terms of vehicle ownership (see figure 5.1).

**Figure 5.1 Vehicle ownership, by income, by region - Wellington outlier - share of households owning at least one vehicle, by annual income**



The fitted probabilities of the model by household type (*ceteris paribus*) are shown in table 5.1. Note that the probability of owning a second vehicle was the conditional probability given the household owned a first vehicle, and the probability of owning a third vehicle was conditional on already owning two vehicles. The unconditional probabilities were much smaller. For example, the unconditional probability that a person living alone would own three or more vehicles was 0.02.<sup>7</sup>

**Table 5.1 Household vehicle ownership: model-fitted probabilities**

Household	Probability of no vehicles	Probability of 1 vehicle	Probability of a 2nd vehicle	Probability of a 3rd vehicle (or more)
Person living alone	0.25	0.75	0.13	0.19
Couple	0.03	0.97	0.63	0.17
Multiperson	0.11	0.89	0.66	0.36
Multifamily	0.07	0.93	0.74	0.54
One-parent	0.17	0.83	0.34	0.23
Two-parent	0.30	0.70	0.58	0.56

The effects on vehicle ownership of household income, density, age, and residing in Wellington are shown in table 5.2. For each type of household and each category of ownership (ie no vehicle, one vehicle, a second vehicle, and a third vehicle or more) the marginal effect of a standardised 10% change in the explanatory factors is shown, except in the case of the binary ‘in-Wellington’ effect. We have also provided

<sup>7</sup> Even this number was somewhat surprising. Nonetheless, census data suggests that in 2006, one in 50 people living alone had access to three or more vehicles, which was equal to 5000 households.

an estimated aggregate impact (the % change column) on total vehicle ownership for each household type, given the change in each explanatory factor, and an indication of what this means in terms of an elasticity, which was evaluated at the mean of the dependent variable – necessary given that the ‘elasticity’ changes depending on the value of the dependent (vehicle ownership) variable.

**Table 5.2 Marginal effects in vehicle ownership model**

Household	Col heading	p(V=0)	p(V=1)	p(V=2 1)	p(V=3 2 1)	% change	'Elasticity'
Person living alone	+10% income	-0.036	0.036	0.023	-0.013	6%	0.58
	Wellington effect	0.186	-0.186	-0.067	0.041	-27%	n/a
	+10% density	0.002	-0.002	-0.001	0.001	0%	-0.03
	+10% average age	0.016	-0.016	-0.037	-0.009	-6%	-0.56
Couple	+10% income	-0.003	0.003	0.045	0.017	4%	0.38
	Wellington effect	0.036	-0.036	-0.236	-0.060	-19%	n/a
	+10% density	0.000	0.000	-0.002	-0.002	0%	-0.02
	+10% average age	-0.016	0.016	0.147	0.105	15%	1.50
Multiperson	+10% income	-0.020	0.020	0.015	0.010	2%	0.21
	Wellington effect	0.199	-0.199	-0.137	-0.069	-19%	n/a
	+10% density	0.001	-0.001	0.000	0.000	0%	0.00
Multifamily	+10% income	-0.019	0.019	0.027	0.009	3%	0.29
	Wellington effect	0.083	-0.083	-0.081	-0.058	-10%	n/a
	+10% density	-0.004	0.004	0.007	0.005	1%	0.08
One-parent	+10% income	-0.053	0.053	0.054	0.020	8%	0.84
	Wellington effect	0.178	-0.178	-0.109	-0.050	-23%	n/a
	+10% density	-0.010	0.010	0.010	0.005	2%	0.16
Two-parent	+10% income	-0.003	0.003	0.055	0.031	6%	0.57
	Wellington effect	0.026	-0.026	-0.235	-0.110	-23%	n/a
	+10% density	0.000	0.000	-0.002	-0.001	0%	-0.02
	+10% average age	-0.012	0.012	0.000	0.000	1%	0.07

Some of the more notable results of the model include the following:

- The average age of couple households had a relatively large effect (elasticity = 1.5) on the probability that these households would have a second vehicle. We surmised that this reflected increasing numbers of people over the age of 50 in couple households (ie with no dependents) with comparatively high disposable incomes.
- There was a significant difference on most measures between households with children (ie one-parent and two-parent households) and those without. For example, households with children in Wellington were more likely to have a vehicle than those households elsewhere in the country, while the opposite was true for households without children.
- Household density reduced the probability of vehicle ownership in the case of a second and third vehicle, but not the probability of having a single vehicle, except in the case of one-parent and multifamily households.

- Income elasticity of vehicle ownership was quite large, especially in cases of households that typically had lower incomes (eg one-parent households had an income elasticity of 0.84, implying that a 10% increase in income would raise vehicle numbers by 8.4%).

Data used to conduct these estimates were census observations on vehicle ownership in 1996, 2001 and 2006.

In the model, households did not choose any particular model of vehicle, but rather the stock of vehicles was determined outside household choice (see section 8).

## 6 Freight demand

The 'Freight demand' submodel projects freight volumes by mode, by industry and by region. Freight volumes were measured in terms of inflation-adjusted economic value of freight, rather than physical measures such as tonne-kilometres. We did this because:

- it allowed us to model the long-run evolution of freight demand in terms of intensity of use as an input to economic activity, rather than a physical task
- service sectors, which are the fastest-growing part of the economy, use freight but do not have easily tracked commodities that can be used to gauge drivers of tonne-kilometres travelled
- there is considerable variation in the economic value of a tonne-kilometre of freight service provided, such as the difference between a refrigerated and unrefrigerated tonne-kilometre.<sup>8</sup>

Freight demand was assumed to grow according to overall economic growth and changing industrial composition of the economy. The core of the model estimated historical growth in freight intensity by industry. A sample of these estimates is shown in figure 6.1. These estimates were based on the use of freight (as a commodity) according to SNZ's 'supply and use' tables (SNZ 2011); hence, the presentation of 1996 and 2007 estimates, which corresponded with years for which supply and use tables had been produced.<sup>9</sup>

Freight volumes, estimated and projected using this approach, provided a way of tracking the economic value of freight demand in the economy over time. These estimates of freight use were not directly comparable to estimates published in past New Zealand studies, such as *National freight demands study* (Paling 2008) or *Development of a New Zealand national freight matrix* (Booz Allen Hamilton 2005). This is because we focused on industries and on GDP, while those other studies focused on tonnes of selected commodities.<sup>10</sup>

Freight intensity was also broken down by mode share for all surface modes (sea, road and rail). To do this we used a combination of SNZ's 'supply and use' tables (SNZ 2011) and, in a few limited cases, estimates from Paling (2008). While it is not a land mode, sea freight was included because it is a ready substitute for some road- and rail-based freight.

We also calibrated the model to account for differences in distances travelled across regions. In doing this we assumed that freight intensity by industry was the same across regions in terms of value, including quality of freight (eg whether refrigerated or not), and thus we could apply commodity-based measures of distances travelled. Distance parameters, by region, were adapted from data in Paling (2008). These

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<sup>8</sup> It is also the case that the modelling of freight based on its economic value is something that has received scant attention in New Zealand and by taking this approach we were attempting to help fill a gap in research.

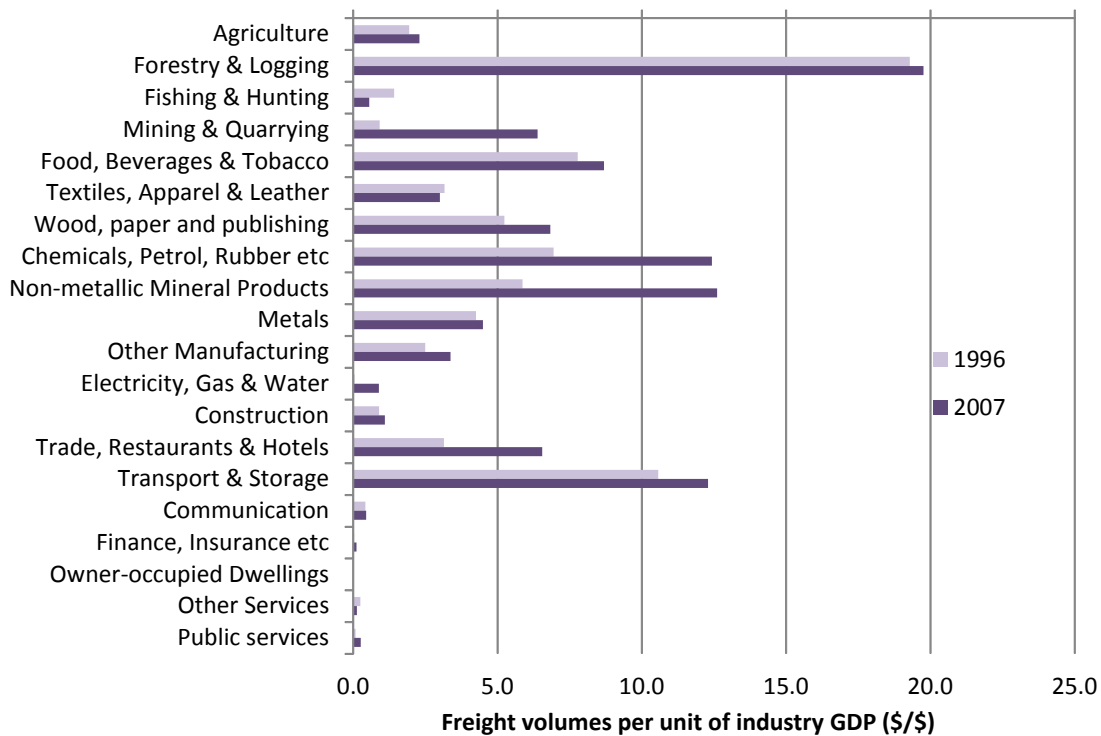
<sup>9</sup> Estimates from the 2003 tables were not presented because freight was not identified as a separate commodity in the supply and use tables. Subsequent to the construction of this model, SNZ has released updated 2007 input-output tables that could be used to update this analysis.

<sup>10</sup> There were, however, some sectors where commodity production was fairly homogeneous and production was reasonably freight intensive. For these sectors, our estimates were very similar to those used produced by Paling (2008).

parameters described the marginal increase or decrease in distance travelled by a tonne of freight, given the demand for freight had originated in a particular region.

Regional freight demand was thus modelled explicitly but the origins and destinations of trips were not. We assigned freight (implicitly) to the regions in which GDP was assigned and thus modelled the origin of freight demand, which was not the same as the origin of a freight trip. For example, growth in freight demand in the manufacturing industry may have come from Auckland, but the goods may have been shipped from, for example, the Port of Tauranga or the Port of Auckland. The relevance of our distance coefficients was to take account of the fact that an increase in manufacturing in the Waikato, for example, would, on average (all else being equal), imply higher kilometres travelled for a given amount of freight relative to the same amount of demand in Auckland, because there is no international port in the Waikato.

**Figure 6.1 Freight intensity of industry GDP**



Projected freight demand was:

$$freight\_vol(i,j,k,t) = gdp(i,j,k,t) \times freight\_intensity(i,k,t) \times distance\_coefficient(j,k)$$

(Equation 6.1)

where:

$i$  denotes industries

$j$  denotes regions

$k$  denotes mode (sea, rail or road)

$t$  is time.



**Table 6.1 Distance coefficients, by industry and region**

Region	Industry							
	AG	FOREST	MINING	OTHM	CONSTR	TRADE	OTHS	PUB
Northland	1.86	1.07	1.03	1.86	1.86	0.99	1.86	1.86
Auckland	0.82	0.52	0.7	0.82	0.82	1.46	0.82	0.82
Waikato	0.69	0.79	1.14	0.69	0.69	0.38	0.69	0.69
Bay of Plenty	1.1	1.14	1.09	1.1	1.1	0.97	1.1	1.1
Taranaki	0.91	1.32	1.14	0.91	0.91	0.79	0.91	0.91
Manawatu-Wanganui	0.84	0.86	0.92	0.84	0.84	0.72	0.84	0.84
Wellington	0.57	1.41	0.89	0.57	0.57	0.36	0.57	0.57
Canterbury	0.91	0.94	0.84	0.91	0.91	1.12	0.91	0.91
Otago	0.86	0.94	1.13	0.86	0.86	0.8	0.86	0.86
Southland	0.81	1.09	0.91	0.81	0.81	0.97	0.81	0.81
Gisborne-Hawke's Bay	1.01	0.96	1.56	1.01	1.01	1.04	1.01	1.01
Upper South Island	1.7	1.27	1.93	1.7	1.7	1.14	1.7	1.7

Freight intensity was assumed to grow (by default) according to historical averages, which have seen freight volumes grow at the same rate or faster than industry GDP over recent years. Our interpretation of this trend was that for most industries, it is easier to increase productivity of use of non-transport inputs. This is not to say that there have not been productivity gains in the freight sector; just that productivity gains have been faster elsewhere. The model allows for alternative user-defined assumptions of freight intensity growth.

