國 立 交 通 大 學

管理學院碩士在職專班

運輸物流組

碩士論文

An Empirical Investigation into the Effects of Gas Price and GDP on Freeway Traffic

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中 華 民 國 九 十 九 年 六 月

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摘要

本研究旨在探討民國九十三年一月至九十八年六月間油價及國內生產毛額對高速公路各收費站通行車輛數之長短期因果關係及跨期動態之衝擊反應，俾提供有關單位交通量管理策略研擬之參考。本研究首先將各收費站通行車輛數通行車輛的月資料依路線（國道 1 號、3 號、5 號）、區域（北區、中區、南區、宜蘭地區、全島）及車種（小型車、大型車、聯結車）加以區隔分析。在實證方法上的選用是以 Engle and Granger 兩階段法及 Johansen 最大概似法進行共整合檢定（cointegration test），來檢定變數間是否存在長期均衡關係。並根據 Granger(1969) 所提出變數預測力的方法，利用 Wald 檢定及 Toda and Yamamoto (1995)之方法來衡量變數間之短期領先落後的因果關係。最後，再輔以向量自我迴歸模型進行後續的衝擊反應函數分析，以了解變數間之動態、跨期的影響與衝擊，俾檢視我國油價、國內生產毛額及高速公路交通量間是否存在緊密的關係。

實證結果發現，兩種共整合之檢定結果皆顯示油價及國內生產毛額與高速公路交通量不存在長期均衡共整合的關係。此說明了長期的交通量之增減並無法由油價及國內生產毛額來加以判定，而係由其他因素所左右。此外，不同 Granger 因果關係的檢定方法雖產生部份結果不一致之現象，但就宜蘭地區而言，兩種 Granger 因果檢定的結果均一致指出該地區之高速公路交通量並不受油價及國內生產毛額的影響。這顯示國道 5 號交通量仍受其他因素所控制，此與該條國道大部分均為旅遊觀光旅次與雪山隧道的該開通未台灣北部及東北部的交通帶來很大的便利性有關。最後，透過衝擊反應函數進行變數間之動態跨期衝擊影響分析中，發現油價及國內生產毛額對部分地區大型車及聯結車有正向且立即的短暫性衝擊。這說明若有關單位欲透過油價調整來長期且有效抑制高速公路交通量恐難達成。

關鍵字： 共整合、Granger 因果關係、衝擊反應函數。

An Empirical Investigation into the Effects of Gas Price and GDP on Freeway Traffic

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Abstract

It is a concept universally acknowledged that when gas price rises, the toll road use will reduce. It is also well-fixed in the minds of many policy makers that they devise energy-related policies based on this premise. With an aim to successfully implement the government's proposed green tax policy for achieving certain levels of environmental protection by increasing the gas price to reduce the usage of vehicles, the causal effect of gas price and traffic volume plays a significant role here. As a result, this study takes a closer look at the conceptual grounds of the notion of causality in Granger's sense. In addition, taking into account that GDP may be also a key component of affecting vehicle usage, it is also incorporated into the study.

Cointegration test for the long term equilibrium relationship, Granger causality test for the short run lead or lag relationship and the analysis of impulse response function are employed to unveil and justify the linkage among the interested variables. The main findings are not in line with what we used to take for granted that no co-integration for the long run, not all the gas price or GDP Granger cause traffic volume and as well as some positive impulse responses of traffic volume to gas price shock and GDP innovation. However, as even the simplest descriptive statistics can be deceptive, our findings must be treated with caution especially when extrapolating any anticipated effects on relative policy making.

Keywords: Gas Price, GDP, Freeway Traffic, Cointegration, Granger Causality,
Impulse Response Function.

Acknowledgements

In this study, I think I am in the same boat same as the other great thinkers of our times - Plato, Aristotle and Galileo among others, bewildered and unable to unveil the real causality between the economic variables in real world. However, there is one thing for sure that there is a cause-and-effect relationship between the assistance I have received from people around me and the finishing process of this thesis over this period of time at National Chiao Tung University. I am indebted to the following persons.

First of all, I would like to express my deepest appreciation to my advisor - Prof. Yu-Chiun Chiou. Thank you for your advice and spending your valuable time with me. There were more than two hundreds of emails exchanges between us regarding my thesis for the past year. You have shed light on my questions and guided me back on the track when I got lost in time series methodologies. Without your guiding hands, this thesis would be like a star out of reach.

And a big thank you to Prof. Jinn-Tsai Wong, Prof. Cherng-Chwan Hwang, Prof. Tai-Sheng Huang, and Prof. Jiuh-Biing Sheu for your encouragement and enlightenment during the thesis discussion class as well as your comments on my writing. Your advices serve as a magnifier highlighting my problem areas in my study, making it possible for me to revise and improve my thesis.

Thanks a lot to the committee members – Prof. Jin-Li Hu and Prof. Rong-Chan Jou for giving such a meticulous reading to my thesis, and offering many constructive suggestions regarding my thesis writing during the oral defense.

Pooh, no other words can express my feelings better toward your big help in every aspect except what you ever quoted for me from George Eliot, "What greater thing is there for two human souls, than to feel that they are joined for life, - to strengthen each other in all labour, to rest on each other in all sorrow, to minister to each other in all pain, to be one with each other in silent unspeakable memories? " Thank you. Thank you for everything.

Finally, Jackie, even though your trying to distract me unwittingly nearly made my study impossible, still, thank you for your understandings and moral support all the time especially when there were clouds in my way to the road I less travelled by in my academic journey. They mean a lot to me. I owe you so much.

