Modelling and Forecasting the Demand for Automobile Petrol in Australia, and its Policy Implications

Zheng Li
Institute of Transport and Logistics Studies
Faculty of Economics and Business
The University of Sydney, NSW 2006, Australia
zhengl@itls.usyd.edu.au

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Abstract

Petrol is the most significant fuel and accounts for the largest consumption share among the various road transport energies. This paper presents different econometric modelling systems to estimate the demand for petrol in the Australian road transport sector, emphasizing the effects of national income and petrol price. Quarterly time series data for Australia over the period 1977-2006 are employed to capture the adjustment process associated with responses through time to changes in those factors. Eight modelling systems for petrol demand are used to compare the forecasting performance of different approaches. The most appropriate model is selected to predict automobile petrol demand in Australia from 2007 through to 2020.

The prediction of a 14-year forecasting horizon shows that Australian automobile petrol consumption will continuously increase under the "business-as-usual" scenario, and increased greenhouse gas emission (primarily CO_2) will be produced and emitted into the environment. Effective policy instruments need to be implemented to contain and then reduce the emissions from automobiles. TRESIS, an integrated transport, land use and environmental strategy impact simulation program, is used to estimate the impacts on CO_2 of several policy instruments. Given the findings from the evaluation of different policy scenarios, the appropriate strategies are suggested in order to contribute to reducing greenhouse gas emission in Australia.

1 Introduction

The needs for transport have been continuously stimulated by globalisation, industrialisation, growing worldwide market opportunities, and booming trade and travel activities. Not only does world economic growth rely on transportation, but individuals have increasingly required public and private transportation to realize more mobile and accessible ways of life. Fossil fuel usage with its associated polluting and global warming outcome continues to attract great attention, particularly from governments and organisations throughout the world.

Energy security is one of the primary reasons that petroleum products have become increasingly important to the contemporary business world. Now oil reserves are regarded as a strategic safeguard by many countries against the economic and political impacts of an energy crisis to ensure the steady supply of energy at a given price so as to protect national economic development. In addition to energy security issues, environmental concerns re-emphasize the demand for fuel in the road transport sector as a major theme. One sixth of the world's greenhouse gas emissions are contributed by automobiles or passenger cars (Potoglou and Kanaroglou, 2007). The recognition that economic development has been conditioned by its perverse effect on the environment has resulted in recent global efforts to decrease the emissions of carbon dioxide and other greenhouse gases in order to reduce anticipated atmospheric warming and other changes in global climate.

Bureau of Transport and Regional Economics (BTRE, 2005) suggested that half of all the world's oil reserves were used in 2004, and petroleum production has reached a peak. Given the significance of fuel to many governments and organisations, the forecasting of fuel demand has become an increasingly important tool for energy planning and decision making.

According to Australian Bureau of Statistics (ABS, 2006a), Australia has over 13.9 million of vehicles, and 80 percent of them are automobiles. Moreover, 85 percent of passenger cars consume petrol in Australia (ABS, 2006a), and automobiles consume 85 percent of total road petrol in Australia (ABS, 2006b). Australia produces the highest greenhouse gas emissions per capita among the developed countries (Turton cited in Saddler *et al*., 2007). Although it only accounts for about 7.5 percent of national emissions in Australia, attention must be paid to the passenger car sector, due to its fast growth rate, its high reliance on petrol, its concentration in urban areas and the limited fuel substitution for automobiles.

The main purposes of this paper are (1) to arouse government and public awareness for energy and environment concerns, by presenting Australia's automobile petrol demand and its impacts today and up to 2020 under the "business-as-usual" scenario; and (2) to support the reduction in greenhouse gas emissions from automobiles, by evaluating various policy scenarios. This paper presents different econometric modelling systems to estimate the demand for petrol in the Australian road transport sector, emphasising the effects of national income and petrol price. Eight different forecasting models are used, and their performances are compared. In addition to prediction, the environment effects of various policy instruments are also examined, and the evaluation of different policy scenarios suggests the appropriate strategy to contribute to the reduction of greenhouse gas emissions in Australia.

The organisation of this paper is as follows. After a brief review of the literature, different forecasting models are presented in the third section, followed by a brief description of the data. Then, the fifth section provides the modelling results, as well as policy scenarios. The final section presents conclusions.

2 Literature Review

Transport fuel consumption and its determinants have received a great deal of attention since the first oil price crisis in the early 1970s. At the time, many econometric studies of fuel demand were carried out to analyse the effects on petrol consumption resulting from the threat of fuel energy scarcity (Espey, 1996). More recently, environment concerns such as global warming have also become increasingly important in the desire to understand global fuel demand. In looking at fuel demand, a large proportion of research has emphasised automobile petrol demand, mainly because the passenger car fleet represent one of the largest groups of petroleum users. Another significant character is that most fuel demand studies focus on quantifying price and income elasticities, and estimating their impacts on fuel consumption and vehicle utilisation.

The estimation of transport fuel elasticities is usually divided into short run and long run. Short run is defined as the response made within one period of the data, mostly within one year (Graham and Glaister, 2002; Goodwin *et al*., 2004). Long run refers to the situation when responses are completed. Besides short run and long run, intermediate run is also introduced by some scholars (Eltony, 1993; Lidman, 2007).

The literature review of this paper contains three main categories. The first part is econometric modelling approaches for fuel demand, including Sterner and Dahl (1992), Gujarati (1995), Makridakis *et al.* (1998), Bowerman *et al*. (2005) and so on. The second part of literatures focuses on elasticity studies for road transport fuel demand, including McRae (1994), Espey (1998), Banaszak *et al*. (1999), Kayser (2000), Graham and Glaister (2002), Goodwin *et al*. (2004), Litman (2007) and so on. The last part considers relevant environmental and energy policies, including Johansson and Schipper (1997), Tiezzi (2005), Hensher (2007) and so on.

