

Working paper 1: Te Puna Taiao baseline vehicle kilometres travelled by transport activities – a research note

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Abbreviations and acronyms

- ARDL Autoregressive distributed lag modelling
- ARIMA Autoregressive integrated moving average
- BITRE Bureau of Infrastructure, Transport and Regional Economics, Australia
- DETR Department of the Environment, Transport and the Regions, UK
- DIC Disposal income constraint
- GDP Gross domestic product
- GFC Global financial crisis
- GHG Greenhouse gas
- MBIE Ministry of Business, Innovation and Employment
- OECD The Organisation for Economic Cooperation and Development
- OLS Ordinary least squares
- RFI Road freight index
- RGDP Real gross domestic product
- RUC Road user charges
- TKM Tonne-kilometre
- VAR Vector autoregressive
- VECM Vector error correction
- VKT Vehicle kilometres travelled

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1 Introduction

Te Puna Taiao is a Waka Kotahi project that seeks to identify and develop interventions that could help reduce greenhouse gas (GHG) emitted by land transport activities. To reduce GHG emissions it is necessary to reduce vehicle kilometres travelled by various land transport modes.

Several studies are being carried to evaluate the types of interventions that should be adopted to facilitate the transition to more sustainable transport modes. To assess the effectiveness of such interventions it is necessary to develop vehicle kilometres travelled baselines for different modes and to carry out forecast under current policy conditions. This involves identifying the key variables that influence the various transport modes based on historical time series data. The baselines and forecasts explain what could occur if no changes are made to current settings and policy directions. Baseline vehicle kilometres travelled are derived for (a) total vehicle kilometres travelled, (b) light passenger vehicle kilometres travelled, (c) bus vehicle kilometres travelled, and (d) heavy goods vehicle kilometres travelled.

2 Baseline development and forecast of vehicle kilometres travelled (VKT)

2.1 Previous studies

Prior to carrying out the baseline and forecasting analysis we reviewed a number of studies that investigated how different factors influenced the demand for car (light passenger), bus and heavy goods (freight) travel.

2.2 Light passenger/car travel

The majority of studies reviewed, mainly from overseas studies, were concerned with light passenger vehicle travel (car travel) and the concept of peak car. The studies on car travel showed that per capita car travel reached a plateau or began to decline in several OECD countries after the millennium, following more than half a century of continuous growth (Millard-Ball & Schipper, 2011; Van Dender & Clever, 2013).

In Great Britain, per capita car travel reached a peak in 2002 and fell by 9% over the subsequent decade. There was much debate whether this trend was permanent or merely a temporary break with historical trends (Goodwin, 2012; Goodwin & Van Dender, 2013; Millard-Ball & Schipper, 2011; Newman & Kenworthy, 2011; Puentes & Tomer, 2009). Some authors, such as Bastian et al. (2016), argued that simple economic models based solely on changes in income and fuel prices "…are able to predict the plateau and decrease of car travel with quite remarkable accuracy." (Bastian, et al., 2016). Others considered these economic factors to be insufficient and focused instead on demographic, spatial patterns, social norms, and other variables (Garikapati et al. 2016; Metz, 2013; van Wee, 2015). For example, Goodwin & Van Dender (2013) argued that: "… an aggregate model focusing on GDP effects and fuel prices is too crude to catch the diversity and dynamics underlying aggregate car travel demand and how it changes …". However, some authors, such as Bastian et al. (2016), emphasised that their conclusions do not rule out the existence of alternative explanations or imply that there are no changes in other variables such as lifestyle and attitude or demonstrate that those variables have no effect on travel patterns. Instead, they simply argue that there is no "…compelling evidence that one needs to assume something else than fuel price and GDP to explain aggregate VKT after 2003."

Stapleton et al. (2017) carried out detailed time series econometric analysis and their results showed that changes in income (GDP) and fuel costs of driving were the main factors influencing car travel. Essentially, they confirmed the finding of Bastian et al. (2016). Therefore, to model light passenger VKT we consider that economic factors such as GDP and fuel prices are important.

2.3 Heavy vehicle goods/freight travel

A literature review was carried out to identify the key issues and the underlying factors that influenced heavy vehicle kilometres travelled in New Zealand. Mackie et al. (2006) found a strong relationship between vehicle kilometres travelled derived from Road Use Charges (RUC) purchased by heavy vehicles as a surrogate for freight volume and real gross domestic product (RGDP). The relationship they used was as follows:

$D Vkt/Vkt = \alpha d RGDP/RGDP$

This expression is then integrated to give:

$$Vkt = K.RGDP^{\alpha}$$

Using the above relationship, Mackie et al. (2006) and data from the period 1997-2005 found a very good fit with an R2 = 0.996, with K = 0.0004 and α =1.35. This indicates that the growth in road freight volume was 1.35 times the growth in RGDP. Using more up to date data, de Pont (2010) found α was 1.31 with a slightly improved fit with the R2 being 0.997. Figure 2.1 below shows the comparative growth between heavy vehicle kilometres and RGDP, while Figure 2.2 shows the model fit.