With all of your assistance and support during the thesis writing process, I am able to lift my spirit, muster my courage and maintain my passion to sail through the rite of the academic passage at NCTU. Thank you everyone for coming into my aid to enrich my life in your own way. Parting is such a sweet sorrow. When I have to farewell my love – NCTU, similar to Earnest Hemmingway who once described his experience in Paris as his moveable feast, luckily, I've also had my share of moveable feast right here at NCTU. If you happen to pass it, kiss it for me.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

To drive or not to drive, that is a question during the rising gasoline price era.

CHAPTER 1 INTROCUTION

1.1 BACKGROUND AND MOTIVATION

Gasoline price fluctuates widely in a recent decade. In Jun. 2008, it reached its peak of USD 139.36 a barrel. That is a far cry from $ 15.77 a barrel in 1998. The price is almost 9 times higher than it was a decade ago.

Soaring gas price triggers the global economy downturn; affects the policy makers of various governments, as well as alters ordinary people's ways of life. As to its devastating effect on the energy-dependent industries, transportation industry is among the hardest hit. "A host of smaller European airlines are likely to go bankrupt in coming months if the oil price does not drop significantly below current levels of USD$130 a barrel. Faced with the unprecedentedly high cost of fuel, airlines will have to hedge against the oil price and cut unprofitable flights and routes to help them stay in the air." (Bowker 2008)

Another hard-hit industry is car manufacturers. With hiking gas prices, small car has become a favorite choice of car buyers. Based on a BBC report in 2009, The Japanese compact cars, with their compact designs and fuel-efficient engines, have gained strong positions and more shares in the United States car market. An online car information provider – Edmunds.com indicated that compact car sales showed a record month in May 2007, accounting for 21 percent market share of the total car market. It means for every five new cars sold that month, one was a compact. By contrast, the demand of gas-guzzling SUV (sport utility vehicle) in the United States has been declining considerably. According to a report from NPR – National Public Radio, the giant auto company DaimlerChrysler suffered a 37 percent drop in its third-quarter earning in 2006 due to a decreasing demand for bigger trucks and SUVs.

With no exception, drivers around the world also suffer from the surge of gas price. Their driving behaviors have also dramatically changed, as more and more people opt out of the convenience of their own cars and opt for either car-pooling with their neighbors or colleagues or switching to public transportations. The increasing use of mass transportation is also an effective way to combat the ever-rising gas price. The Federal Highway Administration of the States (FHWA 2009) reported that travel in the states during October 2008 on all roads and streets decreased by -3.5% compared to it was in the same month in 2007. This drop followed the -4.2% decline in September 2008. In comparison, The Liberty Times revealed a similar situation in Taiwan when gas price reached NTD 34.6 per liter at the end of May in 2008. It's a sharp increase from NTD 30.7 in November 2007. In the same period of time, there were nearly ninety thousand vehicles decreased in freeway traffic volume, an equivalent of 11% drop for the same period last year.

The above statistics from America and Taiwan seem to suggest that there is a negative correlation between gas price and traffic volume, and this is not merely a coincidence. Based on an assumption that higher driving cost would lead to less traffic, Taiwan government recently proposed an introduction of green tax in 2011 (CNA 2009) as a mean to reduce greenhouse gas emission via cutting down the usage of private vehicles. If the tax policy does take place as proposed, an average family will have to pay about NT$ 10,000 a month for water, electricity, natural gas and gasoline. It is two times more than it is now. Such considerable impact on the driving habit of at least over 6 millions of car owners will be imminent.

Although gas price has dropped since its peak, the recent fluctuation of global gas price seems not reaching the end yet. Paul Krugman – the Nobel Economics Prize winner in 2008, still predicted that "oil non-bubble and we are heading into an era of increasingly scarce, costly oil." (Krugman 2008) Similar to what Krugman forecasted that high gas price is not a past history, Allen Greenspan - the former chairman of the Federal Reserve of the United States, also thinks the same line. He predicts (Greenspan 2008) that we are facing a long term energy shortage. Both of them seem to tell the high gas price an ongoing and unavoidable trend.

Therefore, apparently the relationship between gas price and car usage will continue to play a significant role in this proposal. With an aim to successfully implement its green tax policy for achieving certain levels of environmental protection, the policy makers of a government require a clear picture of the causality between gas price and traffic volume in making relevant energy guidelines or regulations. Even though there are evidences that there is a correlation between said 2 variables, it does not mean correlation equal causation. We can not say one must cause the other. In fact, the causality between the price of gas and traffic volume is still a debatable issue that demands extensive studies.

Meanwhile, as gross domestic product (GDP) is also considered as one of the elements affecting the numbers of vehicle's ownership and usage. Just like what Alfresson (2002) puts it, "Historically GDP and energy consumption have been highly correlated". Accordingly, in order to provide local government a reference for devising energy-related policies, this study uses various time series methods, puts the time lag factor into account to examine the effects of gas price and GDP on freeway traffic pairwise.

1.2 RESEARCH OBJECTIVE

The main objectives as follows are achieved.

1. Using the time series of gas price and traffic volume of 23 expressway toll stations in Taiwan, we apply cointegration theories in estimating long-run equilibrium relationship between 2 different types of gas prices and 3 types of different vehicle freeway traffic volumes in 4 different regional areas on National Freeway No. 1, 3 and 5, plus the aggregate traffic volumes through the Island.

2. In parallel, using the same traffic volume, we study the co-integration of freeway traffic and gross domestic product (GDP) in pair.

3. Utilizing the Granger causality test on investigating and determining the short-terms precedence or feedback relationship in pair between “traffic volume and gas price” as well as “traffic volume and GDP”.

4. Tracking out the dynamic response of freeway traffic volume to the exogenous shock of gas price and GDP by performing impulse response function.

1.3 RESEARCH SCOPE

There are certain critical variables which constantly change traffic volume in the real world. However, this study attempts to focus on detecting the short-run Granger causality and the co-integration of long-terms causal relationship between “gas price and freeway traffic” and between “GDP and freeway traffic” only. For a clear picture of the research scope, please find Figure 1.1, 1.2 and 1.3.

