Aggregate Road Passenger Travel Demand in New Zealand

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Abstract

Road passenger transportation, which includes both private vehicles and public transport, is regarded a vital link that connects people and economic activities across New Zealand (NZ)[1]. Although a wealth of past literature has examined the demand for private and public transport both individually and jointly worldwide, little evidence was found analysing the demand for different road passenger transport choices as a system of equations. Given the fact that road passenger transport modes are considered substitutes to one another, there is a strong possibility that an interrelationship exists between the travel demand functions, primarily due to the correlation between their disturbances, a research gap that was thus discussed and addressed in this study. This paper uses the seemingly unrelated regression (SUR) method to develop an aggregate road passenger travel demand model. The Breusch-Pagan test of independence confirms the existence of correlated error terms in the three demand equations. Empirical results from the SUR model delivers various policy implications in terms of achieving a reduction in the demand for both petrol and diesel cars, and also promoting the use of public transport.

Keywords

Road passenger transport demand, car ownership, public transport, seemingly unrelated regression, correlated disturbances

1. Introduction

The Organisation for Economic Co-operation and Development (OECD) [1] states that transport is a main component of economic development, both as a sector in itself and as an important factor input to most other economic activities. Transport, and its associated infrastructure, therefore, has always played a key role in NZ's economic prosperity. Based on a report from Ministry for the Environment (MfE) [2], compared to other transport modes, road transport dominates NZ's travel pattern. Within road transport, according to the Ministry of Transport (MoT) [3], in 2013, light fleet which consists of light passenger

[1]In terms of public transport, buses are the most common form of public transport mode in NZ as all cities and most towns have bus services available. Rail is excluded from this category as this service is only available in Auckland and Wellington, not across the whole country. Therefore the public transport mode for road passengers only refers to buses in this paper.

vehicles (LPVs)[2] and light commercial vehicles (LCVs) account for most of the travel on NZ roads, where LPVs alone contributed over three-quarters of road travel, LCVs a further 16%, and only 8% of road travel was by other types of vehicles. While road transport does provide numerous economic and social benefits, it also generates several negative externalities that have major adverse impacts on health and environment. For instance, road transport is the primary cause of harmful air pollutants in some urban areas where road traffic and congestion are concentrated. Rivers and streams can be polluted by contaminated run-off from arterial roads and highways, and vehicle wastes such as used batteries and tyres present significant management issues as these require careful disposal.

At the national level, use of road transport is escalating. In terms of private vehicles, as the MfE warns, on average, New Zealanders are driving further, owning more cars, choosing an increasing engine size; and the fleet profile is older. **Figure 1** shows motor vehicle and passenger car ownership among 34 OECD members. NZ has the highest motor vehicle ownership (motor vehicle/population ratio) and the fourth highest passenger car ownership (passenger car/population ratio) compared to the other OECD members. This high level of automobile dominance in NZ is at least in part a result of past government transport policies which makes cars the "default" form of personal transport for New Zealanders, including the development of automobile-oriented urban forms and highway improvements in 1950s that have had the effect of encouraging car travel, and the deregulation of the vehicle industry from 1980s which removed import quotas and reduced import tariffs on vehicle imports from overseas, making imported cars more affordable for domestic consumers.

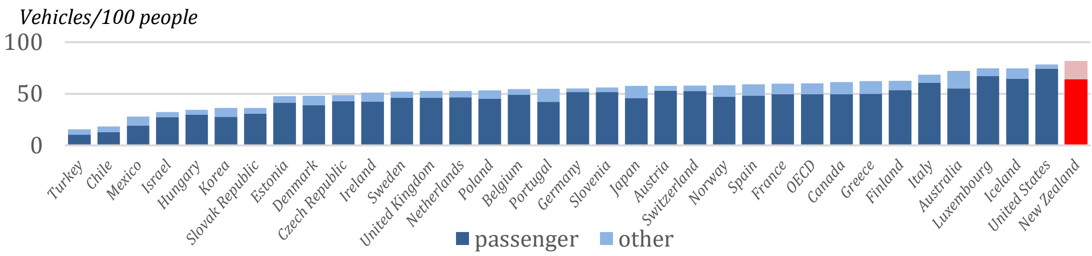

Figure 1. Motor Vehicle Ownership among OECD members in 2010[3]

Although public transport patronage has been growing in recent years and has gained greater social acceptability and contributed to the promotion of environmentally friendly lifestyles, the percentage of people travelling by public transport still remains relatively low compared to car trips. Thus, we can conclude that New Zealanders rely primarily on private vehicles for travel, supplemented with public transportation. Unsurprisingly, due to this car-dependence, energy consumption has increased, congestion on local roads and motorways worsens, and CO_2 emission from the road transport sector increases. Dargay and Gately [4] pointed out that globally, the transportation sector is the most rapidly growing sector in terms of energy and particularly fuel consumption, and it is responsible for a substantial share of the global fossil fuel combustion-related CO_2 emission. Available statistics indicate that in 2005, CO_2 emissions from transport sector represent 30% of overall CO_2 emissions from fossil fuel combustion in OECD countries. In NZ, according to the TomTom traffic index [5], Auckland and Wellington are considered to be the second and third most congested cities among Australasian metropolitan areas, just behind Sydney. In dollar terms, Wallis and Lupton [6] estimated that congestion cost the Auckland region 1.25 billion NZD annually when compared to free flow conditions.

Moreover, per capita of CO_2 emissions are relatively small; ranked fourth in the OECD, just behind the United States, Canada and Australia, in 2010. At the same time, NZ is expecting considerable population growth through an increase in natural population and immigration. By 2031, Statistics NZ [8] forecasted the total population in NZ is to grow to approximately 5.2 million residents. This high level of motor vehicle ownership, coupled with the anticipated huge boost in population, will definitely put greater pressure on the NZ road transport system and its associated infrastructure.

While significant research has been devoted to the total demand for cars, little research has been done on the demand for cars of different fuel types (i.e. petrol and diesel), a classification that is exceedingly useful when examining road user's transport mode preference in the light of energy consumption, CO_2

[2] The MoT defines cars as LPVs. LPVs are passenger vehicles that weigh less than 3,500 kg. This group also includes passenger vans, and sport utility vehicles (SUVs).

[3] Data source: OECD [7]. Note: 2009 data for Canada and Ireland; 2011 data for Australia, Iceland, Japan, Mexico, NZ and Switzerland. 2010 data for the other countries. The OECD totals are based on OECD Secretariat's estimates.

emissions and policy implications. In addition, the demand for public transport has never been modelled as a group along with its major substitute. The purpose of this study, therefore, is to fill the empirical gap in the past literature by developing a multi-equation model of the road passenger transport sector, by proposing and answering the following three key research questions:

1. Whether the disturbances of the demand for the three main road passenger transport choices, namely, petrol cars, diesel cars and buses are correlated?

2. What are the factors affect the demand for road passenger travel in NZ?

3. And by how much will these factors impact on the demand for road passenger travel in NZ?

The present study is thus the first to address the empirical problems identified above by applying a seemingly unrelated regression (SUR) model, using quarterly time series data in NZ from 2001Q1 to 2015Q2. The advantage of the SUR model is that dependent variables which represent aggregate road passenger travel demand (i.e. petrol cars, diesel cars, and buses) are considered as a group when they bear a close conceptual relationship to one another, brought forward by the potential correlation between their error terms. The objective of this paper is thus to develop an aggregate travel demand model of NZ's major road passenger transport modes, by taking into detailed account the effects of correlation between their error terms. The next section discusses findings from the literature. Section three specifies the model and section four outlines the data used in this study. Section five presents the results of stationarity test on all of the variables. Section six shows the estimated results. Section seven presents the test results for cointegration and structural breaks. The last section concludes and suggests some possibilities for future research.