**Table 6.2 Growth in freight intensity (freight value/industry GDP, average growth 2000–2011)**

Industry	Road	Rail	Sea	Total
Agriculture and food manufacturing (AG)	-1.0%	3.0%	2.0%	0.0%
Forestry, logging and wood processing industry (FOREST)	1.0%	0.0%	0.0%	1.0%
Mining, petroleum and chemicals industry (MINING)	4.0%	-12.0%	7.0%	4.0%
Manufacturing industry (excluding wood and food manufacturing) (OTHM)	0.0%	0.0%	6.0%	0.0%
Construction and utilities (water, gas and electricity) industry (CONS)	2.0%	0.0%	0.0%	2.0%
Wholesale & retail, food & beverage, and accommodation services industry (TRADE)	2.0%	0.0%	-1.0%	2.0%
Communications, finance, real estate and professional services industry (OTHS)	-2.0%	0.0%	0.0%	-2.0%
Central and local government administration industry (PUB)	5.0%	4.0%	8.0%	5.0%

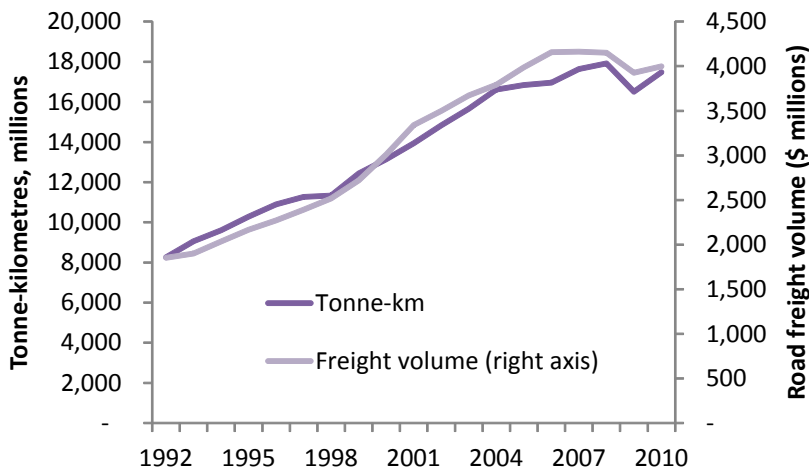
The model does, however, give users the ability to conduct scenarios for industry-specific freight intensity and intensity, by region. Regional intensities, which are essentially distance intensities combined with industrial composition, could be varied to allow for compositional changes within industries or for the construction of new infrastructure such as ports.

We did not directly model substitution between freight modes, as these are highly location- and industry-specific and we were not able to obtain data on relative costs. We held mode shares by industry constant and let differential rates of freight intensity and changes in regional GDP and industry composition drive changes in freight by mode through a composition effect.

Our main focus was on road freight and our estimates of growth in road freight volumes were well correlated with estimates of freight tonne-kilometres from the Ministry of Transport. We did not expect our estimates of freight volumes to perfectly match tonne-kilometre estimates, because the value of a tonne-kilometre of freight can be expected to vary across industries, commodities and the kind of heavy vehicle used.

The model does produce projections of road-freight tonne-kilometres, which are necessary for users to infer demands on the road network from freight (eg physical loads and wear and tear). Our estimates and projections of freight tonne-kilometres were constructed using an equation that relates historical movements in freight volumes to movements in data on heavy-vehicle tonne-kilometres (from the Ministry of Transport).

**Figure 6.2 Relationship between road-freight volumes and tonne-kilometres (Sources: Ministry of Transport, Statistics New Zealand)**



## 7 Prices

The 'Prices' submodel projects:

- international oil prices
- exchange rates
- domestic transport fuel prices
- variable travel-related tax rates (principally fuel excise and RUC rates)
- vehicle prices.

The oil price was modelled as:

$$P(t) = P(t-1) + (P^* - P(t-1))/s + e(t) \quad (\text{Equation 7.1})$$

where the price ( $P$ ) in year  $t$  is a function of the price last year ( $t-1$ ) plus some fraction ( $s$ ) of the deviation between last year's price and the long-run level ( $P^*$ ) last year, in nominal US dollars. The error term ( $e$ ) describes shocks that keep the price from tending towards its long-run level. These shocks were drawn from a random normal distribution with mean  $P^*$ , and standard deviation set to the historical deviation observed in price data (which also could be set by the model user).

The default oil price assumption was entered in nominal US dollars so that user-defined assumptions on the oil price do not get confused with exchange rate and inflation assumptions, which jointly determine the New Zealand dollar cost of oil. The rate of inflation was assumed to be 2% per annum on average.

The exchange rate was modelled in the same manner as oil prices:

$$ER(t) = ER(t-1) + (ER^* - ER(t-1))/s + e(t) \quad (\text{Equation 7.2})$$

Domestic fuel prices (consumer costs at the pump) were then modelled as a function of the exchange rate adjusted for the international price of oil, a constant rate for the importer's margin (MARG), fuel tax rates and a constant rate of GST:

$$PUMP(t) = (OIL(t) \times ER(t) \times MARG) + TAX(t) \times (1 + GST) \quad (\text{Equation 7.3})$$

Fuel tax rates and RUC rates (which appear in the 'VKT and cost' submodel) were assumed, by default, to grow by the rate of inflation.

Vehicle prices were assumed to grow with the rate of inflation. This broadly reflected the connection between inflation and the long-run exchange rate, with a high rate of inflation implying a low exchange rate and higher vehicle prices.

## 8 Vehicle fleet

The 'Vehicle fleet' submodel produces projected numbers of vehicles by age, class, and motive technology or fuel type.

The stock of vehicles was modelled using a cohort component method similar to the 'Population' submodel. The fleet ( $v$ ) evolves according to a transition matrix  $W$ , which varies by technology type ( $i$ ) and varies over time.  $W$  describes rates of entry to the vehicle fleet ( $M$ ) and age-specific scrappage rates ( $S$ ).

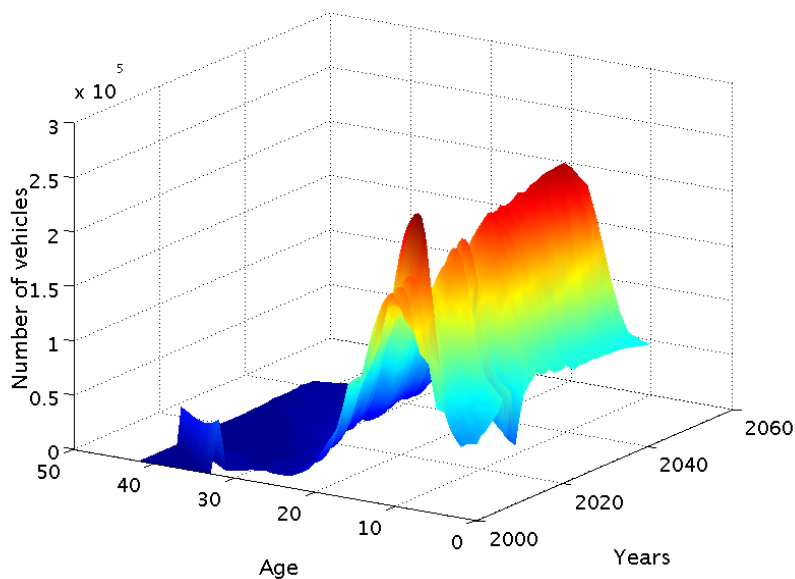
$$v_{it} = W_i v_{it-1}$$

$$W_i = \begin{bmatrix} M_1 & \dots & M_i & \dots & M_k \\ S_1 & 0 & 0 & \dots & 0 \\ 0 & \ddots & 0 & \dots & 0 \\ 0 & 0 & S_i & \dots & 0 \\ 0 & 0 & 0 & S_{k-1} & 0 \end{bmatrix}$$

(Equation 8.1)

Individual vehicle types in the fleet were initially assumed to change independently of household or freight demands. This was partly because we had extremely limited data on the kinds of vehicles held by particular kinds of households or for particular freight tasks. There were also good theoretical reasons to model fleet composition separately from individual vehicle demand. The price of vehicles as a whole in the market will equilibrate to ensure that vehicles are used up to the point of technological obsolescence or until maintenance costs (determined largely in the labour and parts markets) outweigh the utility of vehicle use. This implies that the rate at which new vehicles enter the fleet is contingent upon the existing age structure of the fleet and that imports of new vehicles may well occur in waves. Indeed, as shown in figure 8.1, the current age composition of New Zealand's vehicle fleet appears to have been heavily influenced by a burst of used-car imports around 2005.

**Figure 8.1** Vehicle fleet replacement and cohort effects – evolution of the light-vehicle fleet, by age and year of stock



## 8.1 Model dimensions

The model has 2310 different types of vehicles in it, based on the kinds of vehicles used in the Ministry of Transport's Vehicle Fleet Emissions Model (VFEM). This includes the following break-downs in vehicle characteristics:

- vehicle class
  - light passenger-vehicles
  - light commercial vehicles
  - motorcycles
  - heavy commercial vehicles (HCVs)
  - buses
- fuel types:
  - diesel
  - petrol
  - hybrid (for light vehicles only)
  - electric vehicles (for light vehicles and buses only)
  - plug-in hybrid (for light vehicles only)
- vehicle vintages in individual ages ranging from <1 year old through to 40 years old.

Each class of vehicle is further classified according to size categories (see table 8.1).

**Table 8.1 Vehicle sizes**

Vehicle size	Light passenger-vehicle	Light commercial vehicle	Motorcycle	HCV	Bus
Extra small	<1350cc	<1350cc	-	3.5–5.0t	-
Small	1350–1600cc	1350–1600cc	<60cc	5.1–7.5t	<7500kg
Medium	1600–2000cc	1600–2000cc	-	7.6–10.0t	7501–12,000kg
Large	2000–3000cc	2000–3000cc	>60cc	10.1–12.0t	> 12,000kg
XL	>3000cc	>3000cc	-	12.1–15.0t	-
XXL	-	-	-	15.1–20.0t	-
XXXL	-	-	-	20.1–25.0t	-
XXXXL	-	-	-	25.1–30.0t	-
Over-sized	-	-	-	> 30.0t	-

## 8.2 Vehicle entry and exit

### 8.2.1 Rates of entry and exit

We modelled rates of entry to the fleet demand as, in part, a function of when vehicles need replacing. To do this we projected the number of vehicles being retired from the fleet and we used the rate of departure as a minimum number of vehicles entering the fleet for each broad vehicle class (light passenger, commercial, heavy commercial, buses and motorcycles).

Scrapage rates, the rate at which each modelled type of vehicle exits the fleet, were projected in a deterministic fashion based on average vehicle- and age-specific scrapage rates observed over the past 10 years.

The number of vehicles newly entering the fleet (*REG*), whether new or used, was then modelled as a function of replacement demand for a particular class of vehicle (ie  $SCRAP(i,t-1)/VEH(i,t-1)$  or proportion of vehicles scrapped) plus additional demand to meet growing demands (*GROWTH*):

$$REG(i,t) = SCRAP(i,t-1)/VEH(i,t-1) + GROWTH(i,t) \times VEH(i,t-1) \quad (\text{Equation 8.2})$$

where *i* refers to the class of vehicle, whether light passenger (LPV), light commercial (LCV), heavy commercial (HCV), bus or motorcycle. The composition of new registrations within each type was dealt with separately.

Growth in demand for (non-bus) passenger vehicles (LPV, LCV and motorcycles) was based on growth in household vehicle demand as calculated in the 'Household vehicles demand' submodel.

Growth in demand for HCVs was calculated using growth in road-freight tonne-kilometres from the 'Freight demand' submodel. In doing this we assumed no change in average tonne-kilometres per vehicle over the long term.

We assumed that demand for buses grows with employment (from the 'Population' submodel) – a proxy for growth in peak demand for public transport.

### 8.2.2 Composition and age of incoming vehicles

Projected registrations of incoming vehicles were then distributed across different ages, sizes and motive technologies, according to a series of steps and assumptions depending on the broad class of vehicle.

For buses, HCVs and motorcycles we assumed that the composition of incoming vehicles matched averages over the past decade in terms of age and size of vehicle and motive technology.

For LPVs and LCVs we modelled the share of incoming vehicles that were medium, large or XL vehicles as a function of the cost of fuel relative to incomes (an index variable of changes in the ratio of PRICE\_TO\_GDP) and the level of GDP (small vehicles were calculated as a residual). These relationships were estimated separately for LCVs and LPVs. The model was estimated using the same kind of generalised linear model with *logit* link function as used for the Household Vehicle Ownership econometric model. Econometric results of this model can be found in appendix A. The share of registrations that were small (<1600cc) was calculated as a residual (ie the difference between overall demand and demand for medium, large or XL vehicles).