Figure 2.1 Growth in heavy vehicle kilometres compared to growth in RGDP 1997-2007. Source: Mackie and Bass, 2006



Figure 2.2 Heavy vehicle kilometres travelled vs RGDP (1997-2007). Source: Mackie and Bass, 2006 3,300 7



However, as noted by de Pont (2010), implicit in this model is an assumption that vehicle productivity did not change over the time period spanned by the data ie, the relationship between VKT and freight volume had not changed. Based on this assumption over the ten-year period the growth in RGDP was 37.5% which is equal to an annual rate of 3.2%. De Pont then suggested that if we assume that the long-term average annual rate of growth of RGDP will continue at 3% per annum and if the relationship between RGDP and road freight did not change, then road freight volumes will double every 18 years. This is a compounding effect and thus in 36 years we would expect four times the current freight volume.

De Pont (2010) notes that this pattern of freight growth exceeding GDP is not unique to New Zealand. He cites work carried out in Australia that has predicted that road freight will double between 2000 and 2020 (BITRE, 2006). This is based on 2.7% p.a. RGDP growth and a multiplier of 1.24. De Pont also states that in Europe studies carried out also showed an average freight growth of more than 1.2 times the growth in RGDP over the 25 countries in the European Union (ERF – IRF BPC, 2007). However, De Pont doubts these relationships identified above will hold in the future as technological improvements will lead to greater productivity in freight vehicles. He cites the example of the USA where freight grew by only 0.62 times RGDP between 1980 and 1991 (Cambridge Systematics Inc, 1997) demonstrating that it is possible to achieve economic growth without a disproportionate growth in freight. De Pont considers that the idea of decoupling freight growth from economic growth is very attractive from a sustainability point of view.

De Pont (2010) states that the projected growth in freight VKT is not sustainable for several reasons such as rising oil prices due to supply constraints, the need to meet Kyoto Protocol commitments, concerns with air pollution issues and the need to manage congestion in major cities such as Auckland. The model described the mechanisms by which freight growth will be greater than economic growth. However, as noted by the author, implementing the model is challenging and to develop national aggregates would require considerable information of industry structure at the regional, urban area and sub area levels.

Waka Kotahi commissioned research by Frontier Economics (Simic & Bartels, 2013) to identify key drivers of demand for freight transport. Using various data sets they graphed the five series data sets and this is shown in Figure 2.3.



Figure 2.3 Freight demand – heavy vehicle travel (Source: Frontier Economics Figure 4.1)

As can be seen in Figure 2.3 the two Ministry of Transport data series, the total truck (light red line) and the total truck and trailer TKM (dark red line) exhibit very similar trends to heavy vehicle traffic volume series from the NZ Transport Agency (light blue line), even though the Transport Agency data is for state highways only and is collected from a limited number of telemetric sites around the country. The Frontier Economics analysis also showed that the NZ Transport Agency's VKT data series (based on RUC licence purchases) also exhibit the same pattern (tan line). These series indicate that the rate of growth in freight demand started to decline somewhere between 2003 and 2004, well before the onset of the global financial crisis (Simic & Bartels, 2013).

Next, Frontier Economics (Simic & Bartels, 2013) investigated the historical relationship between freight demand and economic activity. They used the Ministry of Transport's TKM series as a measure of road freight demand as it reflects the amount of goods transported.

Figure 2.4 presents a Road Freight Index (RFI) which was constructed as the ratio of road freight TKM to real GDP. Frontier Economics considered that the RFI points to a possible structural break around 2004. Before 2004, road freight transport demand grew, on average, faster than GDP (6.5% per year compared with 4.1%). After 2004, road freight transport demand grew, on average, by 1.2% compared with 1.3% growth in GDP, causing the RFI to decline slightly.



Figure 2.4 Road Freight Index

Source: Frontier Economics using data from Ministry of Transport and Statistics New Zealand

Frontier Economics (Simic & Bartels, 2013) investigated the issues to consider when modelling freight demand. Three factors were considered by the authors to be important – diesel prices, road user charges and GDP. The authors suggested that GDP needs to be adjusted to account for the changing structure of the New Zealand economy with manufacturing share declining and the service sector increasing.

Frontier Economics also reviewed the different types of econometric models that could be used. They evaluated different static and dynamic models that have been and could be used in investigating freight demand. They suggested that the autoregressive distributed lag (ARDL) model which can accommodate

different lag structures on both dependent and independent variables should be considered. The general form of an ARDL model is shown in Figure 2.5.

Figure 2.5 ARDL model general form



Frontier Economics also pointed out that it is well known that in time series analysis that it is necessary to test whether the variables are stationary or non-stationary. If the variables are non-stationary they need to be tested to determine whether they are cointegrated. Variables that are non-stationary can be made stationary by differencing the variables. Differencing has a drawback as one would lose information from economic theory concerning the long-run equilibrium properties of the data. A growing literature on the subject suggests that cointegration and error correction methods are appropriate and useful ways to analyse trending variables (Simic & Bartels, 2013).