2. Literature Review

For the past few decades, extensive effort has been devoted to investigating various factors affecting the demand for private vehicles, and the demand for public transport around the world. From past research, per capita income, inflation, national unemployment rate, and population indicators are identified as important determinants of both private vehicle ownership and public transport use at the macroeconomic level.

Based on data from a selection of the OECD countries for the time period 1970-1992, Schipper [9] found that per capita income has a major impact on car ownership. Prevedouros and An [10] concluded that income, measured by GDP per capita, along with population and unemployment rate, are key determinants of aggregate car ownership in both developing and developed Asian countries. Both studies reveal that the car ownership increases with an increase in the level of income. Paravantis and Georgakellos [11] estimated an aggregate car ownership model and an aggregate bus fleet model using data from the period 1970 to 2002 in Greece. For the car ownership model, the authors have identified that the percentage of adult population, GDP per capita, bus vehicle-kilometres-travelled (VKT) and car occupancy as important car ownership determinates. For the bus fleet model, percentage of adult population, GDP per capita, and inflation are found to have significant impacts on the bus fleet demand, measured by the number of total buses per 100,000 people.

The rate of unemployment may also be a variable of interest as it is plausible to assume that for those who are unemployed, the ability to possess and afford private transport can be outside their financial budgets, implying there is no other option but to rely on public transport for travel. Therefore we should expect a negative relationship between the unemployment rate and the demand for car travel, but positive relationship between unemployment rate and the demand for public transport.

Empirically, fuel costs were found to be another important factor that affects road passenger transport demand. By applying an asymmetric error correction model, recent research by Chao *et al*. [12] indicated that gasoline prices have significantly positive effects on the two forms of public transport in Taiwan, bus and mass rapid transit (MRT) use. Empirical results from past literature also support the authors' conclusion that elasticity of public transport demand with respect to gasoline price is often inelastic. In other words, the absolute value of price elasticity is ranged somewhere between 0 and 1, as found in various previous studies[4].

Vehicle costs, as Rive *et al*. [17] argued, are inherently hard to measure because the description generally covers not only the cost of purchasing a car, but also the ongoing costs associated with car ownership, such as road costs, repairs, maintenance and insurance. Inflation, therefore, has been used as a proxy to capture such costs in a few studies, because it is plausible to assume that an increase in inflation makes vehicle costs such as maintenance, toll fees, and insurance more expensive, thus reducing the demand for travel. Empirical evidence from Paravantis and Prevedouros [18] showed that inflation had significantly negative effect on the first order autoregressive railway passenger demand models based on the data from 1970 – 1998 in Greece.

[4] See Wang and Skinner [13], Haire and Machemehl [14], Currie and Phung [15] [16] for details.

Only a few studies have examined the relationship between the usage of private cars and public transportation. For example, by applying a binary probit model, Kitamura [19] found that changes in car usage could affect public transportation usage; however, on the other hand, changes in public transport usage had only minor impacts on car usage. This finding implies that the increase in car use, which is a consequence of increasing car ownership, may not be suppressed by improving public transport service.

In the context of NZ, Conder [20] estimated a car ownership model for NZ using aggregate national-level time series data. The aggregate car model was split into two parts: car ownership saturation level and path to saturation. GDP per capita, car price index, and a time trend were included as explanatory variables for the analysis of the likely growth path to saturation estimated using OLS.

Wang [21] conducted a time series analysis to determine the factors that influence the demand for public transport (bus and rail) patronage in both short-term and long-run for NZ's three major cities (Auckland, Wellington and Christchurch), using quarterly data from 1996-2008. Using a partial adjustment (PA) model, the relationship between patronages, measured as the total number of bus or train trips per capita, was modelled as a function of several factors including: service level, real fare, real disposable income per capita, car ownership and real fuel price. The results deliver two important implications. Firstly, fuel price exhibits a positive effect on public transport patronage in all three cities. Secondly, the effect of factors varied across the three cities. For instance, in terms of statistical significance, bus fares were found to have an impact on bus demand in Wellington and Christchurch, but not in Auckland. While in terms of magnitude, income per capita exhibited a negative effect on rail patronage in Wellington, but a positive effect on rail patronage in Auckland.

In addition, past literature indicates that vehicle occupancy, which represents the vehicle loading factor, should also be considered when estimating car ownership models. However for the NZ case, vehicle occupancy is not considered as a possible factor affecting automobile demand as revealed by the MoT [22], the vehicle occupancy is mostly characterised by single vehicle occupant (i.e. the driver is the only person in the vehicle), with 63% of the total distance driven by the driver only. Therefore due to this reason, vehicle occupancy was not included in this study. Car price, on the other hand, was not considered as a potential predictor because it is more relevant to influence road users' decision on whether to own a car or not, but predicting the demand pattern for road passenger travel. Car ownership is also influenced by the fares of alternative transport modes, therefore the bus fare index was included in this study for all of the demand functions. Moreover, percentage of different age groups (i.e. the ratio of total number of people in a certain age group/total population), a related population metric of interest, is considered another potential indicator for road user's travel demand pattern for both private and public transport demand.

In summary, although a wealth of studies has investigated the demand for cars and public transportation, individually and/or jointly, nationally and internationally, little investigation has been undertaken into the demand for cars by different fuel types, a classification that is crucial in examining road user's transport mode preference in the light of energy consumption, CO_2 emissions, and policy implications. Moreover, given the fact that these private and public transport modes are potential substitutes to one another, to the best of our knowledge, only one study from Jou and Chen [23] had considered the relationship among the demand of different road transportation modes, including public transportation, car, and motorcycle, in various townships in Taiwan by applying a SUR model.

3. Model Specification

3.1. Aggregate road passenger transport demand functions

The individual demand equation of each aggregate road passenger transport mode is specified as a function of a number of key determinants, including: income of road passenger transport users, price of the road passenger transport mode, price of substitutionary modes, and some socioeconomic and demographic factors. Therefore the individual demand function for petrol cars, diesel cars and buses can be represented as follows:

$$Q_{it} = f(\, I_t \,, P_{it}, P_t^S, SD_t) \qquad (1)$$

where

Q_{it} = quantity demanded of the i^{th} road passenger transport mode in the t^{th} quarter;

I_t = income of road passenger transport users in the t^{th} quarter;

P_{it} = price of the i^{th} road passenger transport mode in the t^{th} quarter;

P_t^S = price of substitutes of the i^{th} road passenger transport mode in the t^{th} quarter;

SD_t = socioeconomic and demographic factors in the t^{th} quarter

It should be noted that the demand for road passenger travel is normally considered a derived demand as it is not typically demanded just because people prefer travelling (except possibly for a proportion of scenery trips) but because transport supports a range of other activities, which enables passengers to reach a desired destination in order to consume other goods and services. For the case of the demand for buses, in addition to private vehicles, rail service is also one of the main competitors to buses in the context of public transport.

3.2. SUR model

Wang and Kockelman [24] pointed out that, in many transportation studies, variables of interest are often influenced by similar factors and have correlated disturbances. In such cases, these data are best modelled using a system of interrelated equations because their dependent variables share common characteristics. Some transportation examples include: modelling transportation infrastructure performance; analysing the effect of the built environment and residential self-selection on non-work travel; investigating the impact of anticipated transportation improvement on residential land values and estimating static and dynamic urban travel demands[5].