The age of incoming LPVs and LCVs was modelled using a two-step process in which we first used a model that predicted the share of registrations that are new vehicles (*NEW*), based on growth in vehicle prices (from the 'Price' submodel) and GDP. This relationship was estimated econometrically (see appendix A) and entered the model as constant 'elasticities' of demand for new vehicles relative to used vehicles; eg:

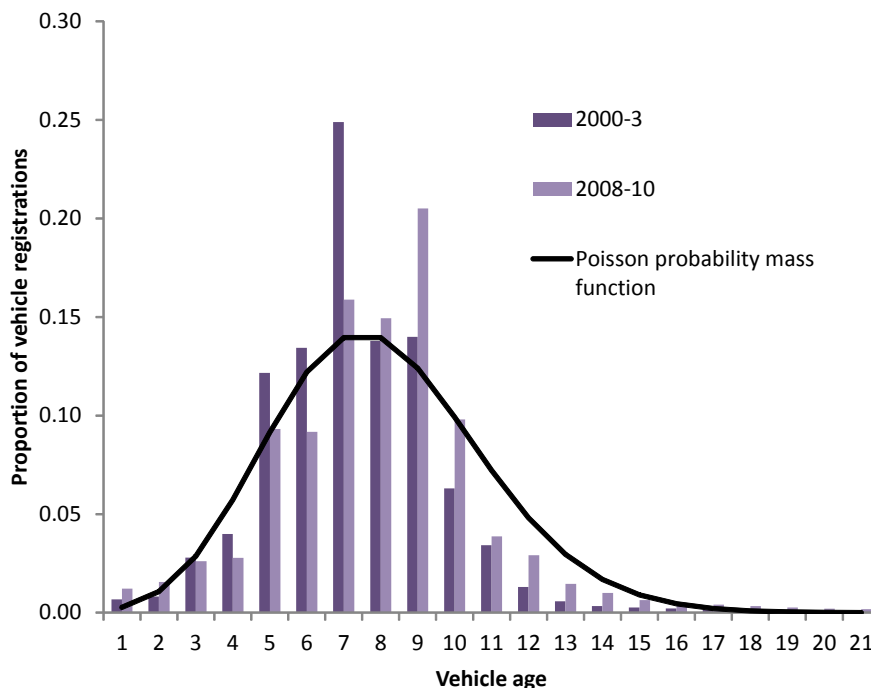
$$NEW(t) = NEW(t-1) \times (1 + (-1.86 \times GDP(t)) + (-1.71 \times PRICE(t))) \quad (\text{Equation 8.3})$$

The coefficients for the sample equation above are for LPVs. The equivalent coefficients for LCVs are -2.24 (GDP) and -1.18 (price). In the equation, GDP enters as growth in GDP per capita. Note that by default, the price variable is not growing in the model; however, this assumption can be altered.

The negative relationship between GDP and new vehicle shares of registrations meant that the effect that higher GDP had on expanding the share of people who can afford used cars dominated any effect of substitution from used to new cars (ie the extensive margin appears as a larger effect than the intensive margin).

The age distribution of incoming used LPVs and LCVs was modelled based on the fit of a Poisson probability mass function to the historical age distributions (see figure 8.3). This specification allowed for easy adjustment to incoming age distributions to model the effects of policies such as emissions standards.

**Figure 8.2** Age of used vehicles when first registered (Source: Ministry of Transport 2012)



We also incorporated observed trend growth rates in the average age of used imports (-1% for LPVs and 1% for LCVs) and accounted for uncertainty in these rates by assuming that they were distributed randomly according to a normal distribution with standard deviation = 0.01. Thus, the age of used imports was defined as:

$$AGE(y, t) = p(AGE=y | \lambda = (N(.99, 0.1) \times AGE^*(t-1))) = [\lambda^y e^{-\lambda}] / y!$$

where  $AGE^*$  is the mean age of imported used vehicles.

Incoming shares of vehicles by motive power were held constant in the case of diesel and petrol vehicles, based on recent shares in new registrations.

The share of newly registered vehicles that were alternative-fuel vehicles (SHARE) was modelled based on logistic growth curves and exogenous assumptions about the shares of registrations in the long term (TARGET). Alternative fuel vehicles include hybrids, electric cars and plug-in hybrids. The logistic growth curve was:

$$SHARE(t) = SHARE(t-1) + (TARGET - SHARE(t-1)) / (1 + S \cdot e^{-b(t-T)})^{1/\nu} \quad (\text{Equation 8.4})$$

The default parameter values for this curve were:

- $TARGET = 0.25$
- $S = 2$  (smoothing/shape parameter)
- $b = 0.3$  (the assumed growth rate)
- $T = 30$  (the time periods at which maximum growth is reached)
- $\nu = 2$  (smoothing/shape parameter).

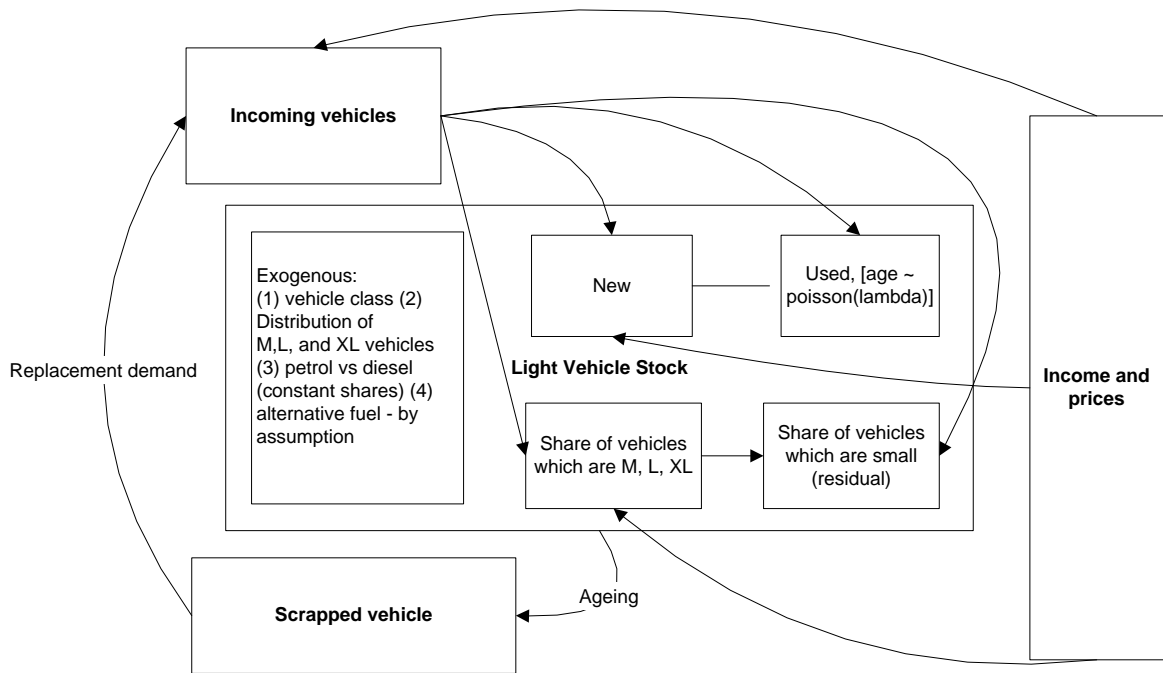
We then modelled the share of incoming alternative-fuel vehicles that were electric vehicles and plug-in hybrids by using the same logistic curves and adjusting TARGET values – by assumption. By default, we assumed that electric vehicles would grow to make up approximately 50% of registrations (ie TARGET = 0.5) and plug-in hybrids was 10% (TARGET = 0.1). These assumptions implied a target of 40% for hybrids, with the share of hybrids in registrations of alternative-fuel vehicles declining over time.

In the case of plug-in hybrids, we imposed a non-zero number of plug-ins (1% of registrations of alternative-fuel vehicles) in the first year of projection. This was necessary to initialise the model, given the absence of plug-in hybrids in registrations in the past.

Figure 8.3 provides a high-level overview of how all of the different dimensions of the fleet model were brought together.



Figure 8.3 Fleet entry, exit and composition



## 9 VKT and cost

The 'VKT and cost' submodel provides a connection between fleet information and travel behaviour and produces projections of:

- cost of travel per kilometre, by vehicle type and age
- vehicle-kilometres travelled, by vehicle type and age
- pollutant and greenhouse gas emissions, by vehicle type and age
- travel-related tax revenue from the transport sector.

### 9.1 Cost per kilometre of travel

Projections of cost of travel per kilometre were based on per-kilometre fuel consumption estimates, the tax-inclusive cost of fuel at the *PUMP* from the 'Prices' submodel, and road user charges (RUCs) for diesel vehicles. Cost estimates included GST:

$$COST(i,j,k,y,t)/KM(i,j,k,y,t) = (EFF(i,j,k,t) \times PUMP(j,t)) + (RUC(i,j,k,t) \times GST) \quad (\text{Equation 9.1})$$

where:

*i* is vehicle class

*j* is fuel

*k* is vehicle size (weight or cc as appropriate)

*y* is vehicle age

*t* is the time subscript.

The fuel consumption or efficiency variable (*EFF*) evolved according to assumed constant efficiency gains over time ( $\alpha$ ), assumed to be the same across all conventional vehicles; ie:

$$EFF(i,j,k,t) = \alpha \cdot EFF(i,j,k,t-1) \quad (\text{Equation 9.2})$$

#### 9.1.1 Fuel efficiency

Fuel efficiency, by vehicle type, was based on estimates of light-vehicle fuel consumption (see table 9.1) from the Ministry of Transport (based on fuel cycle testing) and from Australia's National Transport Commission (2005) in the case of heavy vehicles.

For hybrids and plug-in hybrids, we adopted relative fuel consumption values from Baxter et al (2009), which estimated consumption for hybrid vehicles at 61% of a typical 2-litre petrol car, and consumption by plug-in hybrids at 11% of a typical 2-litre petrol car.

**Table 9.1 Estimated fuel LPV and LCV fleet fuel consumption (l/100km) (Source: Ministry of Transport)**

	<1300cc	1300-1599cc	1600-1999cc	2000-2999cc	3000-3999cc	>3999cc
<b>Petrol vehicle</b>						
2005	6.2	6.7	8.4	9.9	11.9	14.1
2006	6.2	6.6	8.3	9.7	11.6	14.1
2007	6.1	6.6	8.2	9.7	11.3	14.0
2008	6.1	6.5	8.1	9.6	11.1	14.0
2009	6.2	6.6	8.0	9.4	11.0	13.6
2010	6.2	6.5	7.9	9.3	10.8	13.4
<b>Diesel vehicle</b>						
2005	4.7	4.7	6.8	9.4	10.3	11.6
2006	4.7	5.5	6.7	9.2	9.7	11.8
2007	4.8	4.7	6.8	8.9	9.5	11.1
2008	4.5	5.1	6.8	8.9	9.6	10.9
2009	4.6	5.3	6.6	8.8	9.5	11.1
2010	5.7	5.5	6.8	8.7	9.6	10.8

For motorcycles we used the Australian National Transport Commission (2005) ratio of fuel consumption relative to small petrol vehicles to obtain average fuel consumption assumptions of 3 litres per 100km for motorcycles under 60cc, and 4 litres per 100km for motorcycles over 60cc.

Values used for heavy-vehicle and bus fuel consumption, by weight, are summarised in table 9.2. These figures were indicative only given that they came from Australia (with different driving conditions) and there was wide variation in fuel consumption for any given size of vehicle, given variations in load factors, number of axles and distribution of load across axles.

Projected improvements (or declines) in technical fuel efficiencies were controlled purely by assumption. By default we assumed a 0.2% improvement over time.

**Table 9.2 Heavy-vehicle and bus fuel consumption assumptions (adapted from National Transport Commission 2005)**

Weight band	Average consumption litres/100km
<b>HCVs</b>	
3.5–5.0t	19.6
5.1–7.5t	19.6
7.6–10.0t	22.7
10.1–12.0t	22.7
12.1–15.0t	29.5
15.1–20.0t	29.5
20.1–25.0t	40.9
25.1–30.0t	49.4
>30.0t	49.4
<b>Buses</b>	
3501–7500kg	15.6
7501–12,000kg	19.4
>12,000kg	38

### 9.1.2 Road user charge (RUC) rates

RUC rates used in the model were estimates of RUC rates applicable to the categories of diesel vehicles used in this model. Our model did not include a complete description of heavy vehicles necessary to apply actual RUC rate schedules. RUC rate schedules are set out for vehicle weights and types, which include, for example, number of axles or types of truck-and-trailer combinations. For buses and light vehicles we could directly apply RUC rates, but for HCVs we had to estimate the RUC rates applicable to HCVs by weight. To do this we took historical data on RUC-kilometres purchased, by weight and vehicle type, calculated the implied tax paid, and then calculated the weighted average RUC paid per kilometre by vehicle weight.