From the brief review of the existing literature the following main issues emerged:

- (a) There is some suggestion that there has been a decoupling in the relationship between GDP and heavy kilometres travelled. This may be due to the changing nature of the economy with the service sector becoming more dominant. An alternative to GDP would be to use the value of imports and exports of goods (excluding service).
- (b) In modelling heavy VKT it may be necessary to include the value of imports as an independent variable. This is because spending on imports is not included in GDP because imports are produced outside New Zealand and therefore do not contribute to production within New Zealand. However, from a heavy VKT point of view imports may be important, as imports need to be transported. However, including both GDP and imports in a model might cause econometric issues as these variables are highly correlated.

Based on the literature review and taking economic theory into account the following factors are considered likely to influence heavy VKT:

- real gross domestic product
- real value of imports
- real value of imports
- real diesel prices
- real heavy user charges, and
- unemployment.

2.4 Public transport travel

To help identify the key drivers of public transport demand and the different econometric methods used, a brief literature review was carried out. The studies can generally be grouped into two categories: (a) stated preference/revealed preference studies, and (b) econometric analysis. As we are carrying out a desk top analysis, we reviewed only studies that used econometric methods.

Boulahbai & Madre (2000) using a dynamic log-log time series regression model identified that the key factors influencing public transport patronage were volume of supply (seats kilometres per capita), population structure indicators (age, vehicle ownership and home location), the mean price of public transport (revenue in real terms/number of trips) and fuel price. The specification of the model used was:

Log of public transport per capita = log lag of public transport per capita + log seats kilometres per capita + log of population indicator + log of mean price of public transport and the log fuel cost index plus error term.

It is interesting to note that the study showed that without the inclusion of population structure indicators, elasticity with respect to mean income per inhabitant was significant and negative. However, when the 'structural indicators' were added this income elasticity took a zero value or values that fluctuated between positive and negative. Consequently, the population structure indicator and the income indicator cannot be used simultaneously in the model. This appears to support the view that most of the negative effect which an increase in income had, during the study period, on public transport was due to increased car ownership (this being included in the structural indicator) and that the residual effect of income on urban passenger transport was not significant.

In 2002 the Department of the Environment, Transport and the Regions (DETR) in the UK commissioned a study by Dargay & Hanly (2002) to obtain estimates of fare elasticities that could be used in policy calculations to project the change in bus patronage nationally, as a result of a given 'average' fare change, and to explore possible variation in the elasticity. The study after evaluating different methods considered that the use of an econometric time series approach was the most appropriate. The fare elasticities were estimated based on dynamic econometric models relating per capita bus patronage (all journeys) to real per capita income, real bus fares (average revenue per journey), service levels (bus vehicle kilometres), real motoring costs, and demographic variables.

The data on bus patronage included all trips, both full fare and concessionary. As no actual information on fares was available, it was necessary to calculate fares based on data on revenues and journeys. The fare variable was calculated as real average revenues per passenger journey excluding concessionary fare reimbursement. As noted earlier, bus vehicle kilometres per capita were used as a proxy for level of service. The authors acknowledged that the measure of service quality of per capita bus kilometres was a very crude approximation for the many factors that make up the quality of a bus service. It was however, the only feasible measure at the aggregate level and the one most used in studies.

Due to the aggregated nature of the data and to account for lags, a partial adjustment model was used. The dependent variable was bus patronage, and the independent/explanatory variables were service level, bus fare, income, demographic factors, motoring costs and car ownership.

In 2006 a collaborative study undertaken by the Universities of Leeds, Oxford, Westminster, University College London and TRL (Paulley et al, 2006) identified and analysed the factors affecting demand for public transport. While a wide range of factors were examined in the study, the findings relating to fares, quality of service (bus service levels) and car ownership were the most significant.

Greer & Van Campen (2011) used three regression models applied to cross-sectional data for 344 census area units served by the public transportation system in Auckland to ascertain the determinants of public bus ridership for the purpose of commuting to work in the region. In the regression models used, bus passengers who commuted to work was the dependent variable, while the independent/explanatory variables were total commuters, car per household, population density, station distance, distance to city centre, rush hour frequency, and median household income.

The first regression model was a simple log-log model, while a different specification was used in the second regression model. In the second model the dependent variable was transformed into the log of the ratio of bus passengers to total commuters or the log of the fraction of the commuters from the area unit who took the bus to work. Due to spatial autocorrelation a spatial error model was used. Greer found that the spatial error model produced more accurate estimates of parameter values and improved the predictive power of the model. The spatial error model was therefore a significant improvement over the simple log-log model. The third model used was a Poisson regression model with the variables left in their level form.

The results of the regression analysis indicated that the following four factors had a positive effect on commuter bus ridership:

- (a) the total number of commuters from the area unit
- (b) the distance from the centre of the area unit to the nearest rail of ferry terminal
- (c) the population density of the area unit; and
- (d) the combined morning and evening peak hour bus service frequency within the area unit.