Seemingly unrelated regression (SUR) modelling, firstly discussed by Zellner [29], is thus appropriate when analysing factors affecting aggregate road passenger transport demand where the dependent variables are considered as a group but do not have a direct interaction. Generally speaking, a SUR system represents a generalisation of a linear regression model which comprises several regression equations, allowing each to have its own dependent variable and same or different sets of exogenous regressors. The key feature of the SUR model is that in referring to responses of the same set of observational units, the errors of these equations are likely to be correlated. In this sense, the SUR model can be regarded as either a simplified version of the general linear model where certain coefficients in matrix β are restricted to be equal to zero, or as the generalisation of the general linear model where right-hand-side explanatory variables are allowed to be different in each equation. Moreover, as Rentziou *et al*. [30] noted, although the equations are seemingly unrelated, contemporaneous correlation of error terms exist. Therefore if interlinked equations are estimated using OLS separately rather than SUR model which amounts to feasible generalised least squares (FGLS) with a specification of the variance-covariance matrix, coefficients are consistent but generally inefficient.

Suppose y_{it} is a dependent variable, $x_{it} = (1, x_{it,1}, x_{it,2}, \ldots, x_{it,Ki-1})'$ is a K_i-vector of explanatory variables for observational unit i, and u_{it} is an unobservable error term, where the double index it denotes the t^{th} observation of the i^{th} equation in the system, t denotes time and we refer to this as the time dimension. A classical linear SUR model is a system of N linear regression equations:

$$y_{it} = X_{it} + \mu_{it}\ , \qquad i = 1, \cdots, N, \text{ and } t = 1, \cdots, T \qquad (2)$$

Denote $L = K_1 + \cdots + K_N$. Assume that for each $i = 1, \cdots, N$, $x_i = [x_{i1}, \ldots, x_{iT}]'$ is of full rank K_i, and that conditional on all the regressors $X' = [X_1, \ldots X_T]$, the error terms U_t are *i.i.d*. over time with mean $E[u_t|X] = 0$ and homoscedastic variance $\sum = E(u_t u_t'|X)$. In addition we also assume that $\sum$ is positive definite and denote by σ_{ij} the $(i,j)^{th}$ element of $\sum$, that is, $\sigma_{ij} = E\left(u_{it} u_{ij}|X\right)$. Under this assumption, the covariance matrix of the entire vector of disturbances $U' = \lfloor U_1, \ldots, U_T \rfloor$ is given by $E[vec(U)(vec(U))'] = \sum \otimes I_T$.

Moon and Perron [31] proposed further simplification in notation by stacking the observations either in the t dimension or for each i. For instance, if we stack for each observation t, let $Y_t = [y_{1t}, \ldots, y_{Nt}]'$, $\tilde{X}_t = diag(x_{1t}, x_{2t}, \ldots x_{NT})$, a block-diagonal matrix with $x_{1t} \ldots x_{NT}$ on its diagonal, $U_t = [u_{1t}, \ldots u_{Nt}]'$, and $\beta = [\beta_1', \ldots \beta_N']'$. Then,

$$Y_t = \tilde{X}_t'\beta + U_t \qquad (3)$$

In addition, following most transport economics literature, natural logarithm transformation has been applied for both sides of each aggregate road passenger transport demand equation. The advantage of the log-transformation is that the estimated coefficients can be interpreted as elasticities.

3.3 Demand for aggregate road passenger transport: the SUR model

The demand functions in (1) can be estimated efficiently by the SUR model, by taking into account of the potential correlation among disturbances. The SUR model of demand for aggregate road passenger transport modes can thus be specified as a system of three double-log demand equations as follows,

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[5] See Prozzi and Hong [25], Cao *et al*. [26], McDonald and Osuji [27], Gaudry [28] for details.

where we use the ownership of petrol/diesel cars (measured by car registrations per 1,000 population) as a measure of demand for private vehicles, and the total VKT by buses as a measure of demand for buses[6]:

$$\begin{aligned} ln(Car\_P_t) = a_p &+ \beta_{p1}\, ln(GDP\_pc_t) + \beta_{p2}\, ln(Petrol_t) + \beta_{p3}\, ln(Diesel_t) + \beta_{p4}\, ln(Bus_t) \\ &+ \beta_{p5}\, ln(Inflation_t) + \beta_{p6}\, ln(Unemployment_t) + \beta_{p7}\, ln(Young\ people_t) \\ &+ \beta_{p8}\, ln(Middle - aged_t) + \beta_{p9}\, ln(Matured_t) + \beta_{p10}\, ln(Senior_t) + u_{1t} \end{aligned}$$

$$\begin{aligned} ln(Car\_D_t) = a_d &+ \beta_{d1}\, ln(GDP\_pc_t) + \beta_{d2}\, ln(Diesel_t) + \beta_{d3}\, ln(Petrol_t) + \beta_{d4}\, ln(Bus_t) \\ &+ \beta_{d5}\, ln(Inflation_t) + \beta_{d6}\, ln(Unemployment_t) + \beta_{d7}\, ln(Young\ people_t) \\ &+ \beta_{d8}\, ln(Middle - aged_t) + \beta_{d9}\, ln(Matured_t) + \beta_{d10}\, ln(Senior_t) + u_{2t} \end{aligned}$$

$$\begin{aligned} ln(Bus\_VKT_t) = a_b &+ \beta_{b1}\, ln(GDP\_pc_t) + \beta_{b2}\, ln(Bus_t) + \beta_{b3}\, ln(Petrol_t) + \beta_{b4}\, ln(Diesel_t) \\ &+ \beta_{b5}\, ln(Rail_t) + \beta_{b6}\, ln(Inflation_t) + \beta_{b7}\, ln(Unemployment_t) \\ &+ \beta_{b8}\, ln(Young\ people_t) + \beta_{b9}\, ln(Middle - aged_t) \\ &+ \beta_{b10}\, ln(Matured_t) + \beta_{b11}\, ln(Senior_t) + u_{3t} \end{aligned}$$

where,
Car_P_t is the total number of registered petrol cars per 1000 people;
Car_D_t is the total number of registered diesel cars per 1000 people;
Bus_VKT_t is the VKT by buses per 1000 people;
GDP_pc_t is the seasonally adjusted real Gross Domestic Product (GDP) per capita in 2001Q1 price;
$Petrol_t$ is the real petrol price adjusted by Consumers Price Index (CPI) with base year 2001Q1;
$Diesel_t$ is the real diesel price adjusted by CPI with base year 2001Q1;
Bus_t is the price index for urban bus fares, long distance bus fares (excluding coach tours), taxi fares, shuttle fares, and car hire charges;
$Rail_t$ is the price index for urban train fares and long distance train fares[7];
$Inflation_t$ is the seasonally adjusted inflation rate;
$Unemployment_t$ is the seasonally adjusted unemployment rate;
$Young\ people_t$ is the percentage of 15-24 years old population, referred as "young people";
$Middle - aged_t$ is the percentage of 25-44 years old population, referred as the "middle-aged";
$Matured_t$ is the percentage of 45-64 years old population, referred as the "matured";
$Senior_t$ is the percentage of 65 years old and above population, referred as "senior".

4. Data Description

The analysis was undertaken at a national level using aggregate data. The selection of variables for this study is mostly inspired by previous studies and the availability of data. The following vehicle fleet information, bus VKT and demographic and macroeconomic data required for the estimation of the proposed aggregate model formulations were assembled for the analysis period from the first quarter of 2001 to the second quarter of 2015, a period of time over which data are available for all variables.

Vehicle fleet information regarding petrol and diesel car registrations were provided by the MoT. Total bus VKT were provided by the NZ Transport Agency (NZTA). Data on petrol and diesel prices came from the MBIE. The two public transport fare indicators, namely, bus fare index and rail fare index, and some socioeconomic and demographic data, including: population, GDP per capita, inflation, unemployment rate, were obtained from Statistics NZ through *Inforshare*.