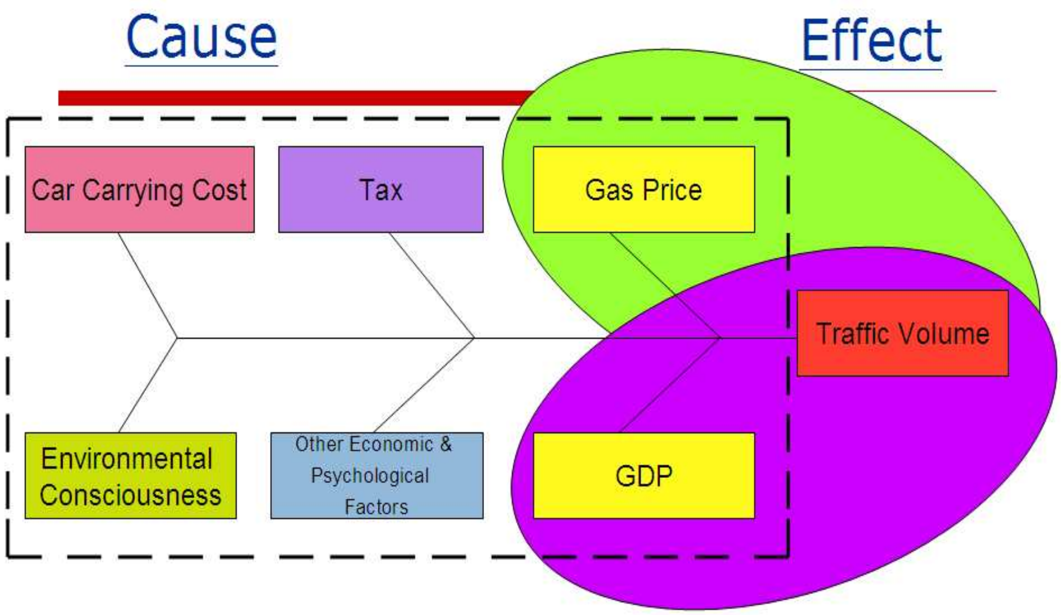


Figure 1.1 Scope of the Study

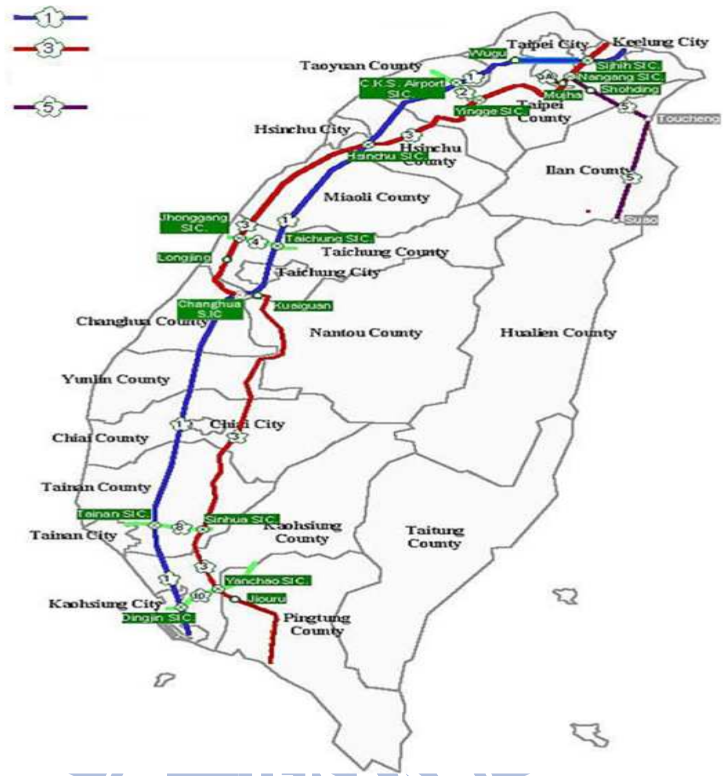


Figure 1.2 Map of National Freeway No. 1, 3 and 5

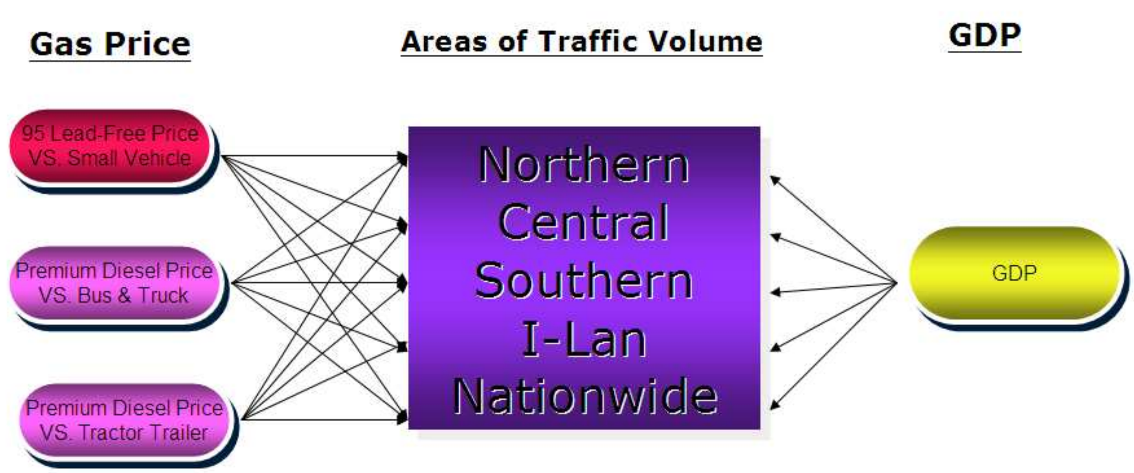


Figure 1.3 The Study of Relationship between Variables in this Research

1.4 RESEARCH PROCEDURE

Within throughout this paper, the following steps and research procedures are taken. The steps of the process are illustrated in Figure 1.4.