The study found that three factors had a negative influence on commuter bus ridership:

- (a) the average number of cars available to a household within the area unit
- (b) the distance from the centre of the area unit to the city centre; and
- (c) median household income within the area unit.

Waka Kotahi commissioned Booz & Company (Wang, 2011) to carry out research on factors that influence public transport patronage. The study detailed the factors that influenced the different public transport modes in three major regions (Auckland, Wellington and Christchurch).

Short-term and long-term models were developed for each major public transport mode (bus, train and ferry) in each region. Six variables were considered in the models. The dependent variable was patronage (in trips per capita). The independent variables were service level (in bus/train kilometres per capita), real fare (in real revenue per passenger), real income (in real disposable income per capita), car ownership (in cars per capita per region) and real fuel price.

Due to the short period that the data was available it was decided that an error correction model was not appropriate, and that the partial adjustment model was used. The study states that the idea behind the partial adjustment model is that an individual's travel behaviour to certain extent is a habit. One's choices today influence one's future decisions. This is modelled by introducing a lagged independent variable on the right-hand-side of the equation and the associated adjustment coefficient (Wang, 2011). Table 2.1 shows the main variables used and their definitions, while Tables 2.2 and 2.3 show the estimated bus and rail elasticities in Auckland, Wellington and Canterbury.

Variable	Definition	Unit
$Q_t^{X M}$	Patronage per capita in region X on mode M at time t	Passenger trips per capita per period
S_t^{XM}	Service kilometres per capita in region X on mode M at time t	Bus-km/train-km per capita per period
$F_t^{X M}$	Fare (real average revenue per passenger) in region X on mode M at time t	New Zealand dollars (NZD) per passenger
C_t^X	Car ownership per capita in region X on mode M at time t	Number of vehicles per capita
I_t	Income (real gross disposable income per capita) at time t	NZD per capita
O_t	Fuel price (real regular petrol price) at time t	cents per litre

 Table 2.1
 Variables used in the model and their definitions (Wang, 2011)

 Table 2.2
 Bus demand elasticities estimates (Wang, 2011)

	Auckland 2003Q3-2008Q2		Wellii	ngton	Canterbury		
	short-run	long-run	short-run	long-run	short-run	long-run	
Bus service	0.46	0.73	n/a	n/a	0.07	0.62	
Bus fare	n/a	n/a	-0.23	-0.46	-0.26	-0.34	
Car ownership	-1.96	-3.10	n/a	n/a	n/a	n/a	
Income	n/a	n/a	n/a	n/a	n/a	n/a	
Fuel price	0.20	0.32	n/a	n/a	0.28	0.37	

Table 2.3 Rail demand elasticities estimates (Wang, 2011)

	Auckland				Wellington			
	shor	t-run	long	j-run	shor	t-run	long-run	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Rail service	0.99	0.88	1.41	1.63	0.74	0.78	2.39	2.53
Rail fare	-0.97	-0.68	-1.37	-1.25	n/a	n/a	n/a	n/a
Car ownership	n/a	n/a	n/a	n/a	-0.32	n/a	-1.04	n/a
Income	1.61	n/a	2.28	n/a	n/a	-0.22	n/a	-0.70
Fuel price	n/a	n/a	n/a	n/a	0.13	0.12	0.42	0.39

The Australian Bureau of Infrastructure, Transport and Regional Economics (BITRE) in 2013 carried out an econometric study of urban public transport in Australian capital cities. The study sought to explain the key factors that could explain public transport patronage between 1977 and 2009. The results of the study were then used to forecast the long-term demand in the various capital cities.

For each capital study, a model of urban public transport patronage was constructed based on the functional specification below:

Urban public transport = F (real fares, household disposal income constraint, GFC effects, and events/supply/trend dummies).

The disposal income constraint (DIC) variable was a composite of several factors, such as mortgage, rent, food costs, petrol prices and the level of household savings. The urban public transport fare and DIC variables were the most important of the explanatory variables. The models succeeded in explaining most of the variation in urban public transport patronage mode share since 1977.

2.5 Baseline models and estimated forecast of vehicle kilometres by transport modes

In this section we report on the baseline development and forecast work for Total Vehicle Kilometres Travelled, Light Passenger Vehicle Kilometres Travelled, Bus Vehicle Kilometres Travelled and Heavy Vehicle Kilometres Travelled.

Quarterly VKT data from 2002q1 to 2019q2 were obtained from the NZ Ministry of Transport for the various land transport modes. Other exogenous data such as GDP (production and expenditure), labour force (employment, unemployment, total employed etc), exports, imports and demographics (age structure etc) were obtained from Statistics NZ. Petrol and diesel prices were obtained from MBIE. To assist our analysis, we have also used information from the Household Travel Survey carried out by the Ministry of Transport.