3 Methodologies

The approaches for econometric modelling and forecasting may be divided into four categories: (1) the first type of models estimate the relationships between explanatory variables and dependent variable over a certain period of time, and consider the underlying economic processes; (2) the second type examine relationships between the past and current values, and forecasts the future on the basis of history only; (3) the third method analyses relationships between various variables at a point in time for different units; and (4) the last approach is to consider relationships between dependent and independent variables for different units for a certain periods of time (Verbeek, 2004). The four types of econometric models require different characteristics of data to specify and quantify the relationships. Specifically, the first two methods require time series data, observations on a single event over multiple time periods; the third one uses cross-sectional data, observations on multiple events observed at a single point in time; and the last one employs panel data, with the two dimensions of time series and cross-sectional data simultaneously.

In this study, time series data are collected for predicting the future petrol demand in Australia. Hence, the first two types of econometric models were selected to build a framework. Among the first category of econometric models, the linear regression model is one well-developed approach. The autoregressive integrated moving average (ARIMA**)** model is an exact example for the second category.

3.1 The Linear Regression Model

The linear regression model is a standard approach in the fuel consumption literature, and it is becoming increasingly common in the traffic literature. Many studies have identified income and fuel price as the major parameters to determine energy consumption (Sammi, 1995; Wohlgemuth, 1997; Banaszak *et al*., 1999, De Vita *et al*., 2006). The demand for petrol can be described by the following equation:

$$TPC_t = f(GDP_t, RPP_t)$$

Where

TPC_t is the road petrol consumption at time period *t*;
GDP_t is the real gross domestic product at time period *t*;
RPP_t is the real petrol price at time period *t*.

Before fully developing the econometric model, the idea of partial adjustment is introduced. The fact that for dynamic models adaptation takes time when some factors such as price and income are changed, consumer may not be able or willing to adjust to the new level of desired consumption, due to inflexibility in the stock of consumer durables (Sterner and Dahl, 1992). Instead they adapt partially, by fraction "*s*". Moreover, the natural log-linear function is applied in order to generate elasticities.

$$\ln TPC_t - \ln TPC_{t-1} = s(\ln TPC_t^* - \ln TPC_{t-1}) + \mu_{t1}$$

$$\ln TPC_t^* = c_0 + c_1 \ln GDP_t + c_2 \ln RPT_t + \mu_{t2}$$

By combining the above two equation, the total petrol demand can be expressed as:

$$\ln TPC_t = sc_0 + sc_1 \ln GDP_t + sc_2 \ln RPP_t + (1-s)\ln TPC_{t-1} + \mu_t$$

Where

c_0 is a constant;
c_1, c_2 and c_3 are the unknown coefficients for corresponding independent variables;
s lies between 0 and 1;
μ_t (random error term) = $\mu_{t1} + \mu_{t2}$

When analysing time series data, seasonal effects may play a significant role. Also for most types of energy demand, seasonal variations (seasonality) are obvious. As quarterly time series data are employed in this study, seasonal dummy variables are built to examine the seasonal fluctuations, given in the following equation.

$$S(D) = a_2 D_{2t} + a_3 D_{3t} + a_4 D_{4t}$$

Where

D_{2t} = 1 for the second quarter, D_{2t} = 0 otherwise
D_{3t} = 1 for the second quarter, D_{3t} = 0 otherwise
D_{4t} = 1 for the second quarter, D_{4t} = 0 otherwise
D_{2t}, D_{3t} and D_{4t} are all equal to 0, for the first quarter;
a_2, a_3 and a_4 are the unknown coefficients.

By including seasonal dummy variables, petrol demand is given as:

$$\ln TPC_t = sc_0 + sc_1 \ln GDP_t + sc_2 \ln RPP_t + (1-s)\ln TPC_{t-1} + a_2 D_{2t} + a_3 D_{3t} + a_4 D_{4t} + \mu_t$$

Both short-run and long-run elasticities can be estimated from the above equation. After removing the lagged TPC from the independent variables, intermediate-run elasticities with respect to price and income can be obtained.

3.2 The Autoregressive Integrated Moving Average Model

The Autoregressive integrated moving average (ARIMA) model combines several time series techniques such as differencing, autoregressive (AR) models, and moving average (MA) models (Kumar *et al.*, 2004). The ARIMA model analyse the stochastic properties of economic time series on their own (Gujarati, 1995). Compared with regression models, ARIMA focuses more on the past or lagged situations of a time series.

A stationary time series always has the same mean, variance and autocovariance at any time (Gujarati, 1995). If a time series is stationary, it can be modelled by an AR process or a MA process or both. According to Bowerman *et al.* (2005), AR considers lagged effects of the time series itself (y_t), a p-order autoregressive or AR (p) is presented as:

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \alpha_t$$

Where

δ is a constant;
y_t is the dependent variable at time period *t*;
ϕ_p is the parameters of y_{t-p} (p = 1, 2, 3 … p);
α_t is an uncorrelated random error term with zero mean and constant variance.

MA considers the effects of the current and past error terms (or randomness), a q-order moving average, or MA (q) is listed as:

$$y_t = \mu_t - \theta_1 \mu_{t-1} - \theta_2 \mu_{t-2} - \ldots - \theta_q \mu_{t-q}$$

Where

μ_t is an uncorrelated random error term with zero mean and constant variance;
θ_q is the parameters of μ_{t-q} (q = 1, 2, 3 … q).

It is often that a stationary time series has the characteristics of both AR and MA, or a time series can be modelled as a combination of past values and past errors. Therefore, ARMA (p, q) can be presented as:

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \mu_t - \theta_1 \mu_{t-1} - \theta_2 \mu_{t-2} - \ldots - \theta_q \mu_{t-q}$$

The above analysis is based on stationary time series. However, time series data may not be always stationary. A time series must be transformed into stationary, then apply the ARMA (p, q). Thus the original time series is ARIMA (p, d, q), where d means: a time series must be differenced *d* times before it becomes stationary (Kumar *et al.*, 2004). Therefore, an ARIMA model is determined by the appropriate values of p, d and q. Box-Jenkins methodology is one approach to ARIMA model. Based on the characters of the time series, Bowerman *et al.* (2005) also divide Box-Jenkins method into nonseasonal modelling and seasonal modelling, which are both based on four stages: identification, estimation, diagnostic checking and forecasting.