There are a few highlights on historical patterns for car ownership and bus VKT data. **Figure 2(a)** shows that the petrol car ownership firstly fluctuated from the beginning of the sample period until around 2007Q4, then dropped sharply and reached its minimum at 2009Q2 and later on increased again. The vehicle ownership for diesel cars however, experienced a rather steady trend across time compared to petrol cars. For the demand for public transport, **Figure 2(b)** illustrates that there's an upwards trend for Bus_VKT over the sample period, but the increase is rather slow and steady, with a peak in 2001Q3.

[6] Ideally, VKT is a better measure of demand than counts, but they are not available for petrol and diesel cars (we only have VKT for bus from NZTA). Therefore this study followed several past research, including: Bjorner [32], Paulley *et al*. [33], Giuliano and Dargay [34], who also used counts, instead of VKT, for demand for cars.

[7] For a detailed description of road transport and rail passenger price indexes, please see "Rail, road, and sea passenger transport service in the CPI" from Statistics NZ: http://www.stats.govt.nz/tools_and_services/newsletters/price-index-news/apr-13-article-air-transport.aspx

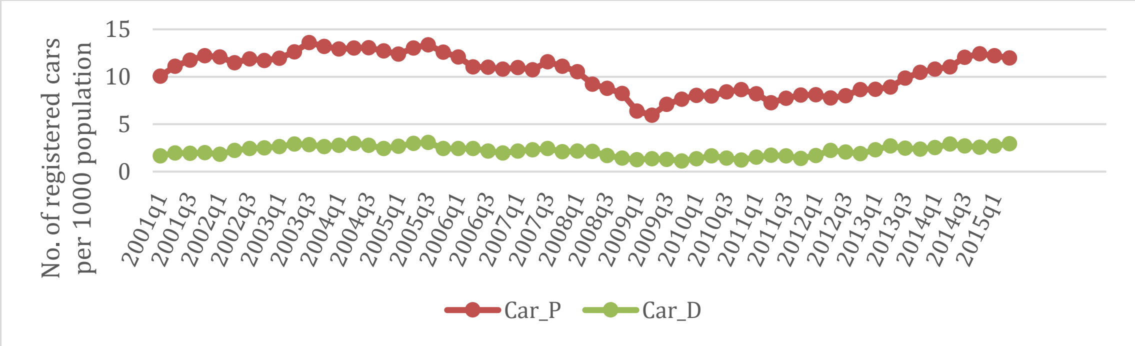


Figure 2(a). Demand for Petrol & Diesel Cars

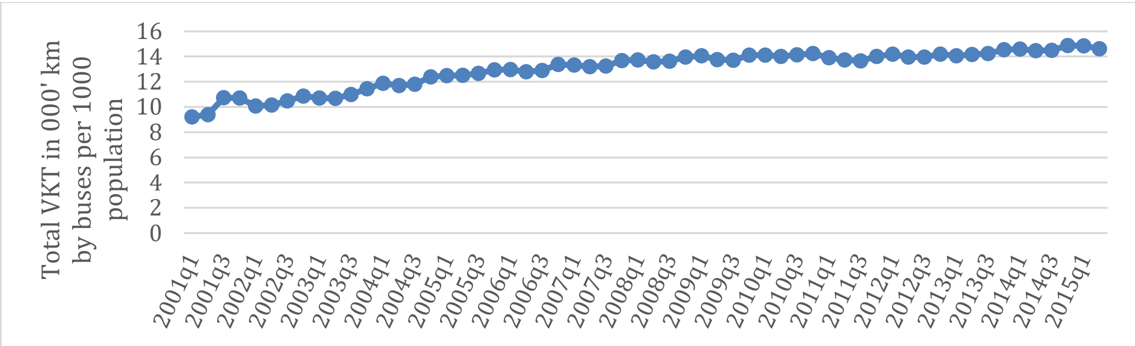


Figure 2(b). Demand for Buses

Table 1 presents a summary of descriptive statistics for variables used in this study. The total number of observations is 58 quarters. For the two car ownership variables, the mean of petrol car ownership (10.44) is considerably larger compared to the mean of diesel car ownership (2.18). Turning our attention to the independent variables. Firstly, the income indicator, real GDP per capita showed that the income per person in NZ is around $8635NZD in constant 2001Q1 dollar. For the two real fuel prices, petrol price has a higher mean value compared to diesel price. Next, the mean values for bus and rail fare indexes are 1080.24 and 1157.78 respectively.

Table 1. Summary Statistics of Variables

Variables	Mean	Std. Dev.	Minimum	Maximum
Dependent variables				
Car_P	10.44	2.07	5.95	13.61
Car_D	2.18	0.54	1.13	3.07
Bus_VKT	12.98	1.51	9.21	14.88
Independent variables				
GDP_pc	8634.55	457.09	7647	9440
Petrol	126.84	20.79	91.65	159.13
Diesel	86.81	19.41	53.17	133.75
Bus	1080.24	137.35	896	1351
Rail	1157.78	216.95	870	1503
Inflation	2.36	1.16	0.3	5.3

Unemployment	5.24	1.14	3.4	7.2
Young people	0.14	0	0.14	0.14
Middle-aged	0.28	0.01	0.26	0.3
Matured	0.24	0.01	0.22	0.26
Senior	0.13	0.01	0.12	0.15

5. Stationarity Test

The first step in time series analysis is to determine whether the levels (in this case, log–levels) of the data are stationary. *Appendix A* shows the plots all the variables against time for visual inspection of stationarity. None of the series looks stationary in its log-levels, and most of them appear to have an upward-sloping trend. To confirm our hypothesis of non-stationarity among variables, one of the most commonly used tests for stationary in time series, the Augmented Dickey-Fuller (ADF) test, is performed. The null hypothesis of the ADF test is that the series has a unit root. The results from **Table 2** indicate that all of the variables are non-stationary as shown by their insignificant *p-values*.

Table 2. ADF Test for Unit Root[8]

Variables	ADF-t	p-value
ln_Car_P	-1.327	0.6169
ln_Car_D	-1.038	0.739
ln_Bus_VKT	-1.411	0.8576
ln_GDP_pc	-2.237	0.469
ln_Petrol	-3.058	0.1166
ln_Diesel	-1.583	0.4923
ln_Bus	-2.898	0.1629
ln_Rail	-2.778	0.2052
ln_Inflation	-1.721	0.4924
ln_Unemployment	-1.582	0.7978
ln_Young people	-2.598	0.2808
ln_Middle-aged	-0.083	0.9933
ln_Matured	-0.506	0.9832
ln_Senior	-2.809	0.1936

Given the fact that all of the variables have unit roots, the next step is to take the first difference of these non-stationary series and apply the ADF test again to see if their first difference is stationary. Generally, if the log-levels of the time series are not stationary, the first differences will be. Results from **Table 3** confirmed that the all of the first differences become stationary at 1% significant level, with the only

[8] Whether or not to include constant and/or trend in the ADF test are determined based on visual inspection of the plots of variables against time from *Appendix A.* In addition, lag lengths are selected using the Schwarz's Bayesian information criterion (SBIC), as Ivanov and Kilian [35] suggest, the SBIC works well with any sample size for quarterly data.

exception of *ln_Matured1*, which is significant at 10% level. Therefore we conclude that all of the variables are *I*(1).