We investigated several time series econometric model specifications, and this included ARIMA, Ordinary Least Squares (OLS), Autoregressive Regressive Distributed Lags (ARDL), Vector Autoregressive (VAR) and Vector Error Correction (VECM). We found that for most transport activities, ARDL and OLS model specifications gave us the best fit. As in all-time series analysis we have tested the data to ensure that it is either stationary or cointegrated. We found that while the data is non-stationary, it is cointegrated. Several tests were also carried out to ensure that there is no autocorrelation. Following a peer review suggestion, we further investigated the use of Vector Error Correction (VEC) models, and the analysis confirmed our previous findings in that the VEC models did not produce better results.

In an Autoregressive Distributed Lag Model (ARDL), the variable of interest is assumed to be a function of the past values of itself (autoregressive) and the current and past values of other variables (distributed lag). They can relatively easily be extended to incorporate panel data. ARDL models can accommodate a variety of lag structures and include well-known models such as static regressions as special cases. In its general form, with p lags of y and q lags of x, the ARDL model can be written as:

$$y_{t} = \delta + \delta_{0}x_{t} + \delta_{1}x_{t-1} + ... + \delta_{q}x_{t-q} + \theta_{1}y_{t-1} + \theta_{2}y_{t-2} + ... + \theta_{p}y_{t-p} + v_{t}$$

The modelling process involved the following steps:

- (a) Graph the key land transport activities to get a better understanding of the shape of the time series trend
- (b) Next identify and assess the independent variables that are likely to be key drivers of the different land transport modes
- (c) Choose the time series model and the independent variables that gives the best explanation (including the right signs, statistical significance, and highest coefficient of determination) for each of the identified transport modes
- (d) Test to ensure that the data in the model is stationary or cointegrate and there are no autocorrelation problems/issues, and
- (e) The specified model having passed the diagnostic tests is then used to forecast the transport activity.

2.6 Total VKT

Figure 2.6 below shows that between 2002 and prior to the Global Financial Crisis (GFC) total VKT increased moderately. VKT then plateaued and then fell slightly during the GFC. However, since 2014 total VKT began to increase and rose sharply from 2015 to 2019, just before the COVID-19 pandemic. Unfortunately, at this stage we do not have VKT quarterly data during the COVID-19 pandemic lockdown and post lockdown, although surveys carried out indicates that VKT declined significantly during the lockdown period but have recovered since post lockdown.



Figure 2.6 Total VKT for all transport modes

Two ARDL regression models were considered to be suitable to simulate total VKT as shown in Tables 2.4 and 2.5 below. The main drivers of Total VKT were petrol prices, total population and the lag of total VKT. Both models fitted the data well and the adjusted R-squared are around 0.99. Testing carried out indicates that the data is cointegrated and no autocorrelation problems are detected. (It should be pointed out the critical values for detecting cointegration by Stata are not correct and we need to use the correct values which are -3.96 at the 1% level, -3.37 at the 5% level and -3.07 at the 10% level).

These models were used to forecast Total VKT and Figure 2.7 shows the forecast up to 2035. It can be seen from Figure 2.7 that Total VKT will continue to grow significantly under present policy settings.

Table 2.4 Total VKT model 1

Source		SS	df		MS	Number of	obs	-	69
Model Residual Total	3. 2. 3.	.7711e+19 .0844e+17 .7920e+19	3 65 68	1.25 3.20 5.57	70e+19 68e+15 64e+17	Prob > F R-squared Adj R-squa Root MSE	ired		0.0000 0.9945 0.9942 5.7e+07
total_vkt_o4c	ma	Coef.	Std.	Err.	t	P> t	[95%	Conf.	Interval]
total_vkt_o4c L	ma 1.	.8939831	.030	9561	29.25	0.000	.832	9486	.9550177
petro total_populati _co	ol1 .on ons	-2062439 425.4488 -3.13e+08	37667 90.09 1.100	70.9 9054 ⊇+08	-5.48 4.72 -2.86	0.000 0.000 0.006	-2814 245.1 -5.32	4703 5256 e+08	-1310176 605.3721 -9.42e+07

. regress total_vkt_o4cma L1.total_vkt_o4cma petrol1 total_population

. predict ehat, residual

(1 missing value generated)

. dfuller ehat

Dickey-Ful	ler test for unit	root	Number of obs	=	68
		Inte	erpolated Dickey-Ful	ler ·	
	Test Statistic	1% Critical Value	5% Critical Value	10%	Critical Value
Z(t)	-6.475	-3.555	-2.916		-2.593

MacKinnon approximate p-value for Z(t) = 0.0000

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	3.329	1	0.0681

H0: no serial correlation

. estat durbinalt

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	3.244	1	0.0717

Table 2.5 Total VKT model 2

Source		SS	df	MS		Numb	er of obs	=	2507	69 2 7
Model Residual	.0599	966868 3611 7 5	3 65	.0199889 5.5565e	956 - 06	F(3, 65) Prob > F R-squared Adj R-squared Root MSE		= = =	0.00	.37 900 940
Total	.0603	328043	68	.000887	177			=	.00	236
ln_total_vkt_	_o4cma	Coef.	St	d. Err.		t	P> t	[95%	Conf.	Interval]
ln_total_vkt_	_o4cma L1.	.8946996	.0	304664	29.	37	0.000	.8338	3541	.9555451
ln_pe ln_total_popul	etrol1 lation _cons	0389396 .1749679 0163241	.0 .1	006979 376054 120602	-5. 4. -0.	58 65 15	0.000 0.000 0.885	0528 .0998 2401	8777 86 47 1238	0250015 .2500711 .2074755