In addition to the above sophisticated econometric models, some simple statistical approaches are also considered in this paper such as a linear trend model, a quadratic trend model, and an exponential trend model. These models analyse trends which is an important component of time series data, and make forecasts based on the observed trend (Levine *et al.*, 2005). The method of ordinary least square is used to compute the values of coefficients in the models. Besides trend models, other simple methods are also selected, including single exponential smoothing, Holt’s linear method and Holt-Winters’ method.

Different forecasts are achieved form the eight models. To choose the best-forecasting model is a significant part of this paper, and then the forecasts will be extended to 2020 with the most accurate prediction of the future petrol demand in Australia. For the evaluation of forecasts, time series data are divided into two sections. The first part is from Quarter 1, 1977 (1997q1) to Quarter 1, 2005 (2005q1) which is used for modelling and estimation of the eight models. The second represents a hold out sample dating from 2005q2 to 2006q4. This second segment of data is used for testing the effectiveness of the forecasts from eight different approaches estimated on the first segment of data. The mean absolute deviation technique is used to compare the forecasting accuracy of the eight models.

According to Levine *et al.* (2005), the mean absolute deviation (MAD) technique is an effective measure of the average of the absolute differences between the actual observations and the predicted values of a time series. The one with the minimum MAD is selected as the best-forecasting model among the eight models.

3.3 TRESIS for Policy Scenarios

TRESIS (Transportation and Environment Strategy Impact Simulator) is a strategic prioritising tool to evaluate the impact of potential policy instruments on urban travel behaviour and the environment. The current version is TRESIS 1.4 (with a 1998 base year), which examines strategic level policy scenarios for the Sydney metropolitan area by a number of performance indicators (Hensher et al., 2005). TRESIS 1.4 is the latest version with a 1998 base year, and it estimates the impacts of spatial, economic, energy and environmental policy instruments for the Sydney metropolitan area by a wide range of performance indicators (Hensher, 2007).

4 Data

The data for this study are quarter time series mainly including total road petrol consumption (TPC), real gross domestic product (GDP), and real petrol price (RPP) for Australia over the period 1977q1 to 2006q4. Consumer price index (CPI) and petrol price index (PPI) are adjusted to 1998q1 as base. Total road petrol consumption is measured in megalitres (million litres), obtained from three sources: Department of Primary Industries, Bureau of Transport and Communications Economics (BTCE), and Department of Industry, Tourism and Resources. Australian Bureau of Statistics (ABS) and BTCE are the main sources for gross domestic product. Real GDP is seasonally adjusted to 1998 as base, measured in million dollars. Petrol price is mainly obtained from BTCE and ABS.

5 Results, Analysis and Evaluation

5.1Linear Regression Modelling Results

The econometric model presented in Chapter 4.2 includes one dependent variable (TPC) and three explanatory variables (GDP, RPP, and lagged TPC). As quarterly data are used in this study, the lag structure up to the fourth lag is considered for three independent variables. Dummy variables are built in the model to examine seasonal effects. The result is given in the following table.

Table 1: Regression Results

	B	Std. Error	t	Sig.	VIF
(Constant)	3.922	.430	9.131	.000	
D2	.022	.006	3.450	.001	2.305
D3	.028	.006	4.908	.000	1.938
D4	.054	.005	9.764	.000	1.770
LNGDP	.267	.033	8.046	.000	21.672
LNTPC1	.265	.089	2.994	.003	22.510
LNRPP1	-.216	.048	-4.498	.000	1.042

F statistic is large enough (425.92) to indicate that there is strong linear relationships between dependent and independent variables in this model. The value of adjusted *R* square is 0.961, which means 96.1 percent of the variation in TPC can be explained by the regression model. This proves this model's goodness of fit, therefore it is appropriate to forecast. All the independent variables are significant at 95 percent of confidence level ($\alpha = 0.05$). Dummy variables (D_2, D_3 and D_4) indicate significant seasonality of the time series.

However, this model has three obvious limitations. First of all, the variance inflation factor (VIF) is larger than 10. This indicates the occurrence of multicollinearity which means that there is some exact linear relationship among explanatory variables. The occurrence of multicollinearity may influence the stability of the regression coefficients. Multicollinearity could be a common problem for regression models with partial adjustment structure, where the lagged dependent variable is incorporated as one of independent variables. The lagged composition can be linear to some other explanatory variables. For example, in this study, the lagged LNTPC (the natural logarithm of TPC) is linear to LNGDP (the natural logarithm of GDP) in this model. However GDP is the critical factor to petrol consumption analysis. Therefore GDP cannot be removed from this model, even with high VIF values.

The second problem of this model is that LNRPP (the natural logarithm of RPP) is not statistically significant at the current period but the pervious period (LNRPP1). Thus, the price elasticity estimated from this model is not comparable to evidences from previous studies, in which all estimated price elasticities are significant at the current time period. Last but not least, it is also difficult to use the estimated results from this model to calculate forecasts, as it has the coefficients of dummy variables in numbers and elasticities in percentages simultaneously, which represent two different effects on the dependent variable. For estimating forecasts, seasonality should be removed from the time series of TPC, in order to quantify the effect on petrol consumption only due to changes in petrol price or income.