1. Collect and describe the data of monthly average fuel prices of 95 unleaded gas price and premium diesel price based on the data provided by CPC Corporation, Taiwan.

2. Convert the nominal quarterly GDP data into a monthly basis deflating it into real terms while taking into account the Consumer Price Index (CPI) (2006 = 100) of the given period of time.

3. Compare and analyze the freeway toll traffic volume on National Freeway No. 1, 3 and 5 in a timeframe from 2004:01 to 2009:06 reported by Taiwan Area National Freeway Bureau, MOTC.

4. Cluster the said collected traffic data into five separate categories by geography: northern, central, southern Taiwan, I-Land area and nationwide to identify the regional characteristics of toll traffic volume variance in different areas in reflecting to gas price and GDP innovation.

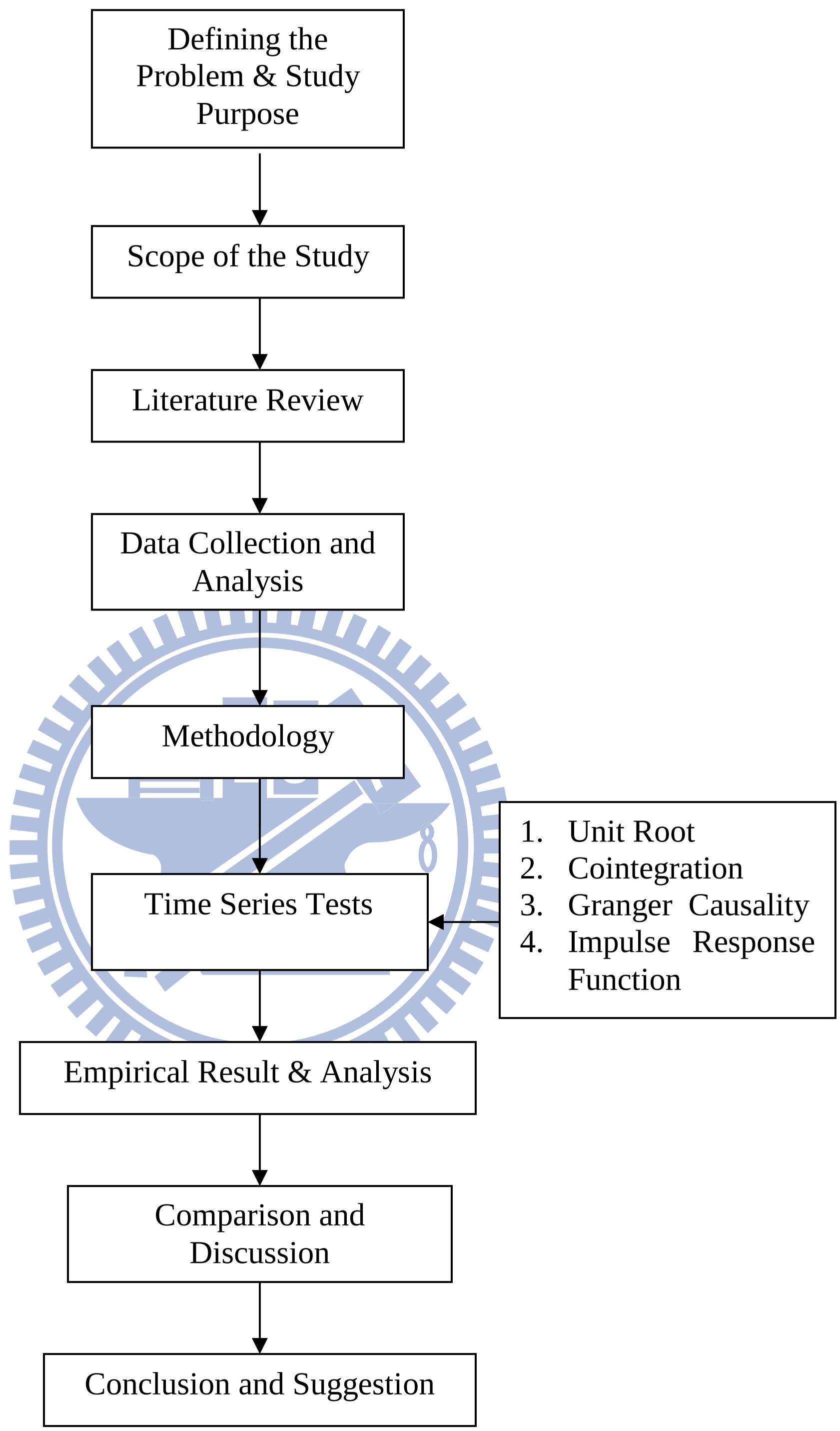


Figure 1.4 Research Flow

CHAPTER 2 LITERATURE REVIEW

Does X really cause Y? This time-honored issue has puzzled the great minds of philosophers of ancient Greek, China and India for over 3000 years. "This seemingly simple question has challenged some of the greatest thinkers in history, including Heraclitus, Plato, Aristotle, Galileo, Hobbes, Hume, Kant, and countless other philosophers and scientists." (Dowd and Town 2002) But the old issue is now unfolded again with new ideas to help unveil the mystery of causality from a different point of view by Clive W.J Granger.