. regress ln_total_vkt_o4cma L1.ln_total_vkt_o4cma ln_petrol1 ln_total_population

. predict ehat, residual

(1 missing value generated)

. dfuller ehat

Dickey-Ful	ler test for unit	root	Number of obs	=	68
		——— Inte	erpolated Dickey-Ful	ller –	
	Test	1% Critical	5% Critical	10%	Critical
	Statistic	Value	Value		Value
Z(t)	-6.487	-3.555	-2.916		-2.593

MacKinnon approximate p-value for Z(t) = 0.0000

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	3.337	1	0.0678

H0: no serial correlation

. estat durbinalt

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	3.252	1	0.0713





2.7 Total light VKT

Total light VKT is made up of light commercial and light passenger VKT. Table 2.6 shows economic factors, such as petrol prices, employment and GDP, were the main explanatory variables that influenced total light VKT. As can be seen from Figure 2.8 total light VKT declined during the global financial crisis but since then has grown significantly.

Table 2.6 Total light VKT

- 1 . use "\\wlgfp2\users\$\ErnestA\Desktop\VKT model Stata dataset.dta"
- 2 . regress light_vkt_o4cma petrol1 employed_total gdp_expenditure_real_sa L1.light_vkt_o4cma

Source	SS	df	MS	Number	of obs	=	69	
			S	F(4, 64	4)	= 3	332.13	
Model	3.1079e+19	4	7.7698e+18	Prob >	F	=	0.0000	
Residual	1.4923e+17	64	2.3318e+15	R-squa	red	=	0.9952	
				Adj R-	squared	=	0.9949	
Total	3.1228e+19	68	4.5924e+17	Root M	SE	=	4.8e+07	3
light_	vkt_o4cma	Coef.	Std. Err.	t	P> t	[95	% Conf.	Interval]
	petrol1	-2529738	369319.7	-6.85	0.000	- 32	67539	-1791937
employ	yed_total	425.1404	241.1507	1.76	0.083	-56.	61338	906.8943
gdp_expenditure	e_real_sa	13776.75	5481.832	2.51	0.014	282	5.533	24727.97
light_	vkt_o4cma							
	L1.	.795649	.0458359	17.36	0.000	.70	40813	.8872167
	_cons	8.56e+08	1.79e+08	4.77	0.000	4.9	7e+08	1.21e+09

3 . predict ehat, residual (1 missing value generated)

4 . dfuller ehat

Dickey-Fuller test for unit root			Number	of obs =	68
			 Interpolated Di 	ckey-Fuller	
	Test Statistic	1% Critic Value	al 5% Criti Valu	cal 10%	Critical Value
Z(t)	-6.911	-3.5	-2.	916	-2.593

MacKinnon approximate p-value for Z(t) = 0.0000

5 . estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	1.898	1	0.1683





2.8 Light passenger VKT

Between 1963 and 1975 growth in light passenger kilometres travelled was generally high and was around 8% per annum. Between 1976 and 2004 growth in light kilometres travelled slowed but was still growing at a health rate of 2.5% per annum. As can be seen from Figure 2.9, from 2006 to 2014 light passenger VKT fluctuated and experienced a slight decrease. Many experts contended that car VKT had peaked, and this led to the phenomenon known as 'peak car'. However, this speculation of peak car has proved to be incorrect as the decline was due mainly to the Global Financial Crisis (GFC). The decline in national GDP, the increase in unemployment and increases in petrol prices were the main reasons for the decline in light passenger VKT. Following recovery from GFC there has been a significant increase in light passenger VKT from 2015 to 2019. We do not yet have quarterly data during the COVID-19 pandemic, but surveys carried out indicates that car VKT declined significantly during the lockdown period but have recovered since the lockdown.

Table 2.7 shows that economic factors (GDP and petrol prices) were the main reasons for the growth in light passenger VKT. Based on the estimated coefficients Figure 2.10 shows the forecast of light passenger VKT to 2035.