A time series consists of trend-cycle, seasonality and randomness. The trend-cycle component refers to changes in the level of a time series, randomness is stochastic fluctuations in a data series, and seasonality is the variation that seasonal factors cause in a series (Makridakis *et al.*, 1998). A centred four moving average ($2x4$ MA) technique can be used to average out the seasonal variation and randomness of a quarterly time series by giving equal weight to each quarter, so as to present the trend and cycle only (Makridakis *et al.*, 1998). Similarly, for a monthly time series, a centred 12 MA is used to achieve trend-cycle component. From an economics point of view, trend-cycle is of the primary significance. In this study, the original time series of petrol consumption is denoted as seasonal TPC, and the one after the $2x4$ MA transformation is denoted as nonseasonal TPC.

Figure 1 shows the original data of total petrol consumption (seasonal TPC), and Figure 2 shows the nonseasonal TPC scatterplots after averaging out seasonality and randomness by a centred four MA. Compared with the patterns of seasonal TPC given in Figure 1, the patterns of nonseasonal TPC are smoother and clearer.

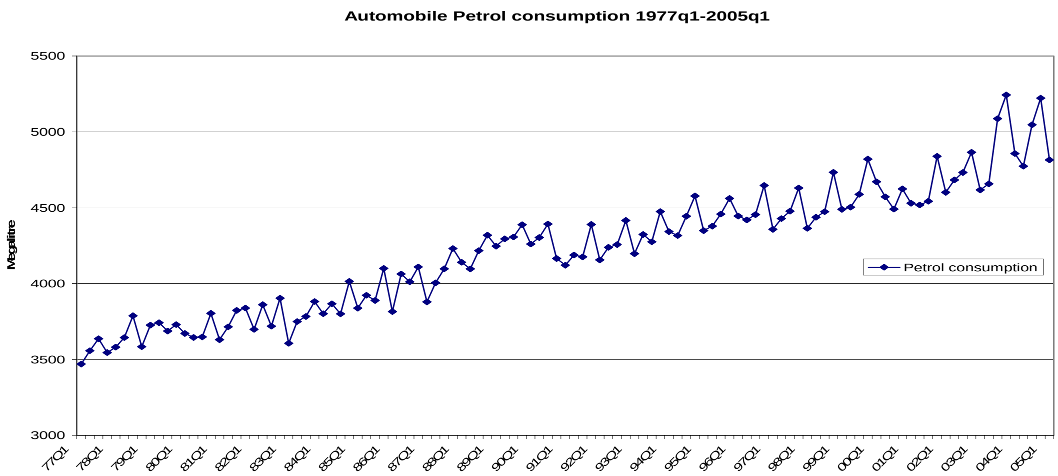

Figure 1: Total Road Petrol Consumption in Australia (Seasonal TPC)

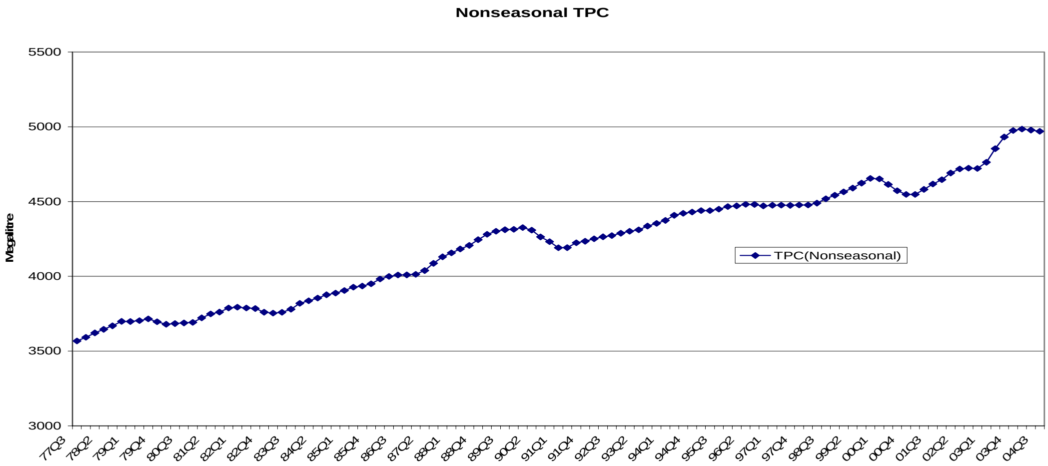

Figure 2: Nonseasonal TPC

The beginning two and final two terms of the data will be removed after the process of a centred four MA. As the original data set for modelling and estimation ranges 1997q1 to 2005q1, the nonseasonal time series after a $2x4$ MA transformation starts at 1977q3 and ends at 2004q3. The new regression result with nonseasonal TPC is given in Table 2.

Table 2: Regression Result Using Nonseasonal TPC

	B	Std. Error	t	Sig.	VIF
(Constant)	2.947	.427	6.900	.000	
LNGDP	.231	.031	7.421	.000	33.956
LNRPP	.076.	.035	-2.160	.033	1.061
LNTPC4	.365	.086	4.245	.000	34.286

The F statistic is 1550.080, which is much larger than the F value in the previous model using seasonal TPC (425.920). The value of adjusted R square becomes 0.978, compared with 0.961 for the previous model. Moreover, there is no obvious pattern in the regression residual scatterplots, which means that residuals are random and uncorrelated from period to period. These suggest that the new model with nonseasonal TPC is better than the previous one using seasonal TPC, for the purpose of forecasting.

All independent variables are statistically significant at 95 percent of confidence level. The coefficient of LNRPP (short-run price elasticity) is statistically significant at the current period, with the value of -0.076. The coefficient of LNGDP shows that the short-run income elasticity is 0.231. The partial adjustment structure (lagged TPC) is significant at the fourth lag. For quarterly data, this refers to the same quarter but one year before. Studies using yearly data (e.g., Sterner and Dahl, 1992) have indicated that the partial adjustment structure is significant at the first lag, which is also one-year period earlier. The coefficient of partial adjustment (s) is 0.635 ($1-0.365$). Long-run elasticities can be calculated through dividing the estimated short-run elasticities by s. The long-run elasticities with respect to price and income are -0.12 and 0.364 respectively. The intermediate-run price and income elasticities can be estimated by the static model without the partial adjustment structure. The corresponding results are -0.105 and 0.361 respectively. The estimated results support the common finding by many researches that petrol demand tends to be more income elastic than price elastic (Dahl, 1994; Wohlgemuth, 1997; Kayser, 2000; De Vita *et al*., 2006).