Granger, Nobel Prize laureate of Economics in 2003, established a set of techniques named Granger Causality test to uncover the mystery and enhance our understanding of causality to a certain degree. For example, if a variable X Granger-causes Y if Y can be better predicted using the histories of both X and Y than it can using the history of Y alone. To put it simply, it does not imply true causality but a statistical way for determining whether one time series is useful in forecasting another. (Granger 1969).

As the real world is much more complicated than a set model, this thesis sets the philosophical questions aside while focusing on the causality examination by adopting Granger's statistical theory. With regard to more detailed Granger causality technique, there are more in depth discussions in the later part of the chapter - 5.3. In the current chapter, we will present certain published on the factors affecting driving choice behavior, the effect of gas price and GDP on traffic and the causal linkage related to the impact on traffic caused by gas price or GDP.

2.1 FACTORS AFFECTING DRIVING CHOICE BEHAVIOR

Jou and Sun (2008) apply logistics regression model to analyze how commuters and non-commuters response to the rising oil price in Taipei. Their results indicate that when personal income and travel cost increase, the frequency of driving car decreases. They also discover the factors behind the auto commuter's choice of car, which include the oil consumption efficiency of car, the frequency of car usage and a willingness to switch to public transportation.

Boarnet and Sarmiento (1998) adopt travel daily data for southern California residents to study the link between road-use patterns at the neighborhood level and non-work trip generation from a sample of 769 individuals. Their results show that the land-use variables are statistically insignificant, thus a link between road land use and travel behavior is inconclusive.

Cullinane (2002) cites Hong Kong as an example of how a good public transport system can discourage car ownership. That is, the better the quality of public transportation is, the lesser, the people want to own a car. His results, based on a survey of 389 university students in Hong Kong, show that good public transport can deter car ownership, with 65% of respondents stating that they are unlikely to buy a car in the next 5 years.

Based on the concept that users' response to toll charges is instrumental to government policy- making, Odeck and Brathen (2008) study elasticity of travel demand and users' attitudes towards tolls in 19 Norwegian road projects. They discover a mean short-run elasticity at -0.45 while -0.82 for the long-term. Furthermore, the study reveals that the road type and project location can vary the elasticity.

Kitamura (1989) uses a sample obtained from the Dutch National Mobility Panel survey to examine the causal structure underlying household mobility. His findings suggest that car ownership is strongly associated with mode of transportation while it has no influence on weekly personal trip generation by household members. He studies the characteristics of mode through a causal analysis of changes in car ownership, number of drivers, number of car trips and number of transit trips. His results show that observed changes in mode use is unable to be explained by assuming that a change in transit use influences car use. It suggests that the increase in car use, which is the result of increasing car ownership, may not be suppressed by improving public transit.

2.2 IMPACT OF GAS PRICE SHOCKS ON TRAFFIC

Unarguably, one of the world's most important economic energy sources, gasoline is critical to global economic growth. The cost of gasoline constitutes a major component of the total cost of driving. Under such assumption, rises in automobile gasoline prices could potentially have a significant impact on driver behavior.

According to a survey of over 500 residents in Austin Texas focusing the aftermath of a severe spike in gas prices that took place in September of 2005, Bomberg and Kockelman (2007) examines how respondents' travel behavior changed during and following the spike. The authors use basic descriptive statistics and employ ordered probit and binary logit models to determine which factors are responsible for behavioral changes in response to gas price spikes. Based on the feedback from respondents, it is indicated a strong tendency to reduce overall driving and/or a car- pool like activities in more efficient tours as a way of coping with high oil prices.

Lu et al (2008) utilizes Grey relation analysis (GRA) to evaluate the relative influence of the fuel price, the gross domestic product, the number of motor vehicles and the vehicle kilometers of travel (VKT) per energy increase in Taiwan. Their finding shows that the relationship between energy requirement and the number of passenger cars declined steadily. The authors conclude that the steady growth of economic development is strongly correlated with vehicular fuel consumption. The relation grade of 0.967 implies that the increase in the number of passenger cars is another important factor for energy increase.

Liddle (2009) embraces US data from 1946 to 2006 to examine whether a systemic, mutually causal and cointegrated relationship exists among mobility demands, gasoline price, income and vehicle ownership. He finds that those variables co-evolve in a transport systems and thus, they can not be easily disentangled in the short-run. On the other hand, estimating a long-run relationship for motor fuel use per capita was difficult because of the efficacy of the Corporate Average Fuel Economy standards (CAFE) of influence fleet fuel economy. His analysis shows that the fuel standard program was effective in improving the fuel economy of the US vehicle fleet and in temporarily lessening the impact on fuel use of increased mobility demand.

2.3 IMPACT OF GDP PRICE INNOVATION ON TRAFFIC

Stern (1993) examines the causal relationship between GDP and energy use for the period 1947-90 in the United States. He carries out a VAR of GDP, energy use, capital stock and employment to test for Granger causal relationships between the variables. It's pointed out there is no evidence that energy use Granger causes GDP.

Ramanathan (2001) uses the concepts of cointegration and error correction to study the long-run relationships between variables representing transport performance and other macro-economic variables in India. The results demonstrate that passenger-kilometres (PKM) in India are likely to increase faster than gross domestic product (GDP), and still much faster than urbanisation. By the same token, tonne-kilometres (TKM) is probably to increase faster than the index of industrial production. Besides, there are strong correlations between TKM and industrial growth. Both the passenger and freight performances are relatively lack of elasticity in price changes. The error correction model (ECM) interprets that both passenger and tonne-kilometres adjust to their respective long-run equilibrium at a moderate rate, with about 35% of adjustment in PKM and 40% of adjustment in TKMs occurring in the first year.