Figure 2.9 Total light passenger VKT

Table 2.7 Light passenger VKT

Source	SS	df	MS	Number	of obs	=	69	
Model Residual	1.0413e+19 5.1131e+17	3 65	3.4710e+18 7.8664e+15	F(3, 6 Prob > R-squar	5) F red	-	441.24 0.0000 0.9532	
Total	1.0924e+19	68	1.6065e+17	Adj R- Root M	squared SE	= =	0.9510 8.9e+07	
light_passe	enger_vkt	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
gdp_expenditure	petrol1 e_real_sa	-3070853 23508.86	577633.6 4326.57	-5.32 5.43	0.000	1	4224467 14868.1	-1917239 32149.62
light_passe	enger_vkt L1.	.692639	.0616229	11.24	0.000		5695695	.8157086
	_cons	1.89e+09	3.74e+08	5.06	0.000	1	.14e+09	2.64e+09

3 . regress light_passeng~t petrol1 gdp_expenditu~a L1.light_passeng~t

4 . predict ehat, residual
 (1 missing value generated)

5 . dfuller ehat

Z(t)

Dickey-Fuller test for unit root Number of obs = 68 Test 1% Critical 5% Critical 10% Critical Statistic Value Value Value

-3.555

-2.916

-2.593

MacKinnon approximate p-value for Z(t) = 0.0000

-8.352

6 . estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.031	1	0.8604

H0: no serial correlation

7 . estat durbinalt

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.029	1	0.8654





2.9 Total bus VKT

As can be seen from Figure 2.11 total bus VKT had increased steadily between 2001 and 2010 and then experienced a slight decline around 2011. From 2011 to 2019 total bus VKT has experienced significant growth of around 40 percent. While bus VKT increased significantly this increase was not due to any significant shift from light passengers to the bus mode, as light passenger VKT also increased significantly during this period.

To forecast bus VKT we modelled the existing situation using an ARDL specification with the lags of bus VKT and diesel prices being the critical independent variables. As can be seen from Table 2.8 below the estimated coefficients are statistically significant at the 1%, 5% and 10% levels and testing carried out showed that the data is cointegrated and is not autocorrelated. This model specification was then used to forecast bus VKT, and this is shown in Figure 2.12. This shows that in the absence of any significant interventions bus kilometres will continue to increase in the future. However, as noted previously this increase in forecasted bus VKT is not due to reduction in light passenger VKT. In other words, little or no mode shift was involved.





Source	SS	df	MS	Number of ob	s =	68
Model Residual	7076.76935 3.09094196	3 64	2358.92312 .048295968	Prob > F R-squared	= = =	0.0000
Total	7079.86029	67	105.669557	Root MSE	u = =	.21976
bus_vkt_o4cma	Coef.	Std. Err.	t t	P> t [95%	Conf.	Interval]
bus_vkt_o4cma						
L1.	1.712333	.0808109	21.19	0.000 1.55	0895	1.873772
L2.	7073304	.0821383	-8.61	0.000871	4205	5432404
diesel_retail	0031783	.0012429	-2.56	0.013005	6612	0006954
_cons	.3255686	.1814991	1.79	0.078037	0175	.6881548

Table 2.8 Bus VKT

. regress bus_vkt_o4cma L1.bus_vkt_o4cma L2.bus_vkt_o4cma diesel_retail

. predict ehat, residual

(2 missing values generated)

. dfuller ehat

Dickey-Fuller test for unit root			Number of obs	=	67
		Inte	erpolated Dickey-Ful	ller ·	
	Test	1% Critical	5% Critical	10%	Critical
	Statistic	Value	Value		Value
Z(t)	-7.803	-3.556	-2.916		-2.593

MacKinnon approximate p-value for Z(t) = 0.0000

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.152	1	0.6969

H0: no serial correlation

. estat durbinalt

.

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.141	1	0.7074

Figure 2.12 Total bus VKT forecast



2.10 Heavy goods VKT

As can be seen from Figure 2.13 heavy goods VKT experienced steady growth from 2001 to around 2007. Around 2008 heavy goods VKT declined and plateaued to around 2013. This was due to the decline in economic activities due to the GFC. Recovery from the GFC led to significant growth in heavy VKT until the COVID-19 pandemic when heavy VKT declined. While we do not have post-COVID data heavy we understand VKT has recovered to its pre-COVID levels.



Figure 2.13 Heavy goods VKT

We investigated several heavy goods VKT models and found that the functional specification as shown in Table 2.9 gave the best explanation. The estimated coefficients are significant at the 1% and 10% levels. Testing carried showed that the data is cointegrated and no autocorrelation problems were detected. Based on this, Figure 2.14 shows that in the absence of policy changes that heavy VKT will increase.

date

2020q1

Table 2.9 Heavy VKT

1 . use "\\wlgfp2\users\$\ErnestA\Desktop\VKT modelling Stat dataset VERSION-3.dta"

2 . reg hgv_vkt_o4cma unemployed_fulltime gdp_product_real_sa

Source		SS	df	MS	5	Numb	er of obs	=		70
Model Residual	1574 1522	73.383 7.4394	2 67	78736.6	917 5215	F(2, Prob R-sq	67) > F uared	= = =	346 0.00 0.92	.44 000 118
Total	1727	00.823	69	2502.91	1048	Adj Root	MSE MSE	=	0.90 15.0	092 076
hgv_vkt_	_o4cma	Coef.	Sto	d. Err.		t	P> t	[95%	Conf.	Interval]
unemployed_fu gdp_product_re	lltime eal_sa _cons	0010358 .0069766 378.5043	.00 .00 14.	001089 002694 .54185	-9. 25. 26.	51 90 03	0.000 0.000 0.000	0012 .0064 349.4	2532 4389 4786	0008185 .0075144 407.5299