Table 3. ADF Test for Unit Root on All Variables in D1

Variables	ADF-t	p-value
ln_Car_P1	-5.306	0.0000
ln_Car_D1	-6.929	0.0000
ln_Bus_VKT1	-6.762	0.0000
ln_GDP_pc1	-7.276	0.0000
ln_Petrol1	-7.499	0.0000
ln_Diesel1	-5.668	0.0000
ln_Bus1	-7.759	0.0000
ln_Rail1	-6.803	0.0000
ln_Inflation1	-6.812	0.0000
ln_Unemployment1	-7.201	0.0000
ln_Young people1	-6.526	0.0000
ln_Middle-aged1	-5.751	0.0000
ln_Matured1	-3.305	0.0655
ln_Senior1	-7.448	0.0000

6. Empirical results and policy implications

Table 4 summarises some test statistics for demand equations estimated by the SUR model. Regarding the fitness of the model, all *F-statistics* meet the standard statistical test. The values of R^2 suggest that the SUR model explains 91.47% to 98.14% of variability in the data.

Table 4. Test Statistics for Demand Equations in the SUR Model

Equation	Observation	Parameter	RMSE	R-square	F-Stat	P
ln_Car_P	58	10	0.0602564	0.9334	65.86	0.0000
ln_Car_D	58	10	0.0861411	0.9147	50.41	0.0000
ln_Bus_VKT	58	11	0.0188612	0.9814	220.24	0.0000

The estimation results from the SUR model of the aggregate road passenger transport demand in NZ are summarised in **Table 5**. It should be noted that only factors that have a significant impact on the demand for petrol cars, diesel cars, and buses are reported. Standard errors are presented in parentheses and the level of statistical significances is marked by asterisks (*** for 1%; ** for 5% level; * for 10% level).

The use of log-log specification enables us to interpret the estimated coefficients as elasticities. For the demand for petrol cars, all of the estimated coefficients have expected signs. Firstly, the estimated value of the income elasticity for petrol cars is 3.99, implying that for every 1% increase in road user's income, on average, the demand for petrol cars is expected to increase by 3.99%. Secondly, the negative coefficient for *ln_Petrol*, -0.61, is also in accord with economic theory; there is an inverse relationship between the cost of using petrol cars and the quantity demanded for petrol cars. Thirdly, the cross price elasticity between diesel cars and petrol cars, represented by the estimated coefficient on *ln_Diesel*, is significant and positive at the 5% level. This implies that when the other variables are unchanged, for every 1% increase in the cost of using diesel cars, the demand for its substitute, petrol cars, is expected to increase by 0.44% on average.

Table 5. SUR Model Results for the Aggregate Road Transport Demand

Explanatory Variables	Petrol Cars		Diesel Cars		Buses	
	ln_Car_P		*ln_Car_D*		*ln_Bus_VKT*	
	Coef.	**t-stat.**	**Coef.**	**t-stat.**	**Coef.**	**t-stat.**
Intercept	-52.49***	-2.98	-87.76***	-4.63	20.27***	3.71
	(15.62)		(23.86)		(5.46)	
ln_GDP_pc	3.99***	4.78	3.45***	2.89		
	(0.83)		(1.19)			
ln_Petrol	-0.61*	-1.88			-0.49***	-4.85
	(0.32)				(0.10)	
ln_Diesel	0.44**	2.22			0.24***	3.80
	(0.20)				(0.06)	
ln_Bus			-1.97***	-3.66	-0.26**	-2.16
			(0.54)		(0.12)	
ln_Rail						
ln_Inflation			-0.09**	-2.21		
			(0.04)			
ln_Unemployment			-0.50**	-2.21		
			(0.22)			
ln_Young people	8.29***	5.03	7.54***	3.20	2.12***	3.54
	(1.65)		(2.36)		(0.60)	
ln_Middle-aged	-9.61**	-2.51	-30.53***	-5.57	2.68**	2.23
	(3.83)		(5.48)		(1.20)	
ln_Matured	-14.87***	-6.78	-24.94***	-7.95	4.31***	5.71
	(2.19)		(3.14)		(0.75)	
ln_Senior			-4.66**	-3.68	1.29**	2.51
			(2.19)		(0.51)	

*** Estimated coefficients significant at 1% level; ** significant at 5%; * significant at 10%

Lastly, three out of four age indictors showed an impact on the demand for petrol cars. The relationship between young people and the demand for petrol cars is positive; while the relationship between both middle-aged and mature people, and the demand for petrol cars is negative. This result gives us a possible implication that young people tend to enjoy the convenience and conformability that they derive from car trips, while older generations prefer other modes of transport apart from automobiles, possibly due to a healthier lifestyle choice of travel and considerations on environment.

For the demand of diesel cars, the income elasticity of diesel car demand, represented by the estimated coefficient on *ln_GDP_pc*, is significant and positive at the 1% level, indicating that for every 1% increase in road user's income, on average, the demand for diesel cars is expected to increase by 3.45%. This income effect is only marginally smaller compared to petrol cars. Moreover, inflation and unemployment were both found to have a significant negative impact on the diesel car demand. Firstly, the estimated coefficients on *ln_Inflation* is negative, suggesting that an inverse relationship between inflation and the demand for diesel cars. This is in line with our expectation as people will tend to reduce their demand for diesel cars if the associated vehicle costs tend to rise. Secondly, the estimated coefficients on *ln_Unemployment* is -0.50, indicating an inverse relationship between unemployment rate and demand for diesel vehicles. As expected, this finding implies that for those who are unemployed, the ability to possess private transport is normally outside of their financial means. The age indicators showed similar trend as they were in the petrol car demand equations, where the estimated coefficient on young population is significant and positive, and the estimated coefficients on middle-aged and mature age groups are significant and negative. Surprisingly, the two fuel cost indicators, *ln_Petrol* and *ln_Diesel* showed no effect on the demand for diesel cars. In addition, the cross price elasticity between public transport and diesel cars is significant and negative at the 1% level, this unexpected sign might be due to the composition of the bus fare index, where it not only represents the cost of urban bus fares, long distance bus fares, but also taxi fares, shuttle fares, and car hire charges. However this bus fare index was the best available choice to represent the cost of taking bus travel for this study.

For the demand for public transport, first of all, the per-capita income, the price of rail service, inflation and unemployment rate were all found insignificant, suggesting that these variables have no impact on the demand of buses. Secondly, the price elasticity for buses is negative, indicating that if the bus fare decreases, the demand for buses will increase. The cross elasticity between diesel cars and buses is 0.24, indicating that when the other variables are unchanged, for every 1% increase in the cost of using diesel cars, the demand for its substitute, buses, is expected to increase by 0.24% on an average base. Additionally, the sign of *ln_Petrol* is significant and negative, this result may be due to the fact that *Bus_VKT* have not been classified based on their fuel types, therefore the estimated coefficient on *ln_Petrol* might be interpreted as the fuel cost for some petrol buses, rather than an indicator for cross elasticity. All of the four age indicators are positive, an indication that New Zealanders are inclined to use public transport as their road transport choice.

The above empirical results from the SUR model also delivers some important policy implications. First of all, in order to achieve a reduction in the demand for automobiles, different policies could be implemented for cars with different fuel types, as the factors that affect the demand for these two major types of private vehicles in NZ differ significantly. For instance, policy makers could consider increasing the petrol tax so as to reduce the demand for petrol cars. As the price of petrol increases, with other predictors remaining constant, less petrol cars are demanded since the cost of using this type of road passenger transport mode is higher. The price elasticity for petrol cars is 0.61, suggesting that for every 10% increase in the average real petrol price, we would observe a 6.1% drop in the demand for petrol cars.