To project RUC rates we implicitly assumed no change in the mix of vehicle types by vehicle weight, and we assumed (by default) that RUC rates did not change in real terms over the projection ‘horizon’.<sup>11</sup>

## 9.2 Vehicle-kilometres travelled

Projections of vehicle-kilometres travelled were based on the historical average vehicle-kilometres travelled per vehicle, by vehicle type and age.

<sup>11</sup> We did not take account of the 2012 changes in RUC rates, which will see RUC rates being purchased by manufacturer gross laden weight rather than actual loads carried.

We then projected changes in kilometres travelled per vehicle, based on changes in the costs of travel and growth in incomes. This was based on assumed constant price and income elasticity of demand for all ages and vehicle technology types; ie:

$$\Delta(VKT_{ij}/VEH_{ij}) = \alpha_i \Delta COST_{i,j,t} + \beta_i \Delta INC_{i,j,t} \quad (\text{Equation 9.3})$$

where:

*i* is the class of vehicle (bus, LPV, LCV, etc)

*j* is a subscript denoting the technology and age combinations within each class of vehicle

$\Delta COST$  is percent change in cost per kilometre for each vehicle included in the model

$\Delta INC$  is percent change in average household incomes in the case of LPVs and motorcycles, and percent change in GDP per capita for other classes of vehicle.

For bus and freight vehicles we assumed by default that the price and income elasticities of demand were zero, as kilometres travelled per vehicle was assumed to rely solely on demand for these services, which was calculated in other components of the model (in the 'Freight demand' and 'Household travel' submodels). The default elasticity for passenger-vehicle classes are summarised in table 9.3.

**Table 9.3 Default elasticities of demand for vehicle-kilometres travelled per vehicle**

Vehicle class	Price elasticity	Income elasticity
Light passenger-vehicle	-0.08	0.01
Light commercial vehicle	-0.04	0.01
Motorcycle	-0.01	0.01

### 9.3 Tax revenue and emissions

Tax rates per kilometre travelled were calculated based on fuel taxes (from the 'Prices' submodel) and fuel use per kilometre per vehicle, plus RUC rates per kilometre for vehicles subject to RUC. These tax rates excluded GST and Emissions Trading Scheme (ETS) costs, which were calculated separately. Tax rates per litre of fuel use included tax attributable to the National Land Transport fund as well as Accident Compensation Corporation (ACC), fuel monitoring and local authority levies. These per-kilometre tax rates, by vehicle, were multiplied by vehicle-kilometres to project revenue growth.

For ETS costs we multiplied fuel consumption (ie vehicle-kilometres multiplied by fuel consumption per kilometre) by the per-litre ETS costs calculated in the 'Prices' submodel.

Emissions were calculated by multiplying fuel use by emissions factors. These are summarised in table 9.4.

**Table 9.4 Emissions factors (g/l) (Source: Ministry of Economic Development)**

	<b>Petrol</b>	<b>Diesel</b>
CO <sub>2</sub>	2311.7949	2650.7509
CH <sub>4</sub>	0.6497	0.1461
N <sub>2</sub> O	0.0500	0.1425
CO	161.0186	11.6523
NO <sub>x</sub>	7.3963	24.7291
NM VOC	31.0343	3.9084
SO <sub>2</sub>	0.0747	4.0139

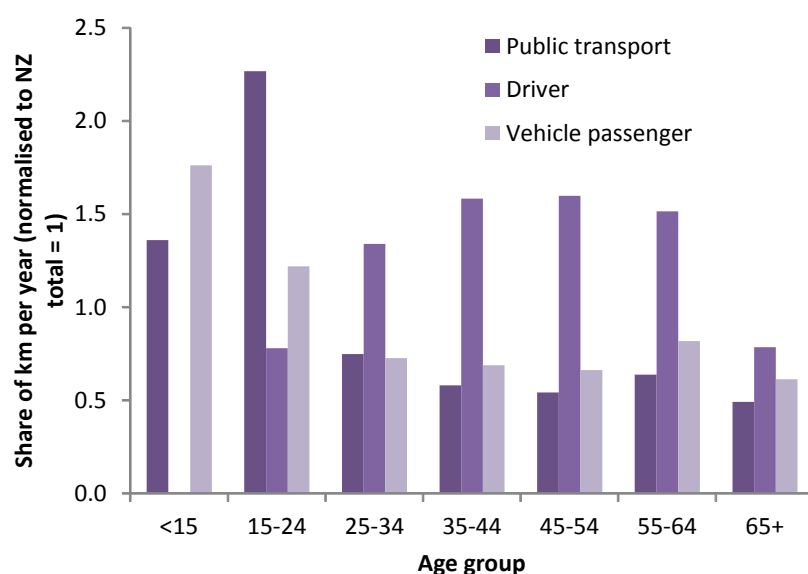
## 10 Household travel

The 'Household travel' submodel adapts household demand projections from earlier submodels to account for region-specific travel mode choices and vehicle travel characteristics. The key outputs are:

- public transport boardings and passenger-kilometres
- private passenger-vehicle travel (VKT) and passenger-kilometres.

Projections follow a multistage process with demand initially projected using high-level national and regional growth rates based on populations, incomes and prices. These are subsequently adjusted to account for the propensity of different age groups to use different forms of travel (public transport, vehicle travel and vehicle passenger or non-driver travel) based on data from the Ministry of Transport's *New Zealand household travel survey* (2004–2008). This data was used to translate changes in the age composition of the population to changes in travel demands, by mode. These distributions are summarised in figure 10.1, which shows, for example, that at the time of this research people between the ages of 15 and 24 were more than twice as likely to use public transport compared with the average for New Zealand as a whole.

Figure 10.1 Travel mode, by age group – normalised distribution (Source: MoT 2012)



### 10.1 Public transport

Public transport boardings were initially assumed to grow at the regional level according to regional population growth ( $\Delta POP$ ), changes in average vehicle travel costs ( $\Delta COST$ ), and growth in average household incomes ( $\Delta INC$ ):

$$BOARDINGS_{j,t} = BOARDINGS_{j,t-1} \times (1 + \Delta POP_{i,t}) \times (1 + \alpha \cdot \Delta COST + \beta \cdot \Delta INC(j,t)) \quad (\text{Equation 10.1})$$

where  $j$  is the region subscript.

We then introduced age-specific differences in mode of travel to adjust these high-level projections based on the evolution of the age composition of regional populations.

The high-level projections were converted to per-capita passenger-kilometre (PASSKM/POP) values:

$$PASSKM_{j,t}/POP_{j,t} = (BOARDINGS_{j,t} \times \alpha_j \cdot (PASSKM_{j,t-1}/BOARDINGS_{j,t-1}))/POP_{j,t} \quad (\text{Equation 10.2})$$

This equation included a coefficient for growth in passenger-kilometres travelled but, by default, we assumed no growth in kilometres per boarding (ie  $\alpha_j = 1$  for all  $j$ ).

Per-capita passenger-kilometres travelled was then assigned to age groups based on the observed national shares (SHARE\*) of public transport passenger-kilometres, by age group ( $y$ ):

$$PASSKM_{j,y,t}/POP_{j,y,t} = (PASSKM_{j,t}/POP_{j,t}) \times SHARE^*_y \quad (\text{Equation 10.3})$$

This yielded the projected passenger-kilometres per boarding per person in each age group. These values were multiplied by the projected numbers of people in the age group in that region, to obtain projected passenger-kilometres by region:

$$PASSKM_{j,t} = \Sigma[POP_{j,y,t} \times (PASSKM_{j,y,t}/POP_{j,y,t})] \quad (\text{Equation 10.4})$$

The model also included a mechanism for arbitrarily raising the number of boardings in a region to accommodate exogenous shifts in preferences or increased accessibility of public transport. If this mechanism is used, the passenger-kilometres that are added to public transport are subtracted from light passenger-vehicle passenger-kilometres.

## 10.2 Private passenger vehicle travel

Projections of private passenger vehicle travel followed much the same procedure as for public transport, though we skipped the first step because the initial projections of vehicle-kilometres travelled were taken from the 'Vehicle fleet' submodel.

We used differences in VKT per vehicle and vehicle occupancy, by region, relative to the national average, to capture the different effects of population growth on travel demands in different regions (see figure 10.2). The relativities between regional VKT and national VKT per vehicle shown in figure 10.2 were held constant over time as model parameters. Projected changes in these relativities could be imposed on the model (via  $\alpha_j$ ) but, with limited data to inform such changes, we held them constant by default:

$$VKT_{j,t} = \alpha_j [(VKT/VEH_j)/(VKT_{NZ}/VEH_{NZ})] \times ((VKT_{NZ,t}/VEH_{NZ,t}) \times VEH_{j,t}) \quad (\text{Equation 10.5})$$

VKT per capita by region was calculated and age distributions (DIST) of (national average) driver VKT, by age group, were applied to obtain age-adjusted region-specific estimates of VKT, in the same manner as for public transport demand:

$$VKT_{j,y,t}/POP_{j,y,t} = (VKT_{j,t}/POP_{j,t}) \times DIST^*_y \quad (\text{Equation 10.6})$$

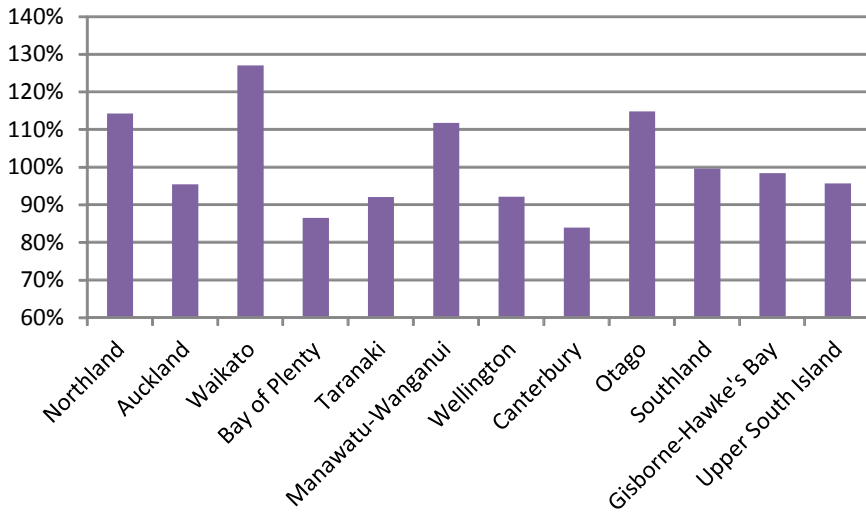
$$VKT_{j,t} = \Sigma[POP_{j,y,t} \times (VKT_{j,y,t}/POP_{j,y,t})] \quad (\text{Equation 10.7})$$

Projected VKT by region was multiplied by regional estimates of average occupancy per vehicle to obtain projected passenger-kilometres. These occupancy numbers were held constant, by default, because we



had no data upon which to inform changes to occupancy rates. More generally, we were not concerned with precise projections of regional activity. The principle reason for including these regional adjustments was so that we could take account of significant structural regional differences that affect national demands – such as inherently higher vehicle-kilometres travelled in regions that are sparsely populated, or lower growth in VKT for regions that have older populations.

**Figure 10.2 Kilometres travelled per vehicle – relative to national average, median 2000–2010 (Source: MoT 2012)**



## 11 Sample of results

This section describes a sample of results produced by the model. The results discussed here are with reference to the assumptions and inputs built into the GUI version of the model (ie the stand-alone application version of the model with a graphical user interface, see figure 1.1). The GUI version of the model has limited flexibility in terms of the assumptions that can be adjusted, compared with the 'base' version. In the stand-alone version there are 63 parameters that can be adjusted directly by the user. The base version of the model includes over 150 parameter assumptions that can be adjusted by users.

### 11.1 Base case

#### 11.1.1 Macroeconomic assumptions

'Base case' or 'business as usual' macroeconomic assumptions are, broadly speaking, informed from historical long-run averages and standard deviations. These are described in table 11.1.

**Table 11.1 Base case macroeconomic assumptions**

Variable	Mean	Standard deviation
Net migration	11,000	12,000
Multifactor productivity growth	1.0%	1.6%
Exchange rate	0.68	0.12
Oil price	\$300	0.2
Unemployment	5.5%	0.00

Assumptions are referred to as 'base case' assumptions because 'business as usual' is a subjective assessment and these assumptions can be altered depending on the user's view of what business as usual looks like. For example, in this case we assumed a long-run unemployment rate of 5.5%. This was based on both historical trends and a judgement that the unemployment rate would approximate more recent historical trends rather than very long-run averages.

Note that the unemployment assumptions included an assumption that it would take five years for the economy to move towards the long-run average of 5.5%. This assumption could be changed but it was not a key input. We also did not assume any fluctuations in employment, but rather a smooth adjustment towards the long-run rate.

The default oil price assumption was equal to US\$300 in the long run and was entered in the nominal US dollar price expected in 30 years' time – corresponding roughly to the forecast horizon of the 2012 International Energy Agency's (IEA) *World energy outlook*, where the oil price outlook tends towards a nominal US\$300 per barrel. The adjustment towards the long-run oil price was assumed to follow the same adjustment formula as for the unemployment rate, except that the smoothing parameter was 30.