Coondoo and Dinda (2002) present a study of income – CO_2 emission causality based on a Granger causality test, using a cross-nation panel data on per capita income and the corresponding per capita CO_2 emission data. It is indicated that three different types of causality relationship holding for different country groups. For the developed country groups of North America, Western and Eastern Europe, the causality is found to run from emission to income. For the country groups of Central and South America, Oceania and Japan causality from income to emission is obtained. As to the country groups of Asia and Africa the causality is found to be bi-directional.

Wu (2006) indicates the ownership of vehicles and growth of its usage are related to the increasing of GDP. She applies Granger causality and forecast error variance decomposition techniques to examine the cointegration and causality between GDP and the number of registered cars in Taiwan and Japan. Her results show that the causality between GDP and car is from GDP of the number to registered car in Taiwan while in Japan the 2 variables are independent.

Xu, Li et al (2007) based on time series data study the relationship between the freeway transportation and the economic development through cointegration theory and Granger causality test method. They put different periods into account and obtain there is no relationship between the tested variables from 1978 to 1991 while there was harmonious and feedback Granger causality relationship during the period of time from 1992 till 2005.

Getzner (2009) studies the environmental impacts of passenger transport, especially CO2 emissions from private car use in Austria. The results of the empirical estimations are interpreted as a driving force of income with respect to car use is very strong while technological developments fall significantly short of reducing car use. Oil price shock brings a significantly negative but temporary effect. He even points out given the current trends of income, and assuming the empirically indicated functional form of the mobility/emission-income relationship, the scenarios show that even in the case of a complete stop to any further road construction and an increasing fuel price despite an annual increase in fuel taxes, passenger transport and private car use will still increase by 10 to 15% until 2020.

CHPATER 3 METHODOLOGY

This chapter is divided into six sections to present the methodologies adopted in this study. The methodology of unit root, choosing the lag length for unit root test, cointegration, vector autoregression model, Granger causality, and impulse response function are discussed as followings.

3.1 UNIT ROOT

In time series models in econometrics, often ordinary least squares (OLS) is used to estimate the slope coefficients of the autoregressive model. The use of OLS relies on the stochastic process being stationary. It means the error term must be time-invariant, that is, white noise. In other words, the necessary and sufficient condition for time series stability is the entire characteristic roots lie within the unit circle while the condition for nonstationarity is the entire characteristic roots lie in or outside the unit root.

When the data-generating process (DGP) is non-stationary, the use of OLS can produce invalid estimates. Granger and Newbold (1974) called such error estimates - spurious regression results: high R^2 values and high t-ratios yielding results with no economic meaning. If the process has a unit root, one can apply the difference operator to the series. OLS can then be applied to the resulting (stationary) series to estimate the remaining slope coefficients. For example, if a series Y_t is I(1), the series $\Delta Y_t = Y_t - Y_{t-1}$ is I(0) (stationary), it is called a difference-stationary series.

3.1.1 The Test of Unit Root

In statistics and econometrics, there are several ways to test whether time series is with a unit root, such as the Dickey-Full, augmented Dickey-Fuller (Dickey and Fuller 1979; Said and Dickey 1984) or the Phillips-Perron (Phillips 1987; Phillips and Perron 1988) among others.

3.1.1.1 Dickey-Fuller unit root test (DF)

Dickey-Fuller unit root test uses the OLS to run the regression on the following three forms and check whether $\delta=0$ is statistically significant.

1. no drift and trend:

$$\Delta Y_t = \gamma Y_{t-1} + e_t \tag{1}$$

2. with drift:

$$\Delta Y_t = \alpha + \gamma_\mu Y_{t-1} + e_t \tag{2}$$

3. with drift and deterministic time trend:

$$\Delta Y_t = \alpha + \beta T + \gamma_\tau Y_{t-1} + e_t \tag{3}$$

Where α is intercept, $\gamma / \gamma_\mu / \gamma_\tau$ is auto-regression term, βT is time trend term and e_t is error term.

In each case, the hypotheses is:

H_0: $\gamma = 0$, $\gamma_\mu = 0$ or $\gamma_\tau = 0$ (unit root, stationary)

H_1: $\gamma \neq 0$, $\gamma_\mu \neq 0$ or $\gamma_\tau \neq 0$ (without unit root, non-stationary)

If the null hypothesis - H_0 is rejected, it's concluded that the rejection of the tested variable existing unit root. The Dickey Fuller test is only valid for AR (1) (first order autoregressive) processes. If the time series is correlated at higher lags, the augmented Dickey Fuller test constructs a parameter correction for higher order correlation, by adding lag difference of the time series. More details are presented in chapter 3.1.1.2.

3.1.1.2 Augmented Dickey and Fuller Unit Root Test (ADF)

If the e_t has an autocorrelation for more than one period, the unit root test can be modified as

$$\Delta Y_t = \alpha + \beta T + \rho Y_{t-1} + \sum_{i=1}^{k} \lambda_j \Delta Y_{t-i} + e_t \tag{4}$$

where α is a constant, β the coefficient on a time trend, ρ the auto-regression term and k the lag order of the autoregressive process. Impose the constant α = 0 and β = 0 corresponding to modeling a random walk and use the constraint β = 0 corresponds to modeling a random walk with a drift. Consequently, there are three main versions of the test.

By including lags of the order i the ADF formulation allows for higher-order autoregressive processes. This means that the lag length i has to be determined when applying the test. One possible approach is to test down from high orders and examine the t-values on coefficients. An alternative approach is to examine information criteria such as the Akaike information criterion, Bayesian information criterion or the Hannan-Quinn information criterion.

The null hypothesis is functioned as the DF test (i.e., H_0: γ=0 for example). It is so called Augmented Dicky-Fuller (ADF) test.