Secondly, because fuel prices do not have an impact on the demand for diesel cars, increasing the level of taxes on diesel would not lead to a possible decline in the demand for diesel cars as observed in petrol cars. Rather, policy makers could consider levelling up the taxation on vehicle-related ongoing costs, such as the vehicle registration fees, annual licensing fees, administration fees, and road user charges for diesel vehicles, in order to achieve an effective reduction of the demand for diesel cars. As suggested by the estimated coefficient on *ln_Inflation*, if vehicle costs increase by 10%, the quantity of diesel cars demanded is expected to decrease by 0.9%.

Thirdly, for the purpose of promoting the use of public transport, policy makers could consider lowering the fares. This of course, will have to be financed; possibly by recycling the revenue from fuel and car taxation. Price elasticity for buses indicates that on average, when the other variables stay the same, a 10% reduction in bus fares is expected to increase the demand for buses by 2.6%. Given the fact that the current fares on public transport remain relatively high, the government might need to consider granting a subsidy to public transport providers, so that the road transport users can enjoy lower fares and increase their demand for public transport.

Last, as the signs of all of the age indicators are positive from the public transport demand equation, public transport authorities could consider increasing trip frequencies so that young people who mainly ride public transport for educational purposes, middle-aged and matured people who represent the majority of commuters, and senior citizens who mostly rely on public transport because they have less mobility, could all benefit from an improved service from public transport.

Moreover, to test whether the estimated correlation between these three equations is statistically significant, we use the Lagrange multiplier (LM) statistic proposed by Breusch and Pagan [36].

$$\lambda = N \sum_{m=1}^{M} \sum_{n=1}^{m-1} r_{mn}^2$$

where r_{mn} is the estimated correlation between the residuals of the M equations (in this case 3) and N is the number of observations (in this case 58). It is distributed as $\chi 2$ with $M(M-1)/2$ degrees of freedom. The results are presented in **Table 6**.

Table 6. Correlation Matrix of Residuals

	r_Car_P	***r_Car_D***	***r_Bus_VKT***
r_Car_P	1.0000		
r_Car_D	-0.1069	1.0000	
r_Bus_VKT	-0.2893	-0.3111	1.0000

Breusch-Pagan test of independence: $\chi 2$ (3) = 11.129, *Pr* = 0.0110

Based on the results from **Table 6**, we can reject the null hypothesis that the covariance between the three different equations are equal to zero at 5% significance level. This implies that the residuals from each SUR regression are significantly correlated with each other, representing identical unsystematic influences. Therefore estimating each equation separately using OLS will give us consistent but inefficient coefficients. SUR model, in this case, is superior as the estimated coefficients are both consistent and efficient. Additionally, because all of the signs are negative, we can conclude that the three road transport modes are substitutes, implying that an increasing effect of the residuals on one mode will decrease the effect of the residuals on the other mode.

7. Test for cointegration and structural breaks

7.1 Cointegration Test

Cointegration refers to the fact that two or more non-stationary time series possess the same order of integration hence a linear combination of these series is stationary. If a stationary linear combination exists, we can conclude that the non-stationary time series are cointegrated. In other words, even if the variables may wander around in a certain period of time, they cannot drift too far apart from each other in the long-run. The deviations from equilibrium (i.e. residuals) are thus stationary, with finite variance, even though time series variables are not. Plots of residuals against time for each SUR equation are summarised in *Appendix B*. From graphical inspection, we conclude that the residuals show little evidence of trend. After estimating the SUR model, follow a two-step cointegration test suggested by Engle and Granger [37], we firstly obtain the residuals and secondly run an ADF test on them in order to test for unit root.

Table 7. ADF Test for Unit Root on the Residuals

Residuals	**ADF-t**	**p-value**
r_Car_P	-4.844	0.0000
r_Car_D	-4.646	0.0001
r_Bus_VKT	-3.253	0.0171

Results from **Table 7** indicate that we can reject the null hypothesis of unit root on the residuals at the 1% level for the equation on petrol and diesel cars, and we can reject the null hypothesis of unit root on the residuals at the 5% level for the equation on buses. Therefore we conclude that the variables are cointegrated, or have a stationary long-run relationship, even though individually they are stochastic. The SUR model is thus valid and can be estimated in its original specification as outlined in *section 7*.

7.2 Structural breaks

Furthermore, based on the graphical illustrations of predicted demand versus actual demand for natural logarithms for petrol cars, diesel cars and buses from *Appendix C*, we can conclude that none of the equations suffer from visible structural breaks as the predicted and the actual data fit nicely with one another, suggesting that the estimated results from the SUR model is valid and robust for future projections of the demand for aggregate road passenger transport.

8. Conclusion and Recommendations

This paper aims at firstly examining whether the error terms of the demand for the three main road passenger transport choices: petrol cars, diesel cars and buses, are correlated and secondly, identifying the factors that have impacts on the demand for each available road passenger transport choice.

The Breusch-Pagan test of independence confirms the existence of correlated error terms of the three demand equations and the empirical results from SUR model indicates that per-capita GDP has an effect on both the demand for petrol and diesel cars, with the values of income elasticity to be 3.99 and 3.45, respectively. However it does not play a role in determining the demand of public transport. Price elasticities for petrol cars and buses are -0.61 and -0.26, respectively, although the own price elasticity for diesel cars was not found to be insignificant. Only one of the cross elasticities for petrol cars is significant. With a positive value of 0.44, the estimated coefficient on *ln_Diesel* implies that when the other variables are unchanged, for every 1% increase in the cost of using diesel cars, the demand for its substitute, petrol cars, will increase by 0.44% on an average base.

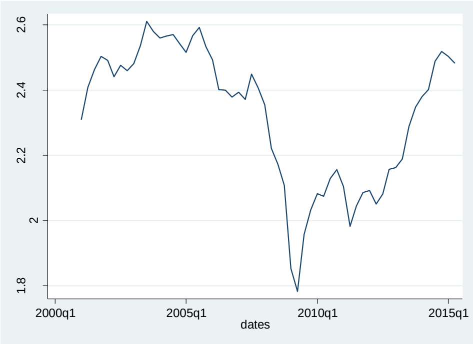
In the case of diesel cars, the cross price elasticity between public transport and diesel cars is negative and significant, this unexpected sign might due to the inclusion of taxi fares, shuttle fares, and car hire charges fares in the bus fare index *ln_Bus*. While for the demand of buses, cross price elasticity between diesel cars and buses is positive and significant. However the sign of *ln_Petrol* is significantly negative, indicating the fact that buses have not been classified based on their fuel types, therefore the estimated coefficient on *ln_Petrol* might be interpreted as the fuel cost for some petrol buses included in the dependent variable, rather than an indicator for cross elasticity.

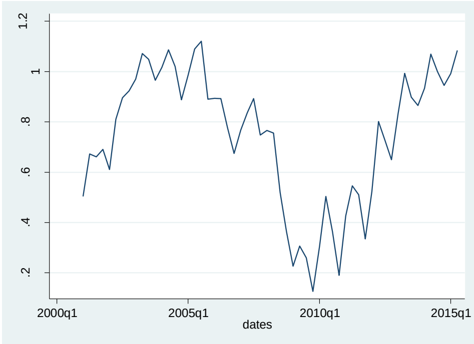
Inflation and unemployment are found to be significant only in the demand for diesel cars equation, implying that the relative importance of these two macroeconomic variables in the demand for the other two road transport modes appears to be relatively minor. The age indicators showed similar trend in the private vehicle demand equations, where the sign on the young population is positive; while for the middle-aged and matured groups, the sign is negative. However for the demand for public transport, the sign on the estimated coefficients for all age groups is positive, suggesting that New Zealanders are inclined to use public transport as their road transport choice. Lastly, in terms of the validity of the SUR model, following a two-step cointegration test, we conclude that the non-stationary time series are cointegrated.