### 11.1.2 Industry assumptions

In the base case, industries were assumed to grow in line with GDP growth, adjusted according to historical trends in their share of GDP. For most industries this implied a declining share of GDP but positive output growth. The only industries with increasing shares were the services and trade sectors.

Alternative assumptions for output growth are controlled by shocking the output of industries. This was not done for this scenario (hence the zeros in table 11.2), but users may take a view that, for example, the 'Agriculture and food manufacturing' industry could expand by 10% due to, for example, increased irrigation (a shock to the productivity of agricultural land). This would be implemented by changing the output shock value to 0.1. This shock would then be implemented as a shock to the sector's output in (by default) 2013.

**Table 11.2 Base case industry freight intensity assumptions**

Industry	Output shock	Growth in (road) freight relative to GDP (1+growth rate)
Agriculture & food manufacturing	0.0	0.99
Forestry & wood-related manufacturing	0.0	1.01
Mining, petroleum & chemicals	0.0	1.04
Manufacturing	0.0	1.00
Construction & utilities	0.0	1.02
Wholesale & retail trades	0.0	1.02
Services	0.0	0.98
Public administration	0.0	1.05

The key transport parameter was the intensity of freight use, by sector, for every unit of GDP. The values shown in table 11.2 reflect historical average growth rates (2000–2011) in freight use per unit of GDP. These show that the cost of, or need for, freight by industry has historically grown slightly faster than industry value added in all sectors. These assumptions mean freight demand will grow more quickly than GDP, if the industry composition of GDP remains unchanged. However, given that the merchandise sector of the economy is generally growing less quickly than the services sector, freight demand will not keep pace with overall economic growth.

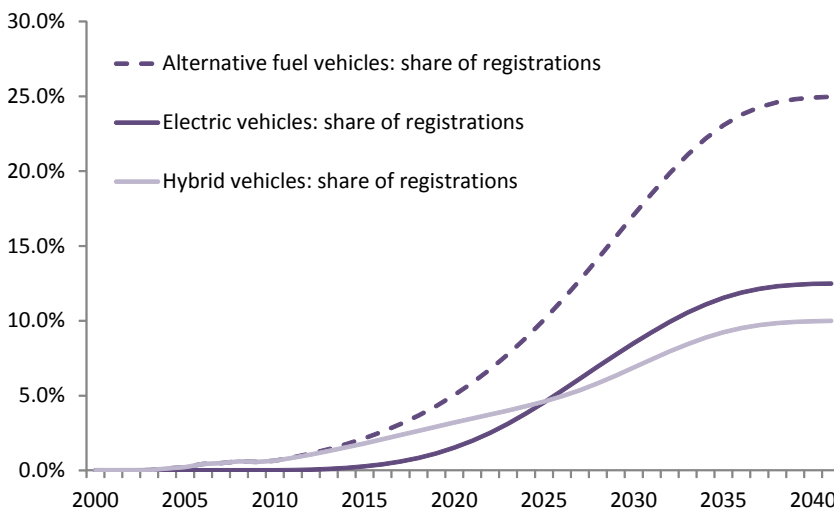
### 11.1.3 Vehicle technology assumptions

Vehicle technology assumptions were used in this submodel to affect the kinds of vehicles that would be imported into New Zealand, and they affected the impacts that prices would have on private vehicle use through effects on fuel efficiency. For example, the assumption about the 'share of alternative-fuel vehicles in new registrations', here assumed to be 25% in year 2040, controlled the availability of, and demand for, non-conventional vehicle technology by setting a target share of new registrations that are either electric, hybrid or plug-in hybrid vehicles. The share of these vehicles in incoming vehicle registrations (imports) was assumed to grow towards this target value according to the logistic function described in chapter 8, with a growth rate that accelerated in the near term as these vehicles were assumed to become more widely available.

**Table 11.3 Base case vehicle technology assumptions**

Parameter	Value
Share of alternative-fuel vehicles in new registrations	25%
Share of electric vehicles in alternative-fuel registrations	50%
Rate of improvement in fuel efficiency of conventional vehicles	99.8%

An assumption was made that by the time alternative-fuel vehicles were making up a quarter of incoming vehicles, half of the alternative-fuel vehicles that were being registered would be electric vehicles. As registrations of alternative-fuel vehicles grew towards the 25% share, the share of electric vehicles would be less than 50% because they too were growing according to a logistic growth curve and they were starting from a lower base (see figure 11.1)

**Figure 11.1 Alternative-fuel vehicle registrations – share of registrations**

The final assumption was around technical efficiency gains for vehicles – holding vehicle (engine) size and fuel type constant. This assumption assumed that the fuel consumption of new vehicles in each year would be 99.8% that of new vehicles in the preceding year – annual improvements of 0.2%.

#### 11.1.4 Travel demand price and income responsiveness assumptions

Table 11.4 summarises base case assumptions around how households adjust their travel choices according to changes in income and costs of travel. These are presented in the form of conventional constant ‘elasticities’ of demand; ie constant decimal percentage changes (1 = 100%) showing the percentage change in activity in response to an equivalent percentage change in income or prices that reflect cost of travel.

**Table 11.4 Base case travel demand elasticity assumptions**

Variable	Income elasticity	Price elasticity
Public transport passengers	-0.001	0.16
Light passenger-vehicle travel	0.01	-0.08
Light commercial vehicle travel	0.01	-0.04

The other elasticities in the table can be interpreted as follows:

- A 10% increase in incomes resulted in:
  - a 0.01% reduction in public transport passengers (boardings)
  - a 0.1% increase in vehicle-kilometres travelled in light passenger and light commercial vehicles.
- A 10% increase in prices (costs of travel) resulted in a 0.8% reduction in vehicle-kilometres travelled in light passenger-vehicles and a 0.4% reduction in light commercial vehicle travel.

The model does not directly assess public transport fares as this is principally a matter of supply-side policy (ie subsidies) rather than demand. However, the price elasticity variable was intended to capture the net effect on demand for public transport from an increase in travel costs that affect all forms of vehicle operation. By default, this effect was assumed to be a 1.6% increase in public transport demand for every 10% increase in travel costs.

### 11.1.5 Regional dimensions

The key assumptions underpinning the regional dimensions of the model were annual average net migration (in absolute numbers of net migrants) and potential supply-side shocks that would increase the accessibility of public transport (PT) from regional policy changes or infrastructure investment, and thereby increase patronage.

**Table 11.5 Base case regional net migration assumption**

Region	Annual average net migration	Shock to PT patronage
Northland	160	1
Auckland	8000	1
Waikato	310	1
Bay of Plenty	1060	1
Gisborne-Hawke's Bay	-680	1
Taranaki	-320	1
Manawatu-Wanganui	-520	1
Wellington	-260	1
Upper South Island	380	1
Canterbury	2200	1
Otago	390	1
Southland	-500	1

The base case assumptions for regional migration were calibrated to historical movements and so the sum of all regions equalled net national inflows.

The shock to PT patronage was set to 1, by default; ie we assumed that PT supply would remain sufficient to meet demand and there would be no shock. A value of 1.10 would raise patronage by an arbitrary 10%. Thus a user can bring supply-side information to bear on the model if they wish. For example, a new urban rail link that is expected to increase public transport patronage by 10% in Wellington could be

reflected in the model by introducing a value of 1.1 in the ‘shock to PT patronage’ cell alongside the Wellington region.

Regional migration assumptions affect demand for transport because, at the margin, people in urban areas would be less likely to own a car, likely to travel fewer kilometres in a car, and more likely to use public transport.

### 11.1.6 Tax rates

In the base case we assumed taxes (excise, ETS and RUC rates) would grow by the rate of inflation. ‘Real’ (inflation-adjusted) taxes could be made to increase or decrease by adjusting the real rate of growth of taxes.

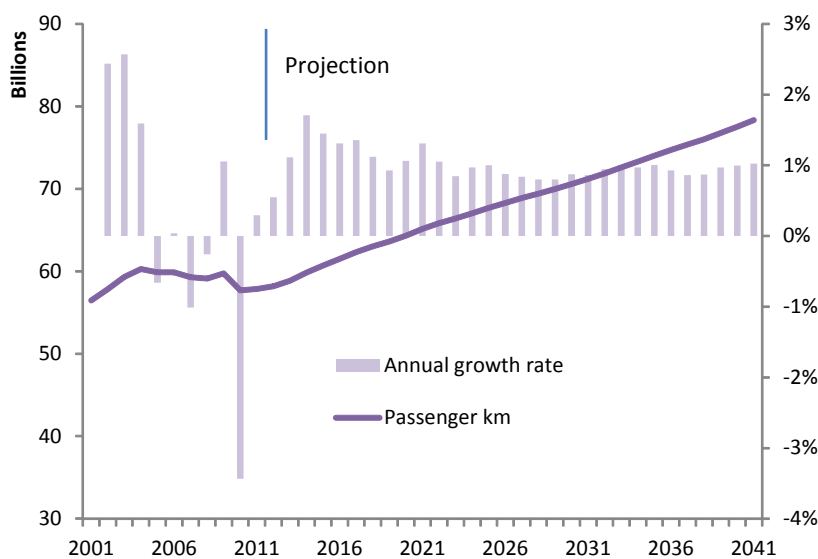
**Table 11.6 Base case variable tax rate increases**

Variable	Real rate of growth
Excise taxes	0.0%
ETS costs	0.0%
Light diesel vehicle RUC rates	0.0%
Heavy diesel vehicle RUC rates	0.0%

### 11.1.7 Results

Travel demand was projected to grow by an average 1.0% per annum over the next 30 years, measured in terms of passenger-kilometres (see figure 11.2). This encompassed all non-freight (HCV) road-based transport. This rate of growth was five times higher than the estimated average growth rates of the past decade, where passenger-kilometres grew by only 0.2% on average (and declined in a majority of years), and grew by as much as 3.5% in 2010.

**Figure 11.2 Growth in travel demand – passenger-kilometres**



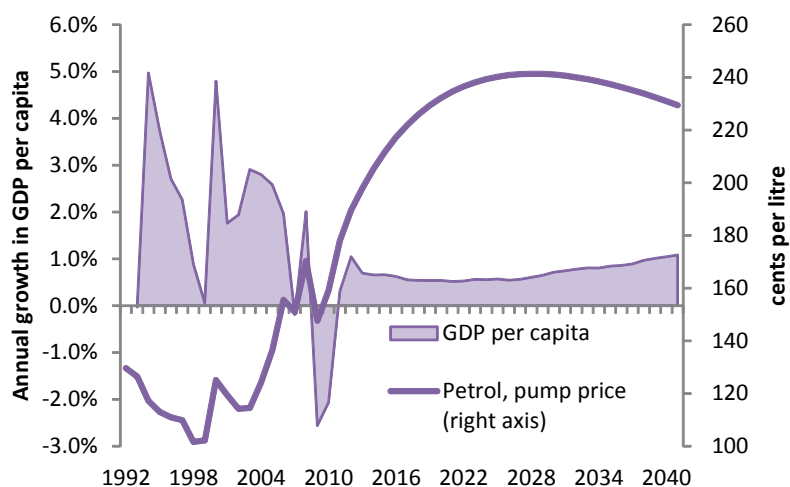
Two-thirds of the projected growth in travel demand was due to population growth. There was also a population composition effect. With the population getting older and households becoming smaller, the number of households was predicted to grow more quickly than the working-age population; growth in passenger-kilometres per household would, by this effect, be expected to grow at an average of 0.1% per annum over the next 30 years.

Our projection departed from recent trends in travel demand on a per-capita basis – in recent years there has been a slump in private travel demand, due to rapid increases in the costs of travel (through tax increases and higher oil prices) followed by a recession-related slump in incomes.

We assumed that incomes would gradually recover from the slump and that the cost of travel, while rising somewhat in real terms, would not increase at anything like the rate of the past decade (see figure 11.3). Consequently, travel demand would rebound somewhat.

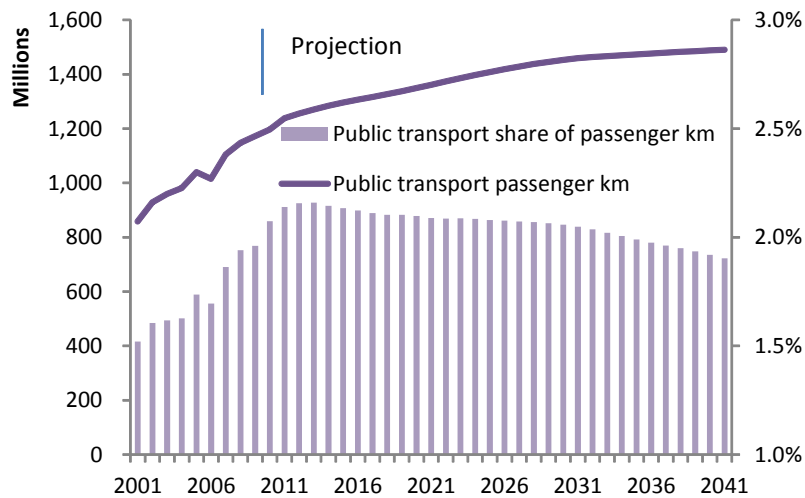
If incomes grow and costs of travel rise more moderately, we would expect slower growth in PT patronage, other things being equal. In recent years the increasing cost of travel and slump in incomes has helped to drive an increase in PT use as a share of overall travel demand – up from an estimated 1.5% in 2001 to 2.1% in 2011. In our model, this trend was projected to reverse over the next three decades because PT demand would decline as incomes grow.