One of the recent studies in estimating the road transport fuel demand elasticities with respects to price and income for Australia is Samimi (1995). The result comparison of two studies is given in the following table.

Table 3: Result Comparison between this Study and Samimi (1995)

	Samimi (1995)	**This study**
Energy type	Petrol and diesel	Petrol
Country	Australia	Australia
Data	Time series	Time series
Periodicity	Quarterly	Quarterly
Time frame	1980 to 1993	1977 to 2005
Methodology	Cointegration with error correction model	Linear regression with partial adjustment
Elasticities		
Short-run price	insignificant	-0.076
Intermediate-run price	N/A	-0.105
Long-run price	-0.12	-0.12
Short-run income	0.25	0.231
Intermediate-run income	N/A	0.361
Long-run income	0.52	0.364

The long-run price elasticity estimated in this study is the same as Samimi's results (-0.12 for both), despite the short-run estimate is insignificant in Samimi (1995). The income elasticities estimated from two studies are similar in the short run (0.231 for this study and 0.25 for Samimi's). They have different long-run estimates, and also this study's result is 0.364, which is smaller than Samimi's 0.52. This can be partly explained by the conclusion of Espey (1998) that short-run income elasticities have tended to be constant over time, while long-run income elasticities have decreased over time.

The estimation of transport fuel elasticities is usually classified into short run, intermediate run and long run. Short run is within one year in some studies (e.g., Goodwin *et al.*, 2004), however it may be up to two years in other studies (e.g., Litman, 2007). Whether the short run for petrol consumption is within one year or two years is also evaluated in this study, as it employs seven quarters' horizon for testing the accuracy of forecasts. The short-run price and income elasticities are applied to achieve the forecasts for the beginning four quarters. For the rest of three quarters, the short-run and intermediate-run elasticities are used, if the short-run elasticities produce more accurate forecasts (with smaller MAD) than the intermediate-run, then it can be concluded that short run should be within two years. If the intermediate-run elasticities produce smaller MAD, short run should be within one year. The comparison is given in the following table (assuming the effects of price and income are reversible).

Table 4 Forecasts Estimated by Using Different Elasticities

Year/Quarter	Real values ($2x4$ MA)	Short-run elasticities		Short-run + intermediate-run	
		Forecasts	Errors	Forecasts	Errors
04Q4	4966.86	4964.45	2.41	4964.45	2.41
05Q1	4917.22	5039.38	-122.16	5039.38	-122.16
05Q2	4824.19	5048.69	-224.49	5048.69	-224.49
05Q3	4771.62	5040.78	-269.15	5040.78	-269.15
05Q4	4736.19	5036.49	-300.30	5073.98	-337.79
06Q1	4731.77	5095.29	-363.52	5165.91	-434.14
06Q2	4755.54	5032.45	-276.90	5075.58	-320.04
		MAD=	**222.71**	MAD=	244.31

When applying the short-run elasticities for the entire seven quarters' forecasting horizon, the value of MAD is smaller. Therefore, short run should be up to two years for road vehicle petrol demand elasticities. Long-run forecasts have not been evaluated here, as long run is at least over five years (Eltony, 1993) and even over 15 years (Litman, 2007). Evaluating long-run forecasts requires more hold out sample data. This will leads to the loss in the degree of freedom, which may negatively impact the extrapolation of patterns in the time series.

For regression modelling, only nonseasonal data is used to estimate forecasts. The rest of seven models employ both seasonal TPC and nonseasonal TPC for predicting petrol demand. These results are listed as follows.

6.3 ARIMA Modelling Results

According to Box-Jenkins method, ARIMA modelling is estimated based on the Sample Autocorrelation Function (SAC) and the Sample Partial Autocorrelation Function (SPAC). After estimating the appropriate seasonal and nonseasonal ARIMA models, the forecasts are given in the following table.

Table 5: Forecasts Estimated from Seasonal and Nonseasonal ARIMA Modelling

Year/Quarter	Seasonal ARIMA Forecasts	Year/Quarter	Nonseasonal ARIMA Forecasts
05Q2	4809.25	04Q4	4964.14
05Q3	5037.24	05Q1	4960.28
05Q4	5219.94	05Q2	4985.36
06Q1	4880.98	05Q3	5003.81
06Q2	4869.63	05Q4	5022.96
06Q3	5098.52	06Q1	5039.20
06Q4	5282.66	06Q2	5051.95

Forecasts can also be estimated from the rest six models. After obtaining all models' results, the MAD technique is used to evaluate the corresponding forecasting performance of each model based on either seasonal data or nonseasonal data, given in Table 6 and Table 7 respectively.

Table 6: MADs of Different Forecasting Models Using Seasonal Data

Year/Quarter	**Real values**	**Linear Trend**			**Quadratic Trend**			**Exponential Trend**			**Single Exponential Smoothing**		
		Forecasts	Errors	Error%	Forecasts	Errors	Error%	Forecasts	Errors	Error%	Forecasts	Errors	Error%
05Q2	4790.63	4901.86	-111.23	-2.32%	4899.60	-109.23	-2.27%	4902.30	-111.67	-2.33%	4958.81	-168.18	-3.51%
05Q3	4633.43	4913.77	-280.34	-6.05%	**4911.39**	-278.22	-6.00%	4915.87	-282.43	-6.10%	4958.81	-325.38	-7.02%
05Q4	4891.58	4925.68	-34.10	-0.70%	**4923.18**	-31.86	-0.65%	4929.47	-37.89	-0.77%	4958.81	-67.23	-1.37%
06Q1	4726.00	4937.58	-211.59	-4.48%	4934.96	-209.24	-4.42%	4943.11	-217.11	-4.59%	4958.81	-232.82	-4.93%
06Q2	4596.84	4949.49	-352.64	-7.67%	4946.74	-350.18	-7.61%	4956.78	-359.94	-7.83%	4958.81	-361.97	-7.87%
06Q3	4791.90	4961.39	-169.49	-3.54%	4958.52	-166.91	-3.48%	4970.50	-178.60	-3.73%	**4958.81**	-166.91	-3.48%
06Q4	4923.30	4973.30	-50.00	-1.02%	4970.30	-47.29	-0.95%	4984.25	-60.95	-1.24%	**4958.81**	-35.51	-0.72%
		MAD = 172.77 3.68%			**MAD = 170.14 3.63%**			MAD = 178.37 3.80%			MAD = 194.00 4.13%		