3 . predict ehat, residual

4 . dfuller ehat

Dickey-Fuller test for unit root

Number of obs = 69

		Inte	erpolated Dickey-F	uller ———
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-7.887	-3.553	-2.915	-2.592

MacKinnon approximate p-value for Z(t) = 0.0000

5 . estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.109	1	0.7412

H0: no serial correlation

6 . estat durbinalt

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.103	1	0.7483

Figure 2.14 Heavy goods VKT forecast



3 Limitations

3.1 Methodology of quarterly VKT

The current method of calculating vehicle kilometres travelled (VKT) began in 2001. It is reported as quarterly data but is not seasonal, ie it does not reflect quarterly use nor is it seasonally adjusted. Quarterly published VKT is derived from annual vehicle odometer readings.

No detailed methodology is available for the published VKT data. The calculation involves distributing the count across the preceding four quarters while also incorporating an estimate for vehicles newer than three years that do not require annual testing.

There were issues with using the reported quarterly odometer VKT data in an auto regressive timeseries analysis. These were overcome by using an order four centred moving average to smooth the data.

3.2 Commercial vehicles

There were found to be issues with modelling the reported light commercial VKT timeseries data. This covers vans (VAN), utility vehicles (UTE) and sports utility vehicles (SUV). ARDL models for commercial light vehicles were all dismissed.

They are the fastest growing sector in new light vehicles while the purchase of more standard cars has been declining as shown in Figure 3.1.





Source:

 $\underline{https://www.mia.org.nz/Portals/0/Long\%20trun\%20trends\%20light\%20vehicles\%20by\%20segment\%20group\%20to\%202020.pdf$

The vehicles classified as commercial have in recent years become a favourite for families as private passenger vehicles.

The nomenclature of light vehicle subclassifications as passenger or commercial does not reflect the use for each subset of vehicles. The classification of passenger and commercial is descriptive of their body types and seemed to have been used to be indicative of their fuel type. This suggests that a cautious approach be taken in interpreting output from existing models where light passenger and light commercial is used.

The ARDL model for total light vehicle VKT is sound, as is that for light passenger vehicles (cars). The VKT for light commercial vehicles (SUV, UTE, VAN) can be calculated by the difference between total light and light passenger VKT.

3.3 Forecasting with ARDL models

The reliability of the forecast is dependent on the accuracy of forecasting the explanatory variables. The limitation of all these forecasted values of explanatory variables is that they are strongly influenced by exogenous factors that cannot be modelled. Fuel prices are the most volatile. That said, the historical data for 1990 to 2019 shows their trends to be moving relatively consistently, and variance to be within bounds set by market forces without dramatic disruptive changes.

The approach taken in forecasting these explanatory variables was to use the Holt-Winters algorithm, a seasonal exponential smoothing algorithm (ETS AAA) and harmonic analysis of unique longer waveform periods of each variable. The forecast variables were used in conjunction with each of the ARDL models' coefficients to forecast quarterly VKT to 2035 for that vehicle type.

4 Conclusion

The view taken in this study was to approach modelling by assuming nothing; to seek quality data that covered a long enough period to be useful; and to test everything.

The selected ARDL models for total VKT (two models are offered), total light VKT, light passenger VKT, bus VKT and truck (heavy) VKT were, after much trial and experimentation, identified as the preferred time-series approaches for forecasting VKT in New Zealand.

The fit of all five models across the 20-year time-series was shown to be good. The use of economic and societal factors, combinations of which varied between models for vehicle types, proved valid in modelling VKT.

This set of ARDL models will provide a valid baseline for our environmental impact modelling of future integrated interventions, while noting that they have wider uses in land transport analysis, modelling and planning.

The ongoing COVID-19 situation appears to have had little long-term effect on national VKT, but it is too early to conclude this.

Also, the NZ Government's climate change-focused emissions reduction plan has a target for reducing light vehicle VKT. This set of baselines will be an invaluable reference in evaluating the impact and effectiveness of these new policies, investment focus and interventions.

Te Puna Taiao, our environmental impact modelling initiative for which this work has been undertaken, is currently focused on greenhouse gas (GHG) emissions. The potential for activities within Waka Kotahi leverage that could be achieved through a combination of evidence-based interventions need to be reliably modelled. A key objective of this initiative is to show how investment in transport infrastructure through the National Land Transport Programme can be optimised, for example, by assuring that we are investing in the right activities and interventions, in the right combination and at the right levels, to reduce the impact of land transport. Not only through decarbonising transport, but wider environmental, health and sustainability benefits.

Te Puna Taiao has already been of value in realising the impact of the targets set by the NZ Government's emissions reduction plan, which was published in May 2022, and this modelling initiative will play an even greater role in understanding what is necessary in meeting these targets.

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