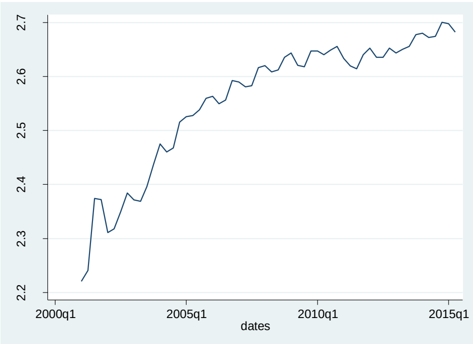
The above empirical results from the SUR model also delivers some important policy implications. First of all, in order to achieve a reduction in the demand for automobiles, different policies could be implemented for cars with different fuel types, as the factors that affect the demand for these two major types of private vehicles in NZ differ significantly. To achieve a reduction in the demand for petrol cars, policy makers could consider increasing the petrol tax; on the other hand, for achieving a reduction in the demand for diesel cars, policy makers could consider levelling up the taxation on vehicle-related ongoing costs, such as the vehicle registration fees, annual licensing fees, administration fees, and road user charges for diesel vehicles. For the purpose of promoting the use of public transport, policy makers could consider lowering the fares by granting a subsidy to public transport providers. This of course, will have to be financed; possibly by recycling the revenue from fuel and car taxation.

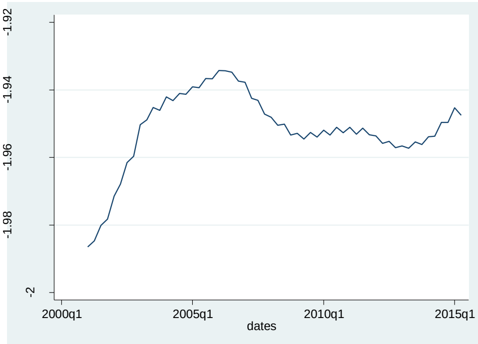
One limitation in this study is that there is possibility of endogeneity with petrol and diesel prices as explanatory variables in petrol and diesel car regressions. Future research could consider the use of an instrument such as price of other petroleum based products like kerosene, as it would not be correlated with unobservables affecting vehicle demand, but correlated with fuel prices. Additionally, there are a few recommendations for possible future research. Firstly, in regards to the variables, road density and also road length may be more useful indicators as long as a sufficient quantity of quarterly (not annually) data become available. Secondly, the current study only modelled the total VKT by all types of buses as a measure of road passenger's demand for public transport. In fact, total VKT by bus represents both the VKT by urban/suburban buses and special use buses (e.g. tourist buses) in NZ. These two different types of buses, in nature, should exhibit dissimilar trends and different fluctuation patterns. Thus with the availability of data, separating one of the dependent variables Bus_VKT for passenger bus only may presumably result in better estimations. Thirdly, since public transport can be viewed as a substitute for (at least some types of) private car transport, a sensible course of action when modelling road passenger transport demand would be to investigate regional, rather than national demand patterns. Regional analysis could be explored by extending the existing SUR model to a spatial environment so that potential spatial effects can be incorporated via autocorrelation in spatial error terms. Lastly, the main purpose of this study is not to predict future road passenger travel demand; the model presented in this research can be used to derive demand implications and construct a forecasting model for private and public transport, given detailed assumptions about energy and economic conditions. In that case, we can thus project and compare energy consumption and CO_2 emissions from both private vehicles and public transport in the future.

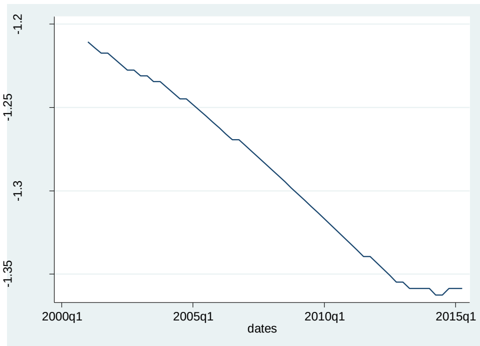
Appendix A Log-Value of Variables vs. Time