Year/Quarter	**Real values**	**Holt's Linear Method**			**Holt-Winters' Method**			**ARIMA**		
		Forecasts	Errors	Error%	Forecasts	Errors	Error%	Forecasts	Errors	Error%
05Q2	4790.63	4978.34	-187.71	-3.92%	4900.09	-109.46	-2.28%	**4809.25**	-18.62	-0.39%
05Q3	4633.43	4991.47	-358.03	-7.73%	5042.89	-409.46	-8.84%	5037.24	-403.81	-8.72%
05Q4	4891.58	5004.59	-113.01	-2.31%	5209.74	-318.16	-6.50%	5219.94	-328.36	-6.71%
06Q1	4726.00	5017.71	-291.72	-6.17%	4918.55	-192.56	-4.07%	**4880.98**	-154.99	-3.28%
06Q2	4596.84	5030.83	-433.99	-9.44%	4950.29	-353.45	-7.69%	**4869.63**	-272.79	-5.93%
06Q3	4791.90	5043.95	-252.05	-5.26%	5094.43	-302.53	-6.31%	5098.52	-306.62	-6.40%
06Q4	4923.30	5057.08	-133.78	-2.72%	5262.84	-339.54	-6.90%	5282.66	-359.36	-7.30%
		MAD= 252.90 5.36%			MAD= 289.31 6.09%			MAD= 263.51 5.53%		

Table 7: MADs of Different Forecasting Models Using Nonseasonal Data

Year/Quarter	Real values (2X4MA)	Linear Trend			Quadratic Trend			Exponential Trend			Single Exponential Smoothing		
		Forecasts	Errors	Error%	Forecasts	Errors	Error%	Forecasts	Errors	Error%	Forecasts	Errors	Error%
04Q4	4966.86	4868.93	97.93	1.97 %	4859.51	107.35	2.16%	4905.58	61.27	1.23 %	4970.05	-3.19	-0.06 %
05Q1	4917.22	4880.69	36.52	0.74 %	4870.76	46.46	0.94 %	**4919.34**	-2.13	-0.04 %	4970.05	-52.84	-1.07 %
05Q2	4824.19	4892.46	-68.27	-1.42 %	**4882.00**	57.81	-1.20 %	4933.15	-108.95	-2.26 %	4970.05	-145.86	-3.02 %
05Q3	4771.62	4904.22	-132.60	-2.78 %	**4893.23**	121.61	-2.55 %	4946.99	-175.36	-3.68 %	4970.05	-198.43	-4.16 %
05Q4	4736.19	4915.99	-179.80	-3.80 %	**4904.46**	168.27	-3.55 %	4960.86	-224.68	-4.74 %	4970.05	-233.87	-4.94 %
06Q1	4731.77	4927.75	-195.98	-4.14 %	**4915.67**	183.90	-3.89 %	4974.78	-243.01	-5.14 %	4970.05	-238.28	-5.04 %
06Q2	4755.54	4939.51	-183.97	-3.87 %	4926.87	171.33	-3.60 %	4988.74	-233.19	-4.90 %	4970.05	-214.51	-4.51 %
		MAD= 127.87		2.67%	**MAD= 122.388**		**2.56%**	MAD= 149.80		3.14%	MAD=	155.28	3.26%
Year/Quarter	Real values (2X4MA)	Holt's Linear Method			Holt-Winters' Method			ARIMA			Regression		
		Forecasts	Errors	Error%	Forecasts	Errors	Error%	Forecasts	Errors	Error%	Forecasts	Errors	Error%
04Q4	4966.86	4962.24	4.62	0.09%	4984.13	-17.27	-0.35%	4964.14	2.71	0.05%	**4964.45**	2.41	0.05 %
05Q1	4917.22	4954.43	-37.21	-0.76 %	4998.21	-80.99	-1.65 %	4960.28	-43.07	-0.88 %	5039.38	-122.16	-2.48 %
05Q2	4824.19	4946.62	-122.43	-2.54 %	5012.29	-188.09	-3.90 %	4985.36	-161.17	-3.34 %	5048.69	-224.49	-4.65%
05Q3	4771.62	4938.81	-167.18	-3.50 %	5026.36	-254.74	-5.34 %	5003.81	-232.18	-4.87 %	5040.78	-269.15	-5.64 %
05Q4	4736.19	4931.00	-194.81	-4.11 %	5040.44	-304.25	-6.42 %	5022.96	-286.78	-6.06 %	5036.49	-300.30	-6.34 %
06Q1	4731.77	4923.19	-191.42	-4.05 %	5054.52	-322.75	-6.82 %	5039.20	-307.43	-6.50 %	5095.29	-363.52	-7.68 %
06Q2	4755.54	**4915.38**	-159.83	-3.36 %	5068.60	-313.05	-6.58 %	5051.95	-296.41	-6.23 %	5032.44	-276.90	-5.82 %
		MAD= 125.36		2.63%	MAD= 211.59		4.44%	MAD= 189.96		3.99%	MAD= 222.71		4.67%

Some important findings from the estimated MAD results include:

1. When using seasonal data, the quadratic trend model is the best-forecasting model, with the lowest MAD value of 170.14 and forecasting error of 3.63 percent. When using nonseasonal data, the best one is also the quadratic trend model, with the MAD value of 122.388 and forecasting error of 2.56 percent. It also can be identified that the simple models (except Holt-Winters' method) outperform those sophisticated models (e.g., ARIMA).