**Figure 11.3 Incomes and prices – real GDP growth and inflation-adjusted (2007) pump price of petrol**



PT demand would still grow, and fractionally faster than population growth over the next decade or so (0.95% per annum as compared with 0.8% per annum population growth), but it would grow more slowly than private vehicle travel demand. As a consequence, the share of PT in overall passenger-kilometres travelled would be flat and then gradually declining over the next 30 years (see figure 11.4).

Figure 11.4 Public transport in demand – passenger-km and percent share of total passenger



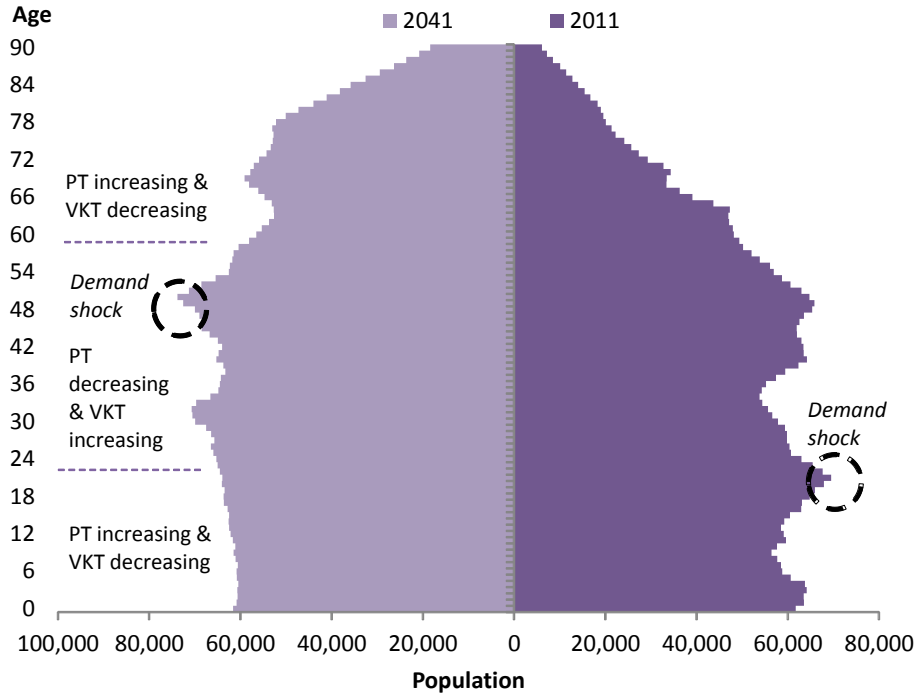
Note that this result reflected underlying *demand* drivers. An increase in supply conditions related to public transport, such as an increase in accessibility, would most likely change this outlook. At the same time, it would take a large change to reverse the general trend towards declining PT use as incomes grow.

Slowing population growth and an ageing population had a significant effect on the projections in terms of keeping a lid on transport demand. However, there was the potential within the aggregates for noticeable shocks to transport demand due to blips in age composition of the population, and life-cycle effects.

For example, there is currently a small bulge in the population that is entering working age (see figure 11.5). In 30 years' time, these people will enter a phase of life where they would be likely to live in households of couples without children (see figure 11.6). At this stage of life they would be likely to purchase a second car, simply because they have more disposable income than at most other points in their adult life. This would result in a lift in demand for private passenger vehicles. On the other hand, the younger (say under 20 years) portion of the population would be a much smaller than it is today and consequently demand for public transport would be proportionately lower than it is today, relative to overall travel demand.

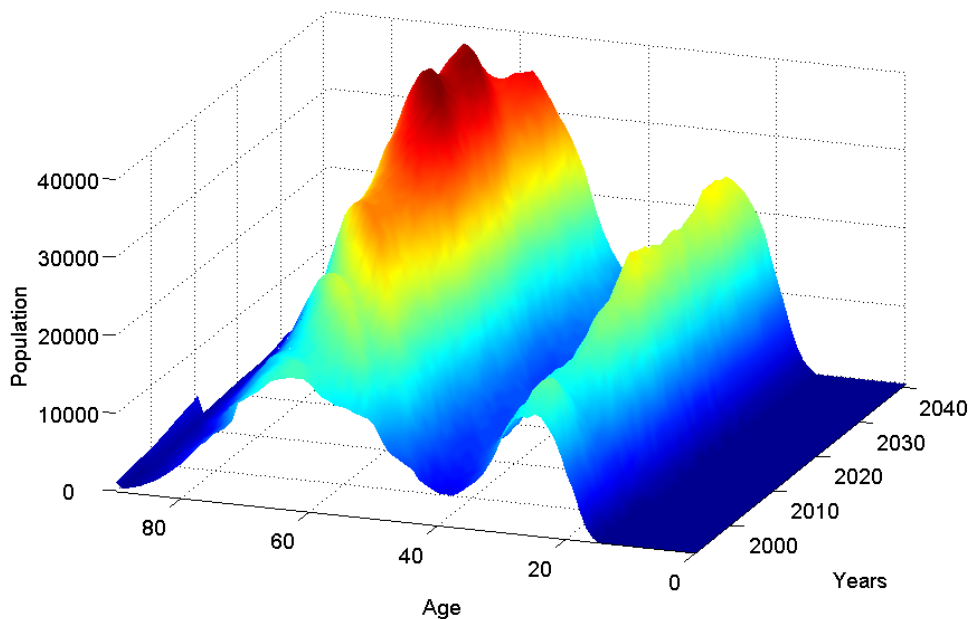


**Figure 11.5 Population age composition – stylised impacts on aggregate demand from age composition changes**

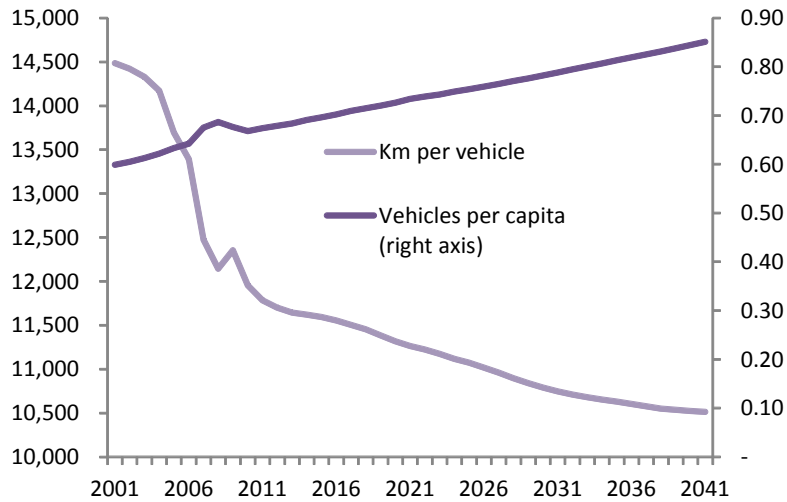


At the same time, most of New Zealand’s population growth will be in Auckland, and the comparatively high population density of the Auckland region and the wider availability of public transport options there mean that while per-capita vehicle ownership rates would, at times, be lifted by changes in population age composition, the actual use of vehicles (per vehicle) would be declining (see figure 11.7).

**Figure 11.6 People living in couple households**



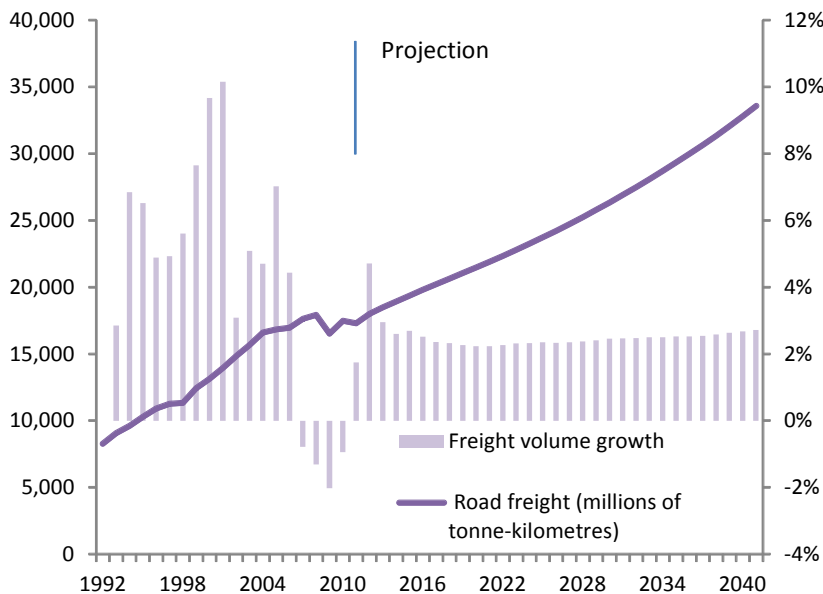
**Figure 11.7 Household vehicle ownership and travel per vehicle – average km travelled per vehicle and light-vehicle ownership per capita**



Demand for freight transport was projected by our model to grow roughly 1 percentage point faster than real GDP growth (2.5% versus 1.4%). However, demand growth would be slower than in the past decade when it averaged 2.8% per annum. This was because the services sector is expected to be the fastest-growing sector in the economy by quite some margin, and economic growth is not expected to be as brisk as it was pre-2008.

For sectors that were heavy freight users, freight demand (in value terms) would rise at a rate faster than value added, increasing the intensity or relative cost of freight relative to other inputs to production. This was because productivity growth in the freight sector is slower than for other parts of the economy.

**Figure 11.8 Freight growth**



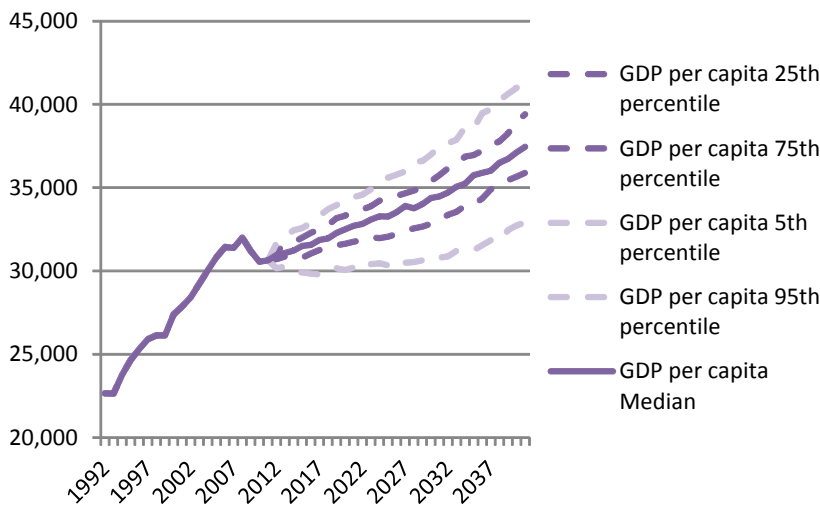
## 11.2 Stochastic results

Stochastic results from the model were driven principally by the sensitivity of the model to variations in incomes and prices. Future versions of the model may well consider adding additional sources of randomness or uncertainty.

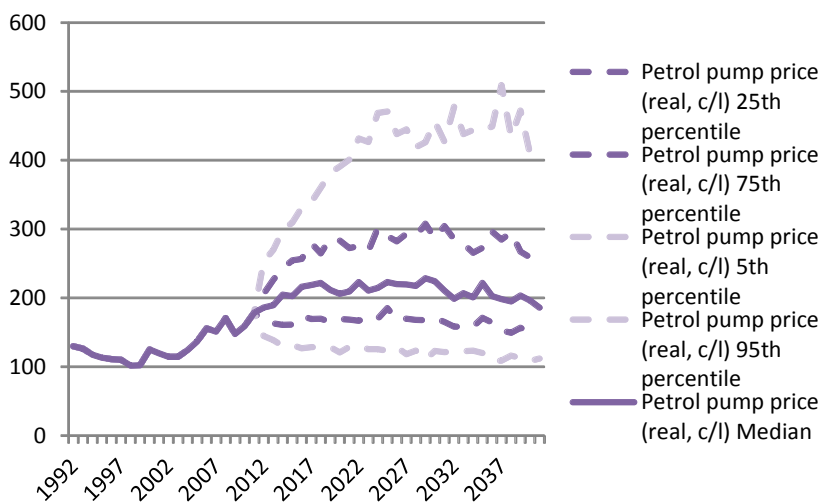
Fuel prices and travel costs were the largest single source of uncertainty, with domestic pump prices of petrol declining 0.9% per annum over the projection horizon in the 5th percentile of model results, versus prices rising by 1.8% per annum in real terms in the 95th percentile, and growing extremely rapidly in the next decade (5.5% per annum between 2012 and 2022). This is shown in figure 11.10. The reason for the very high degree of variation in the fuel price is that it reflected the combined effects of uncertainty in the international price of oil and also the exchange rate.