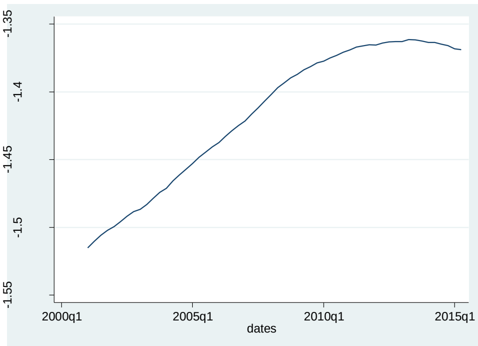


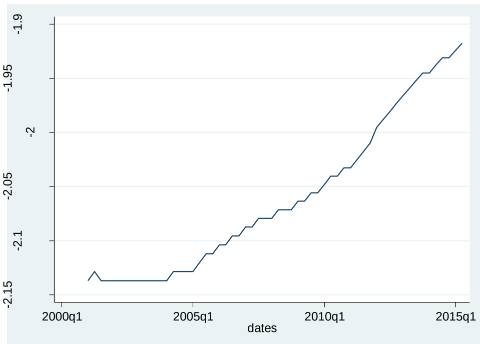


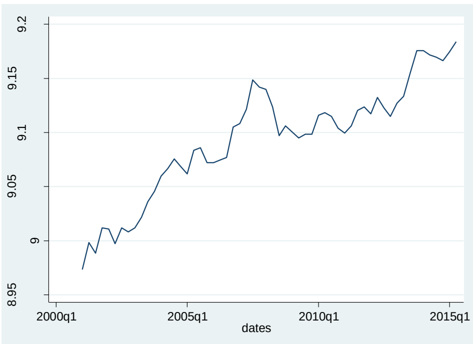


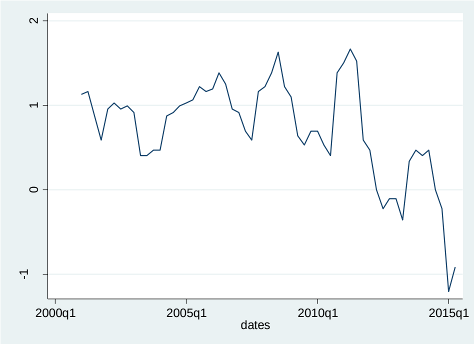


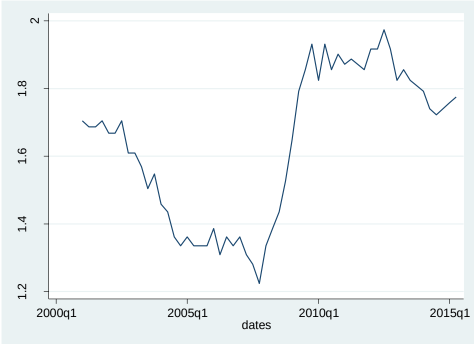


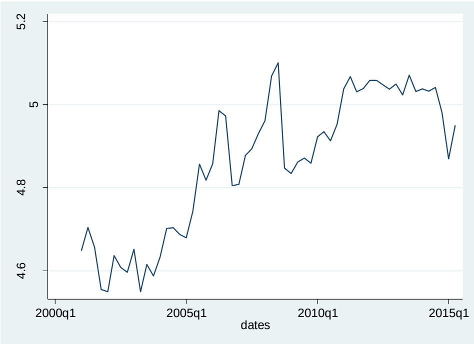


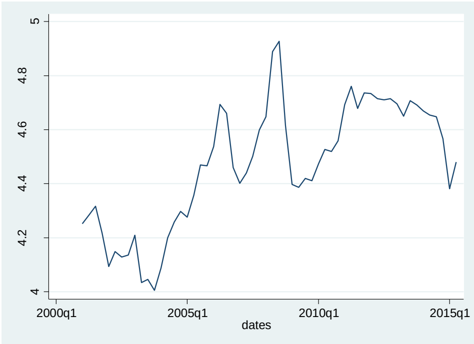


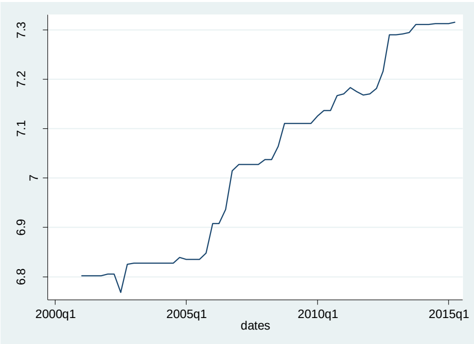


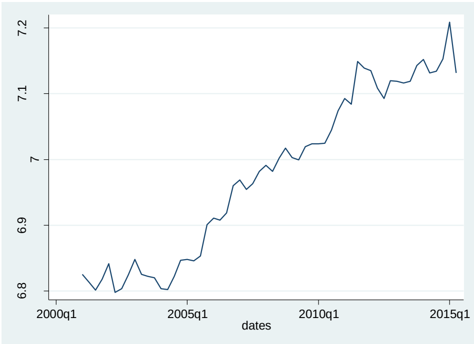




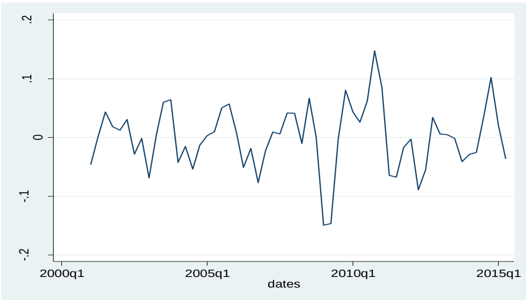


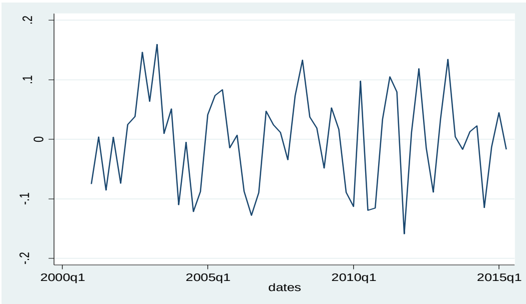


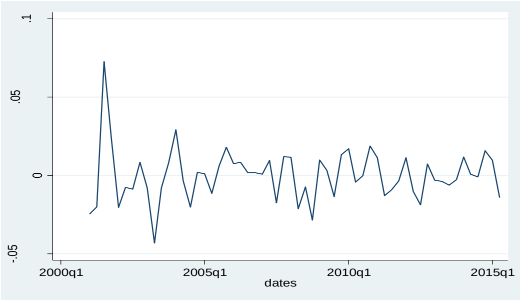




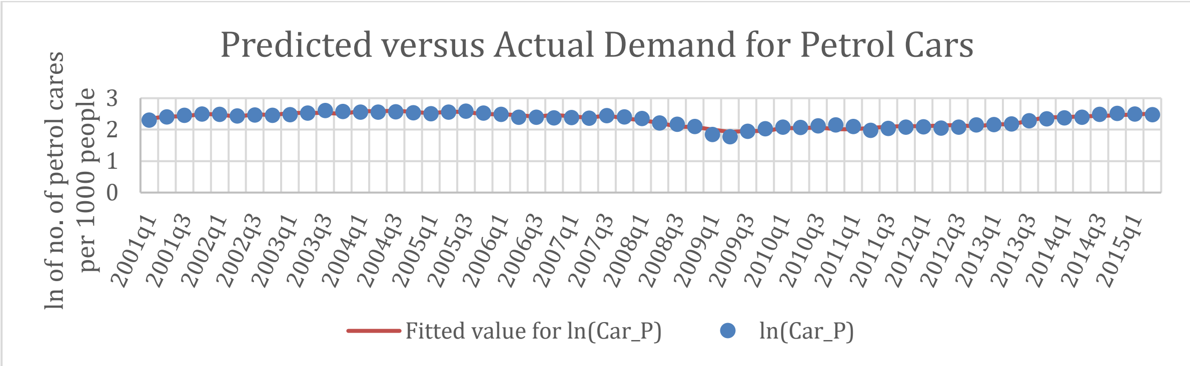
Appendix B Residuals vs. Time

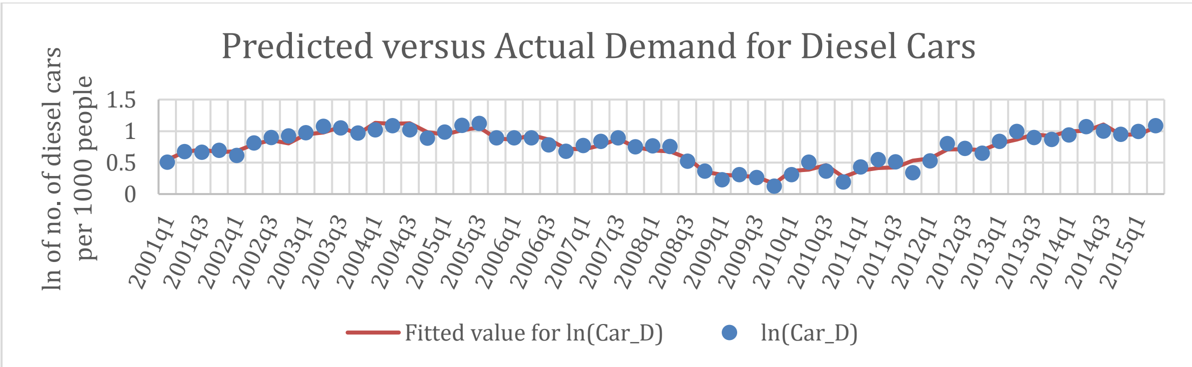


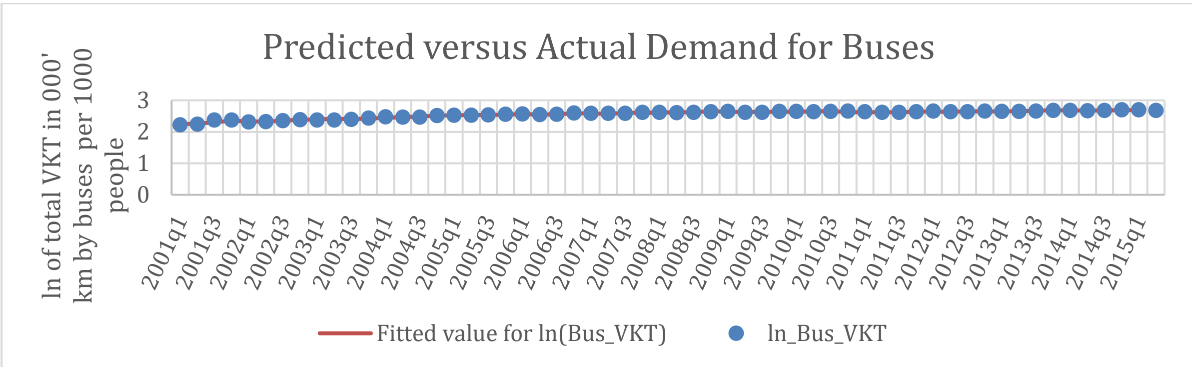




Appendix C Predicted vs. Actual Demands







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