2. For each model, the MAD value based on nonseasonal data is smaller than the MAD based on seasonal data. Therefore, the forecasting performance of each model improves after replacing seasonal data with nonseasonal data.

3. For each model, its forecasting accuracy tends to decrease, as the forecasting horizon is increasing.

4. Most estimated forecasts are larger than the real value of observations, because most forecast errors are negative.

5. The demand for road petrol in Australia tends to increase over time, according to the forecasts from all models.

Although quarterly seasonal data and nonseasonal data (after the centred four MA transformation) are different at the same quarter, theoretically, there should be no difference after aggregating quarterly data into yearly data, if the seasonal component of each quarter keeps constant from year to year. A centred four MA transformation is a combination of two simple four moving averaging processes, given in the following equations.

$$T_{2.5} = \frac{(Y_1 + Y_2 + Y_3 + Y_4)}{4} \quad \text{(Simple four MA)}$$

$$T_{3.5} = \frac{(Y_2 + Y_3 + Y_4 + Y_5)}{4} \quad \text{(Simple four MA)}$$

$$T_3 = \frac{T_{2.5} + T_{3.5}}{2} = \frac{(0.5Y_1 + Y_2 + Y_3 + Y_4 + 0.5Y_5)}{4} \quad \text{(Centred four MA)}$$

For quarterly data, Y_1 and Y_5 are at the same quarter in two different years. Thus, the seasonal and random components are not removed but averaged out by giving equal weight (0.25) to each quarter. Therefore, two sets of yearly data should be equal if adding up seasonal and nonseasonal quarterly data into yearly data. By adding up quarterly figures into yearly figures from 1978 to 2005, the mean absolute difference in percentages between seasonal and nonseasonal data (yearly) is only 0.22 percent over the same period. This slight difference can be explained by the inconstant seasonal component in different years.

Considering (1) the slight difference between yearly seasonal and nonseasonal TPC, and (2) more accurate forecasts when using nonseasonal data, the quadratic trend model with nonseasonal TPC is selected as the final model for forecasting. The result shows the annual demand for petrol in the Australian road transport sector is expected to reach 22,179.44 megalitres by 2020 which is a 20.80 percent increase relative to the year of 2000, given that the actual petrol consumption in 2000 is 18,360.60 megalitres. The passenger car sector has been the main road petrol consumer in Australia. In 2000, around 88 percent of road petrol was consumed by automobiles (ABS, 2001). This share has only dropped by three percent, according to the latest issue of Survey of Motor Vehicle Use (ABS, 2007), and now automobiles account for approximately 85 percent of the total road petrol consumption in Australia. Assuming this figure to keep constant at 85 % until 2020, 18,852.52 megalitres of petrol would be consumed by automobiles by 2020, which is approximately 30 percent higher than automobile petrol consumed in 2000, and it is expected to exceed the total road transport petrol consumption in 2000.

The rising demand for petrol will produce more greenhouse gas emissions. Facing the future scenario of increasing emissions, the key challenge is to develop decision support tools to analyse and evaluate the impacts of potential policies on greenhouse gas emissions, so as to find the appropriate way to reducing CO_2 from passenger cars. As the above forecasting models are all developed under the "business-as-usual" scenario, their common limitation is the absence of estimating the impacts of different policies or intervention on automobile petrol demand and emissions. The next section will preset TRESIS results of evaluating the impacts of several selected instruments on the reduction of passenger car emissions.

6 Policy Scenarios

Three different policies are evaluated by TRESIS 1.4, including a carbon tax, a congestion charge and improved fuel economy, and none of them has been implemented in Australia yet. Specifically, three policies are a 50c/kg carbon tax, a 5c/km metropolis-scale congestion charge (or variable user charge) and a five-percent annual improvement in the average fuel economy of Sydney automobiles. The scenarios in 2018 are presented in the following table.

Table 8: Policy Scenarios of Selected Instruments in 2018 (Policy enacted from 2011)

Indicators	50c/kg Carbon tax	5c/km Variable user charge 7am – 6pm	Fuel efficiency improvement by 5% annually
TCO_2 (kg)	-5.9%	-2.95%	-22.57%
TVKM (km)	-5.57%	-2.92%	5.02%
VehOpCost	33.0%	-2.95%	-22.88%
Government revenue ($)			
TGovtVehReg	-0.42%	-0.16%	0.24%
TGovtExcise	-5.91%	-2.95%	-22.55%
TGovtCarbT	9.375E+08	0	0
TGovtSalesT	1.14%	-0.202%	-4.14%
TPark	-0.83%	2.78%	0.49%
TRCong	0	2.076E+09	0
TPT	32%	41.99%	-15.69%
Subtotal	*30.53%*	*65.02%*	*-13.17%*
Commuter Mode growth			
TDA	-3.72%	-4.77%	1.88%
TRS	-3.34%	-5.26%	1.71%
TTrain	27.88%	33.56%	-13.87%
TBus	19.77%	33.06%	-10.36%

This study focuses on the environment impacts of different policies, therefore total annual carbon dioxide (TCO_2) is the most significant indicator. According to TRESIS results, although pricing and taxation instruments would positively stimulate public transport, they are far less effective for reducing CO_2 compared with technological advancement. A five-percent improvement in passenger car fuel efficiency from 2011 to 2018 would lead to a 22.57 percent reduction in CO_2 (TCO_2) by 2018. While, a 50c/kg carbon tax is expected to reduce emissions by 5.9 percent only, and a 5c/km variable charge could decrease CO_2 by 2.95 percent. Moreover the carbon tax would add an additional 33 percent annual cost in driving cars (VehOpCost). Hence, a carbon tax is not a cost-effective tool to decrease CO_2 emissions in Australia; even the government would gain 30.53 percent extra in revenue. Annual car operating cost is expected to decrease by 22.88 percent through improvements in car fuel efficiency. Therefore improved fuel efficiency is a relatively cost-effective approach to the reduction of CO_2, although there would be some cost in replacing old vehicles.