The test procedure is firstly run the unrestricted model and obtains $RSS_{UR.}$

$$\Delta Y_t = \alpha + \beta T + \rho Y_{t-1} + \sum_{i=1}^{k} \lambda_j \Delta Y_{t-i} + e_t \tag{5}$$

Secondly, run the restricted model and obtains RSS_R

$$\Delta Y_t = \alpha + \beta T + \sum_{i=1}^{k} \lambda_j \Delta Y_{t-i} + e_t \tag{6}$$

Then compute the F-statistic as: $F^* = \dfrac{(RSS_R - RSS_{UR})/2}{RSS_{UR}/(n-k)}$

Compare F to the critical values Φ that are tabulated by Dicky-Fuller (1981).

The null hypothesis:

H_0: ρ=0 (unit root, non-stationary)

H_1: ρ≠0 (without unit root, stationary)

3.1.1.3 Phillips–Perron Unit Root test (PP)

Although, ADF test is the most common way for unit root test, it does not allow having autoregressive residuals with heteroscedasticity in the disturbance process of the test equation. To overcome such restrictions, the Phillips-Perron (PP) test offers an alternative method for correcting for serial correlation in unit root testing. In general, it makes a non-parametric correction to the t-test statistic to capture the effect of autocorrelation present when the underlying autocorrelation process is not AR(1) and the error terms are not homoscedastic.

There are also three types of Phillips-Perron unit root tests as follows:

(1) type with zero mean

$$Y_t = \alpha Y_{t-1} + \mu_t \tag{7}$$

(2) type with single mean

$$Y_t = \mu + \alpha Y_{t-1} + \mu_t \tag{8}$$

(3) type with constant and time trend term

$$Y_t = \mu + \alpha Y_{t-1} + \delta t + \mu_t \tag{9}$$

where μ_t is the innovations process.

The above three types are computed based on autoregressive model. Same as ADF test, if the null hypothesis is rejected, it means the tested variable is stationary series without unit root.

In some conditions, the PP test tends to be more powerful than ADF test but, on the other hand, similar to ADF, it also suffers potentially severe finite sample power (DeJong John, David et al. 1992; Chen 2009) and suffers from severe size distortions(Schwert 1989; Chen 2009). Size problem: actual size is larger than the nominal one when autocorrelations of μ_t are negative, and therefore, are more sensitive to model misspecification (the order of autoregressive and moving average components). We can plot ACF to help us detect the potential size.

Even though a variety of alternative procedures have been proposed that try to resolve these problems, particularly - the power problem, there are new drawbacks in them as well. (Maddala and Kim 1998) That's the reason the ADF and PP tests continue to be the most widely used unit root tests.

3.2 CHOOSING THE LAG LENGTH FOR THE UNIT ROOT TEST

An important practical issue for the implementation of the unit root test and vector autoregressive (VAR) model is the specification of the lag length p. Sun and Ma (2004) point out there are some commonly used procedures to chose the lag length of a VAR system. One of them is called the 'general-to-specific' approach, which starts from a maximum lag length and then testes down the significance of the longest lags. Ng and Perron (1995) finds out there is some empirical evidence that this approach has a high probability of over-fitting the true model. On the contrary, the approach of 'specific to general" starts from a minimum lag length and then expanding the VAR by accepting the significant extra lagged variables added in. “Both approaches involve testing the causal variables implicitly, which may created a pre-test bias.” Sun and Ma (2004)

Different from above mentioned two approaches, explicit statistical criteria as if Akaike’s information criterion (AIC), Schwarz’s Bayesian information criterion (SBC) are as well frequently used for lag length selection. As AIC and SBC are well-known, the definition of each is presented without further discussions:

$$\text{AIC} = \ln\left|\tilde{\Sigma}\right| + \frac{2}{T}\ \text{(number of freely estimated parameters)}, \tag{10}$$

and

$$\text{SBC} = \ln\left|\tilde{\Sigma}\right| + \frac{\ln T}{T}\ \text{(number of freely estimated parameters)} \tag{11}$$

where $\tilde{\Sigma}$ = estimated covariance matrix and T= number of observations.

If p is too small then the remaining serial correlation in the errors will bias the test while if p is too large then the power of the test will suffer. Monte Carlo experiments suggest it is better to error on the side of including too many lags. Hall (1994) and Ng and Perron (1995) also improved under some restriction, SBC tends to select a more optimal lag length. (Reimers 1992; Phylaktis 1999; Yau and Nieh 2003; Xu Hai-cheng 2007)

3.3 COINTEGRATION

This section briefly introduces the concepts of cointegration. The biggest problem with differencing is that lose valuable long term information in the data. One possible alternative solution to this is cointegration methods which get long run solutions from non stationary variables. The definitions of cointegration given by Engle and Granger are listed as follows.

Definition 1.

Engle and Granger (1987): If a series y_t with no deterministic components, can be represented by a stationary and invertible ARMA process after differencing d times, the series is integrated of order d, that is, $y_t \sim$ I(d).

Definition 2.

Engle and Granger (1987): If all elements of the vector y_t are I(d) and there exists a cointegrating vector $\beta \neq 0$ such that $\beta' y_t \sim$ I(d-b) for any b > 0, the vector process is said to be cointegrated CI (d,b).

The reduction in the order of integration implies a special kind of relationship with interpretable and testable consequences. Cointegration is an econometric property of time series. If two or more series are themselves non-stationary, and a linear combination of them is stationary, then the series are said to be cointegrated.

As indicated cointegration is a linear combination of 2 variables - X and Y or more series which are non-stationary, then the series are said to be cointegrated. In other words, if they are I(k) series and may be co-integrated becoming stable process of I (k-b, b>=1), it is called the I(k) series are cointegrated. (Engle and Granger 1987; Yang 2009)

It is often said that cointegration is a mean of correctly testing hypotheses concerning the relationship between two variables having unit roots (i.e. integrated of at least order one). It means a series is said to be "integrated of order d" if one can obtain a stationary series by "differencing" the series d times.