GDP per capita varied significantly also, with the upper (95th) percentiles of GDP per capita averaging 1.0% growth per annum, and the bottom 5th percentile averaging 0.3% per annum, with much of that growth coming later in the projection period (see figure 11.9).

**Figure 11.9 GDP per capita – stochastic – real \$95/96**

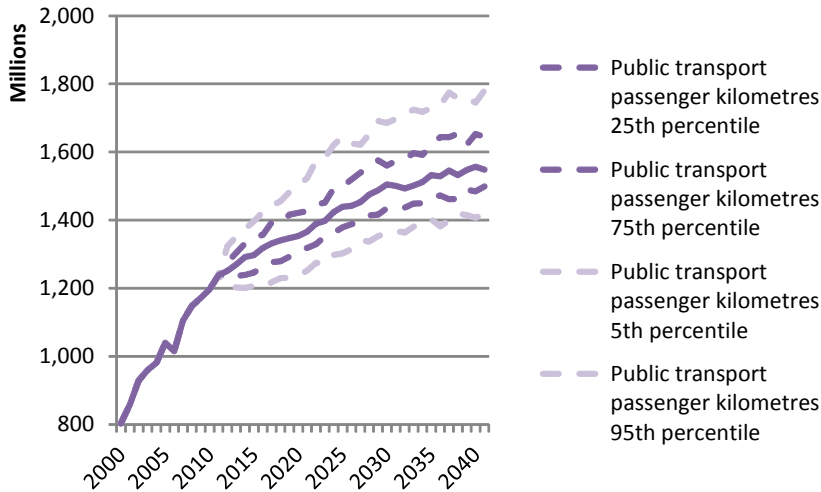


**Figure 11.10 Petrol pump price – stochastic – real (\$2007)**

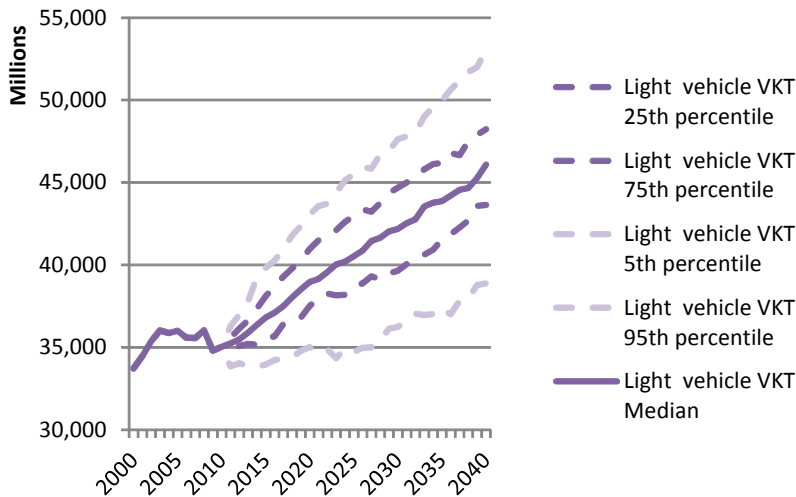


The implication of a high degree of uncertainty in prices is because price-sensitive demand is the most uncertain part of the demand projection. For example, growth in light private-vehicle-kilometres travelled and public transport passenger boardings varied widely between the 5th and 95th percentiles – though of course these results were the reverse of each other in the sense that the (high) 95th percentile of vehicle-kilometres travelled broadly related to the (low) 5th percentile of model results for public transport boardings. This can be seen in figures 11.11 and 11.12.

**Figure 11.11 Vehicle travel – stochastic – vehicle-kilometres travelled (VKT)**

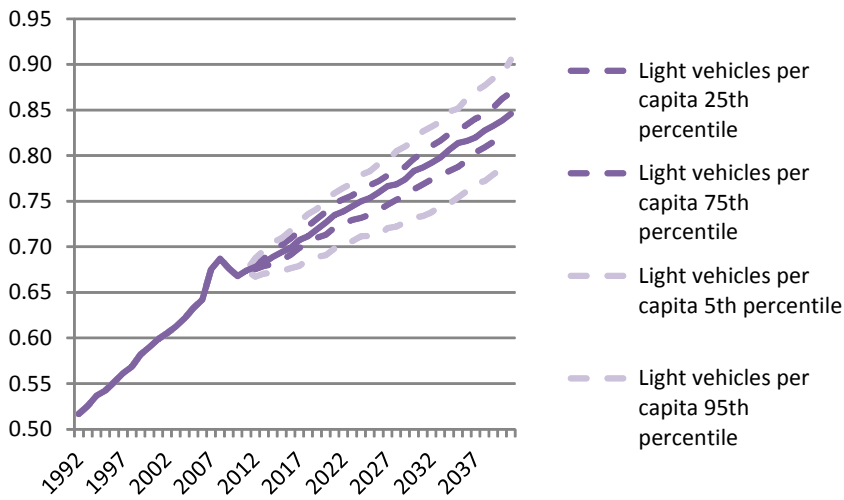


**Figure 11.12 Public transport demand – stochastic – passenger-kilometres**



The variability or uncertainty in travel demands contrasted with vehicle ownership (see figure 11.13) and freight demand results. In the model, neither of these was especially sensitive to price. Freight demand was an integral part of economic activity and was connected to growth in the economy and not to prices. Vehicle ownership was taken to be the result of people purchasing an option to drive a vehicle, rather than actually driving the vehicle. Thus it was not heavily affected by price compared with actual travel behaviour.

**Figure 11.13 Household vehicle ownership - stochastic - vehicles per capita**



At the same time, there was limited upside potential for vehicle ownership even when income growth was very high. This is because there was a non-linear (declining) relationship between income growth and vehicle ownership rates at the household level - not everyone needs or wants multiple vehicles. In the 95th percentile, vehicle ownership per capita grew at 0.9% per annum compared with per-capita GDP growth of 1% per annum. Note that while this does not look to be a major difference in relative growth rates, strong growth in the economy was partly connected to higher-than-average inward net migration and a consequent increase in the number of people in the population of working age and more likely to own a vehicle or multiple vehicles.

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## Appendix A: Econometric results

### A.1 Household vehicle ownership model results

**Table A.1** Dependent variable: Alone one vehicle

Method: Generalized Linear Model (Quadratic Hill Climbing)

Sample (adjusted): 1 36

Included observations: 36 after adjustments

Family: Normal

Link: Logit

Dispersion computed using Pearson Chi-Square

Coefficient covariance computed using observed Hessian

Convergence achieved after 5 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ALON_INC/CPI	0.00	0.00	5.88	0.00
WEL_DUM	-0.85	0.12	-7.06	0.00
DENS	0.00	0.00	-4.52	0.00
ALON_AGE	-0.01	0.01	-2.64	0.01
Mean dependent var	0.74	S.D. dependent var		0.04
Sum squared resid	0.02	Log likelihood		79.85
Akaike info criterion	-4.21	Schwarz criterion		-4.04
Hannan-Quinn criter.	-4.15	Deviance		0.02
Deviance statistic	0.00	Pearson SSR		0.02
Pearson statistic	0.00	Dispersion		0.00

**Table A.2** Dependent variable: Couple one vehicle

Method: Generalized Linear Model (Quadratic Hill Climbing)

Sample (adjusted): 1 36

Included observations: 36 after adjustments

Family: Normal

Link: Logit

Dispersion computed using Pearson Chi-Square

Coefficient covariance computed using observed Hessian

Convergence achieved after 10 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-8.16	3.43	-2.38	0.02
CPLE_INC/CPI	0.00	0.00	1.93	0.05
WEL_DUM	-0.94	0.19	-4.94	0.00
DENS	0.00	0.00	-3.27	0.00
CPLE_AGE	0.21	0.08	2.73	0.01
Mean dependent var	0.97	S.D. dependent var		0.01
Sum squared resid	0.00	Log likelihood		142.28
Akaike info criterion	-7.63	Schwarz criterion		-7.41
Hannan-Quinn criter.	-7.55	Deviance		0.00
Deviance statistic	0.00	Restr. deviance		0.00
LR statistic	123.22072	Prob(LR statistic)		0
Pearson SSR	0.0007699	Pearson statistic		0.00

**Table A.3 Dependent variable: Multi-person one vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 6 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MULTI_INC/CPI	0.00	0.00	52.32	0.00
WEL_DUM	-1.26	0.09	-14.29	0.00
DENS	0.00	0.00	-4.17	0.00
Mean dependent var	0.87	S.D. dependent var		0.04
Sum squared resid	0.01	Log likelihood		90.61
Akaike info criterion	-4.87	Schwarz criterion		-4.74
Hannan-Quinn criter.	-4.82	Deviance		0.01
Deviance statistic	0.00	Pearson SSR		0.01
Pearson statistic	0.00	Dispersion		0.00

**Table A.4 Dependent variable: Multi-family one vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 7 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MULTIF_INC/CPI	0.00	0.00	42.52	0.00
WEL_DUM	-0.98	0.15	-6.64	0.00
DENS	0.00	0.00	-2.75	0.01
Mean dependent var	0.93	S.D. dependent var		0.03
Sum squared resid	0.01	Log likelihood		92.05
Akaike info criterion	-4.95	Schwarz criterion		-4.82
Hannan-Quinn criter.	-4.90	Deviance		0.01
Deviance statistic	0.00	Pearson SSR		0.01
Pearson statistic	0.00	Dispersion		0.00

**Table A.5 Dependent variable: One parent one vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)

Sample (adjusted): 1 36

Included observations: 36 after adjustments

Family: Normal

Link: Logit

Dispersion computed using Pearson Chi-Square

Coefficient covariance computed using observed Hessian

Convergence achieved after 7 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.68	0.53	-3.15	0.00
ONEP_INC/CPI	0.00	0.00	5.99	0.00
WEL_DUM	-1.05	0.19	-5.48	0.00
DENS	0.00	0.00	-3.64	0.00
Mean dependent var	0.83	S.D. dependent var		0.05
Sum squared resid	0.04	Log likelihood		69.69
Akaike info criterion	-3.65	Schwarz criterion		-3.47
Hannan-Quinn criter.	-3.59	Deviance		0.04
Deviance statistic	0.00	Restr. deviance		0.10
LR statistic	43.16	Prob(LR statistic)		0.00
Pearson SSR	0.04	Pearson statistic		0.00
Dispersion	0.00			

**Table A.6 Dependent variable: Two-parent one vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)

Sample (adjusted): 1 36

Included observations: 36 after adjustments

Family: Normal

Link: Logit

Dispersion computed using Pearson Chi-Square

Coefficient covariance computed using observed Hessian

Convergence achieved after 10 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-10.34	3.19	-3.24	0.00
TWOP_INC/CPI	0.00	0.00	2.39	0.02
WEL_DUM	-0.97	0.23	-4.27	0.00
DENS	0.00	0.00	-3.06	0.00
TWOP_AGE	0.47	0.15	3.15	0.00
Mean dependent var	0.98	S.D. dependent var		0.01
Sum squared resid	0.00	Log likelihood		147.09
Akaike info criterion	-7.89	Schwarz criterion		-7.67
Hannan-Quinn criter.	-7.82	Deviance		0.00
Deviance statistic	0.00	Restr. deviance		0.00
LR statistic	131.83	Prob(LR statistic)		0.00
Pearson SSR	0.00	Pearson statistic		0.00

**Table A.7 Dependent variable: Alone 2nd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 6 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ALON_INC/CPI	0.00	0.00	5.40	0.00
WEL_DUM	-0.78	0.14	-5.67	0.00
DENS	0.00	0.00	-5.42	0.00
ALON_AGE	-0.06	0.01	-11.02	0.00
Mean dependent var	0.13	S.D. dependent var		0.02
Sum squared resid	0.01	Log likelihood		100.55
Akaike info criterion	-5.36	Schwarz criterion		-5.19
Hannan-Quinn criter.	-5.30	Deviance		0.01
Deviance statistic	0.00	Pearson SSR		0.01
Pearson statistic	0.00	Dispersion		0.00