However, one concern is that improved car fuel efficiency would increase car usage and reduce public patronage. Results show that the modal share for car drive along (TDA) would increase by 1.88 percent in 2018; meanwhile the model share for train travel (TTrain) would decrease by 13.87 percent. There would be a 5.02 percent increase in total annual vehicle kilometres (TVKM), and the number of passenger cars is expected to grow by 0.17 percent approximately. All these changes would put great challenges to road systems and create problems, such as traffic congestion.

Weighing each policy's benefits and limitations, in stead of a single approach, a combined strategy of the vehicle technological advancement (improved car fuel efficiency) with pricing instrument (a variable user charge) is suggested to reduce car usage and greenhouse gas emissions in Australia. A carbon tax is not considered, as its cost is much higher. As an example, this combined policy scenario of a five-percent of car fuel economy improvement and a 5c/km variable user charge is also estimated. 25.39 percent of CO_2 emissions would be reduced by 2018, which is more effective than either of the two policies. Moreover, this combined strategy would significantly stimulate public transport usage (e.g., a 14.77 percent increase in the bus-travel model share). Meanwhile, the model share of private car is expected to decrease (e.g., a 2.064 percent decrease for driving alone). Therefore, emission and congestion problems could be addressed simultaneously. However, public transport services should be improved to support the successful implementation of the combined strategy so as to address the increasing public patronage.

7 Conclusions

This paper has used eight models (classified into simple and complicated methods) to estimate petrol demand in the Australian road transport sector. The reason for using different models is to compare forecasts from various models so that the most accurate forecasting model can be selected to predict petrol demand from 2007 to 2020. To evaluate forecasting performance of different models, a hold out sample was employed to test the effectiveness of corresponding forecasts. This would contribute to answering the question that which method is appropriate to petrol demand forecasting. This question has been remained unanswered, as previous studies have not measured the errors between the forecasts and the actual values of fuel demand, but tended to use increasingly sophisticated methods to estimate elasticities and forecasts.

However, the comparison of different models through the MAD technique shows that simple methods (e.g., the quadratic trend model) have produced better forecasting results than sophisticated methods (e.g., ARIMA). This finding is supported by empirical studies (e.g., Fildes and Makridakis, 1995; Fildes *et al.*, 1998) which have concluded that simple forecasting methods perform at least as well as statistically sophisticated ones, mainly because simple methods better extrapolate the patterns of a time series. Although these empirical studies are not in the area of fuel demand, they have made the conclusion based on a large number of surveys from various forecasting areas. Therefore, the key conclusion of this study is that sophisticated methods do not always make better forecasting than simple models, and to purely improve the complexity of forecasting models does not always lead to more accurate forecasts. However, some simple statistical techniques may improve forecasting performance significantly by making data more suitable for predicting. For example, in this paper, the estimated forecasts of petrol demand became more accurate after using a centred four moving average to average out seasonal and random components of the time series.

Therefore, the forecasting performance is not determined by the sophistication of a model, but the appropriateness of a model. According to Makridakis *et al.* (1998), the selection of a proper forecasting model needs to address the following key elements.

1. *Objectives of forecasting.* If the key purpose is to better understand how the dependent (such as petrol consumption in this study) is influenced by other factors, regression methods should be developed to identify and measure the specific influence. However when achieving the forecasts is the primary reason, time series methods are more suitable, such as ARIMA.

2. *Characteristics of time series.* A time series consists of seasonality, trend-cycle and randomness. Seasonality is not a significant factor to the method selection. When the trend-cycle dominates the randomness in a time series, sophisticated methods are more appropriate. However if the randomness is stronger than the trend-cycle, simple methods are preferred.

3. *The number and frequency of forecasts.* From a practical point of view, simple methods are suitable for the situation where a larger number of forecasts are frequently required, as sophisticated models require more effort time.

It needs to be noted that compared with simple models, sophisticated models might be more suitable in delivering improved goodness of fit of the history, however they do not always deliver more accuracy in predicting the future. This paper also recommends using some hold out time periods to investigate the effectiveness of various forecasting models so as to select the appropriate mode

This paper has used both elasticity and time series approaches. Elasticities are estimated from the regression model with partial adjustment. The estimated price and income elasticities are -0.076 and 0.231 respectively in the short run, and -0.12 and 0.364 in the long run. The estimated results support the common finding from many previous fuel demand studies that petrol consumption is more income elastic, compared with the effect of price.

The selected best-forecasting model indicates that the demand for road transport petrol in Australia is expected to increase by over 20.80 percent from 2000 to 2020, in which automobile petrol demand would increased by approximately 30 percent over the same period and reach 18,852.52 megalitres by 2020. Besides the increasing scenario of fuel consumption, the passenger car sector would continue to act as the largest contributor to total transport emissions in Australia. Therefore, the key challenge is to find the appropriate way to decrease CO_2 without negative impacts on the national economy. TRESIS is employed to achieve this goal, and it suggests a mix of improved fuel efficiency and a variable user charge to address emissions and congestion problems from automobiles, in the context of cost effectiveness. However, the successful implementation of this strategy is based on the effectiveness of public transport. Public transport service should be improved in terms of frequency, capacity and reliability to accommodate the increasing patronage so as to satisfy the needs for transportation due to economic and individual requirements.

The final conclusion of this paper is that automobile petrol demand studies will continue to be of particular interest to academics and governments throughout the world, because of the major theme that is to discover effective policies to reduce reliance on fossil fuel (particularly petrol), to ensure energy security and to protect the environment.

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