**Table A.8 Dependent variable: Couple 2nd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 6 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-8.49	2.16	-3.94	0.00
CPLC_INC/CPI	0.00	0.00	5.06	0.00
WEL_DUM	-0.96	0.13	-7.55	0.00
DENS	0.00	0.00	-4.11	0.00
CPLC_AGE	0.14	0.05	2.95	0.00
Mean dependent var	0.61	S.D. dependent var		0.07
Sum squared resid	0.02	Log likelihood		79.80
Akaike info criterion	-4.16	Schwarz criterion		-3.94
Hannan-Quinn criter.	-4.08	Deviance		0.02
Deviance statistic	0.00	Restr. deviance		0.15
LR statistic	162.34	Prob(LR statistic)		0.00
Pearson SSR	0.02	Pearson statistic		0.00

**Table A.9 Dependent Variable: Multi-person 2nd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 5 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MULTI_INC/CPI	0.00	0.00	26.83	0.00
WEL_DUM	-0.57	0.08	-7.04	0.00
Mean dependent var	0.65	S.D. dependent var		0.05
Sum squared resid	0.03	Log likelihood		74.64
Akaike info criterion	-4.04	Schwarz criterion		-3.95
Hannan-Quinn criter.	-4.01	Deviance		0.03
Deviance statistic	0.00	Pearson SSR		0.03
Pearson statistic	0.00	Dispersion		0.00

**Table A.10 Dependent variable: Multi-family 2nd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 7 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MULTIF_INC/CPI	0.00	0.00	30.88	0.00
WEL_DUM	-0.43	0.12	-3.70	0.00
Mean dependent var	0.74	S.D. dependent var		0.05
Sum squared resid	0.05	Log likelihood		67.80
Akaike info criterion	-3.66	Schwarz criterion		-3.57
Hannan-Quinn criter.	-3.62	Deviance		0.05
Deviance statistic	0.00	Pearson SSR		0.05
Pearson statistic	0.00	Dispersion		0.00

**Table A.11 Dependent variable: One parent 2nd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 7 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.42	0.19	-12.82	0.00
ONEP_INC/CPI	0.00	0.00	9.20	0.00
WEL_DUM	-0.59	0.08	-7.76	0.00
DENS	0.00	0.00	-3.46	0.00
Mean dependent var	0.34	S.D. dependent var		0.04
Sum squared resid	0.01	Log likelihood		89.53
Akaike info criterion	-4.75	Schwarz criterion		-4.58
Hannan-Quinn criter.	-4.69	Deviance		0.01
Deviance statistic	0.00	Restr. deviance		0.07
LR statistic	115.86	Prob(LR statistic)		0.00
Pearson SSR	0.01	Pearson statistic		0.00
Dispersion	0.00			

**Table A.12 Dependent variable: Two parent 2nd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 8 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.99	0.34	-5.93	0.00
TWOP_INC/CPI	0.00	0.00	8.85	0.00
WEL_DUM	-1.04	0.12	-8.54	0.00
DENS	0.00	0.00	-4.06	0.00
Mean dependent var	0.73	S.D. dependent var		0.06
Sum squared resid	0.03	Log likelihood		74.60
Akaike info criterion	-3.92	Schwarz criterion		-3.75
Hannan-Quinn criter.	-3.86	Deviance		0.03
Deviance statistic	0.00	Restr. deviance		0.13
LR statistic	95.70	Prob(LR statistic)		0.00
Pearson SSR	0.03	Pearson statistic		0.00
Dispersion	0.00			

**Table A.13 Dependent variable: Alone 3rd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 6 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ALON_INC/CPI	0.00	0.00	-2.79	0.01
WEL_DUM	0.25	0.11	2.24	0.03
DENS	0.00	0.00	2.10	0.04
ALON_AGE	-0.01	0.01	-2.13	0.03
Mean dependent var	0.19	S.D. dependent var		0.02
Sum squared resid	0.01	Log likelihood		91.67
Akaike info criterion	-4.87	Schwarz criterion		-4.69
Hannan-Quinn criter.	-4.81	Deviance		0.01
Deviance statistic	0.00	Pearson SSR		0.01
Pearson statistic	0.00	Dispersion		0.00

**Table A.14 Dependent variable: Couple 3rd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 10 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-8.90	2.33	-3.82	0.00
CPLE_INC/CPI	0.00	0.00	3.06	0.00
WEL_DUM	-0.52	0.13	-3.88	0.00
DENS	0.00	0.00	-4.81	0.00
CPLE_AGE	0.12	0.05	2.45	0.01
Mean dependent var	0.16	S.D. dependent var		0.03
Sum squared resid	0.01	Log likelihood		97.70
Akaike info criterion	-5.15	Schwarz criterion		-4.93
Hannan-Quinn criter.	-5.07	Deviance		0.01
Deviance statistic	0.00	Restr. deviance		0.03
LR statistic	73.87	Prob(LR statistic)		0.00
Pearson SSR	0.01	Pearson statistic		0.00



**Table A.15 Dependent variable: Multi-person 3rd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 7 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.03	0.22	-4.63	0.00
MULTI_INC/CPI	0.00	0.00	1.95	0.05
WEL_DUM	-0.31	0.14	-2.24	0.02
Mean dependent var	0.35	S.D. dependent var		0.04
Sum squared resid	0.06	Log likelihood		64.42
Akaike info criterion	-3.41	Schwarz criterion		-3.28
Hannan-Quinn criter.	-3.37	Deviance		0.06
Deviance statistic	0.00	Restr. deviance		0.07
LR statistic	5.73	Prob(LR statistic)		0.06

**Table A.16 Dependent variable: Multi-family 3rd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)  
 Sample (adjusted): 1 36  
 Included observations: 36 after adjustments  
 Family: Normal  
 Link: Logit  
 Dispersion computed using Pearson Chi-Square  
 Coefficient covariance computed using observed Hessian  
 Convergence achieved after 5 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MULTIF_INC/CPI	0.00	0.00	6.06	0.00
WEL_DUM	-0.25	0.10	-2.59	0.01
Mean dependent var	0.53	S.D. dependent var		0.05
Sum squared resid	0.05	Log likelihood		65.98
Akaike info criterion	-3.55	Schwarz criterion		-3.47
Hannan-Quinn criter.	-3.52	Deviance		0.05
Deviance statistic	0.00	Pearson SSR		0.05
Pearson statistic	0.00	Dispersion		0.00

**Table A.17 Dependent variable: One-parent 3rd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)

Sample (adjusted): 1 36

Included observations: 36 after adjustments

Family: Normal

Link: Logit

Dispersion computed using Pearson Chi-Square

Coefficient covariance computed using observed Hessian

Convergence achieved after 6 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.94	0.14	-13.47	0.00
ONEP_INC/CPI	0.00	0.00	5.22	0.00
WEL_DUM	-0.33	0.06	-5.56	0.00
DENS	0.00	0.00	-2.47	0.01
Mean dependent var	0.23	S.D. dependent var		0.02
Sum squared resid	0.01	Log likelihood		107.05
Akaike info criterion	-5.73	Schwarz criterion		-5.55
Hannan-Quinn criter.	-5.66	Deviance		0.01
Deviance statistic	0.00	Restr. deviance		0.01
LR statistic	40.08	Prob(LR statistic)		0.00
Pearson SSR	0.01	Pearson statistic		0.00
Dispersion	0.00			

**Table A.18 Dependent variable: Two-parent - 3rd vehicle**

Method: Generalized Linear Model (Quadratic Hill Climbing)

Sample (adjusted): 1 36

Included observations: 36 after adjustments

Family: Normal

Link: Logit

Dispersion computed using Pearson Chi-Square

Coefficient covariance computed using observed Hessian

Convergence achieved after 8 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.02	0.20	-10.16	0.00
TWOP_INC/CPI	0.00	0.00	6.55	0.00
WEL_DUM	-0.56	0.08	-7.13	0.00
DENS	0.00	0.00	-3.62	0.00
Mean dependent var	0.32	S.D. dependent var		0.03
Sum squared resid	0.01	Log likelihood		90.30
Akaike info criterion	-4.79	Schwarz criterion		-4.62
Hannan-Quinn criter.	-4.73	Deviance		0.01
Deviance statistic	0.00	Restr. deviance		0.04
LR statistic	61.59	Prob(LR statistic)		0.00
Pearson SSR	0.01	Pearson statistic		0.00
Dispersion	0.00			

## A.2 Household income model

**Table A.19** Dependent variable: Real HH income

Method: Pooled Least Squares

Sample (adjusted): 1998 2011

Cross-sections included: 6

Total pool (balanced) observations: 84

Variable	Coefficient	Std. Error	Prob.
C	-3.27	0.94	0.00
LOG(AGE?)	1.03	0.56	0.07
_ALON--LOG(GDE_WKAGE)	1.16	0.17	0.00
_CPLE--LOG(GDE_WKAGE)	1.35	0.17	0.00
_MULTI--LOG(GDE_WKAGE)	0.83	0.17	0.00
_MULTIF--LOG(GDE_WKAGE)	0.75	0.24	0.00
_ONEP--LOG(GDE_WKAGE)	0.87	0.31	0.01
_TWOP--LOG(GDE_WKAGE)	1.10	0.21	0.00
<i>Fixed Effects (Cross)</i>			
_ALON--C	-2.7		
_CPLE--C	-3.8		
_MULTI--C	2.0		
_MULTIF--C	3.7		
_ONEP--C	1.3		
_TWOP--C	-0.4		
R-squared	0.99	Prob(F-statistic)	0
Adjusted R-squared	0.99	S.D. dependent var	0.41
S.E. of regression	0.04	Akaike info criterion	-3.71
Sum squared resid	0.09	Schwarz criterion	-3.34
F-statistic	948.13	Durbin-Watson stat	1.93

## A.3 Vehicle size models

**Table A.20 Dependent variable: Share of LCV registrations larger than 1600cc**

Method: Generalized Linear Model (Quadratic Hill Climbing)

Sample (adjusted): 2000 2010

Included observations: 11 after adjustments

Family: Normal

Link: Logit

Dispersion computed using Pearson Chi-Square

Coefficient covariance computed using observed Hessian

Convergence achieved after 4 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
PRICE_TO_GDP	-0.03	0.009513	-3.03726	0.0024
GDP	0.000024	2.04E-06	11.51007	0
Mean dependent var	0.898895	S.D. dependent var		0.019619
Sum squared resid	0.000903	Log likelihood		36.03033
Akaike info criterion	-6.18733	Schwarz criterion		-6.11499
Hannan-Quinn criter.	-6.23294	Deviance		0.000903
Deviance statistic	0.0001	Pearson SSR		0.000903
Pearson statistic	0.0001	Dispersion		0.0001

**Table A.21 Dependent variable: Share of LPV registrations larger than 1600cc**

Method: Generalized Linear Model (Quadratic Hill Climbing)

Sample (adjusted): 2000 2010

Included observations: 11 after adjustments

Family: Normal

Link: Logit

Dispersion computed using Pearson Chi-Square

Coefficient covariance computed using observed Hessian

Convergence achieved after 4 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
PRICE_TO_GDP	-0.05466	0.008376	-6.5254	0
GDP	2.03E-05	1.83E-06	11.11091	0
Mean dependent var	0.750436	S.D. dependent var		0.034208
Sum squared resid	0.003096	Log likelihood		29.25402
Akaike info criterion	-4.95528	Schwarz criterion		-4.88293
Hannan-Quinn criter.	-5.00088	Deviance		0.003096
Deviance statistic	0.000344	Pearson SSR		0.003096
Pearson statistic	0.000344	Dispersion		0.000344

## A.4 Vehicle age (new) models

**Table A.22** Dependent variable: Share of LPV registrations that are new vehicles

Method: Least Squares

Sample (adjusted): 2000 2010

Included observations: 11 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(NEW_VEH_PRICE/CPI)	-1.71401	0.19168	-8.94203	1.94E-05
C	4.386433	0.885855	4.951639	0.001119
LOG(GDP_POP)	-1.85752	0.491935	-3.77594	0.005419
R-squared	0.945874	Mean dependent var		-1.04127
Adjusted R-squared	0.932342	S.D. dependent var		0.137451
S.E. of regression	0.035753	Akaike info criterion		-3.59739
Sum squared resid	0.010226	Schwarz criterion		-3.48887
Log likelihood	22.78563	Hannan-Quinn criter.		-3.66579
F-statistic	69.90145	Durbin-Watson stat		1.547072
Prob(F-statistic)	8.58E-06			

**Table A.23** Dependent variable: Share of LPV registrations that are new vehicles

Method: Least Squares

Sample (adjusted): 2000 2010

Included observations: 11 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(NEW_VEH_PRICE/CPI)	-1.17518	0.115733	-10.1542	0
LOG(GDP_POP)	-2.24731	0.23026	-9.75987	0
R-squared	0.920696	Mean dependent var		-0.31709
Adjusted R-squared	0.911885	S.D. dependent var		0.073765
S.E. of regression	0.021897	Akaike info criterion		-4.64201
Sum squared resid	0.004315	Schwarz criterion		-4.56966
Log likelihood	27.53103	Hannan-Quinn criter.		-4.68761
Durbin-Watson stat	2.035898			