In practice, co-integration is used for such series in typical econometric tests, but it is more generally applicable and can be used for variables integrated of higher order. However, these tests for co-integration assume that the co-integrating vector is constant during the period of study. In reality, it is possible that the long-run relationship between the underlying variables change (shifts in the co-integrating vector can occur). The reason for this might be technological progress, economic crises, changes in the people's preferences and behavior accordingly, policy or regime alteration, and organizational or institutional developments. This is especially likely to be the case if the sample period is long.

3.3.1 The test of Cointegration

3.3.1.1 The Engle and Granger two-step procedure

The Engle and Granger two-step procedure is a residual based test. Given two variables of interest, the first step of the Engle-Granger procedure involves the estimation of the following statistic cointegrating regression:

$$Y_t = d_t + \beta X_t + \varepsilon_t \text{ for } t=1, 2, \ldots, T \tag{12}$$

where d_t denotes a deterministic term which may be either an intercept (α) or an intercept plus linear trend (α + βt). In the second stage, possible cointegration between the series is examined via analysis of the order of integration of the residuals $\{\hat{\varepsilon}_t\}$ from (12) using a Dickey-Fuller test as below.

$$\Delta b_t^2 = (\rho - 1) b_{t-1}^2 + v_t \tag{13}$$

The null of no cointegration (H_0: ρ − 1 = 0) is tested via the t-ratio of (ρ− 1).

3.3.1.2 Johansen Maximum Likelihood Method

Another approach named maximum likelihood (ML) method proposed by Johansen (Johansen 1988; Johansen 1991) can be also used to analyze long-run equilibrium relationship or cointegrating vectors. There are two statistics to take into account - the trace and maximum eigenvalue. Johansen's methodology takes its starting point in the vector autoregression (VAR) of order n given by

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots. + A_n Y_{t-n} + \varepsilon_t \tag{14}$$

where Y_t is lag length n $(p \times 1)$ vector endogenous variable. The VAR model of the first difference can be re-written as follows:

$$\Delta Y_t = \sum_{j=1}^{n-1} \pi_j \Delta Y_{t-j} + \pi Y_{t-n} + \varepsilon_t \tag{15}$$

where π_j is a short term adjusting coefficient to describe short-term relationship, π is long term innovation vector that includes long term information hint in the regression to test those variables' whether existence long term equilibrium relationship or not.

Meanwhile rank of π decides the number of cointegrated vector. π has three kinds of style:

a. $rank(\pi) = n$, then π is full rank. It means all of variables are stationary series in the regression (Y_t)

b. $rank(\pi) = 0$, then π is null rank. It means variables do not exist cointegred relationship.

c. $0 < rank(\pi) = r < n$, then some of variables exist r cointegrated vector.

Johansen approach has used rank of π to distinguish the number of cointegrated vector. In other words, to examine rank of vector means to test how many of non-zero of characteristic roots existence in the vector. Two different likelihood ratio tests listed in equtations (16) and (17) respectively.

<u>a. Trace test:</u>

$H_0 : rank(\pi) \le r$(at most r integrated vector)
$H_1 : rank(\pi) > r$(at least r+1 integrated vector)

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i) \tag{16}$$

T is sample size, $\hat{\lambda}_i$ is estimated of characteristic root. If test rejects H_0 that means variables exist at least r+1 long term cointegrated relationship.

<u>b. Maximum eigenvalue test:</u>

$H_0 : rank(\pi) \le r$(at most r integrated vector)
$H_1 : rank(\pi) > r$(at least r+1 integrated vector)

$$\lambda_{\max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1}) \tag{17}$$

If the null hypothesis is accepted, it means variables have r cointegrated vector. The method is starting to test from variables do not have any cointegrative relationship which is r=0. Then it adds the number of cointegrative item until H_0 can't be rejected, which means variables have r cointegrated vector.

3.4 VECTOR AUTOREGRESSION MODEL (VAR)

Vector autoregression (VAR) is an econometric used to capture the interrelation of time series and the dynamic impacts of random disturbances (or innovations) on the system of variables. All the variables in a VAR are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all the other variables in the model. The main uses of the VAR model are the impulse response analysis, variance decomposition, and Granger causality tests.

A VAR model describes the evolution of a set of k variables (called endogenous variables) over the same sample period (t = 1, ..., T) as a linear function of only their past evolution. The variables are collected in a k × 1 vector y_t, which has as the i^{th} element $y_{i,t}$ the time t observation of variable y_i. The mathematical representation of a VAR is:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_P y_{t-p} + e_t \tag{18}$$

where y_t is a k x 1 vector of endogenous variables, c is a $k \times 1$ vector of constants (intercept), $A_1 \ldots, A_P$ are matrices of coefficients to be estimated and e_t is a $k \times 1$ vector of error terms that may be contemporaneously correlated but are uncorreclated with their own lagged values as well as uncorrelated with all of the right-hand side variables.

In the VAR model, all the variables used have to be of the same order of integration. As a result, we have the following cases:

- All the variables are I(0) (stationary): one is in the standard case, ie. a VAR in level.
- All the variables are I(d) (non-stationary) with d>0:
    - The variables are cointegrated: the error correction term has to be included in the VAR. The model becomes a Vector Error Correction Model (VECM) which can be seen as a restricted VAR.
    - The variables are not cointegrated: the variables have first to be differenced d times and one has a VAR in difference.

The information criteria can be used to choose the optimal lag length in a VAR(p) by allowing a different lag length for each equation at each time and choosing the model with the lowest AIC, SBC or other information criteria value.

3.5 GRANGER CAUSALITY

In Granger's point of view, a universally acceptable definition of causation to this subtle and difficult concept may well not be possible, but a definition that seems reasonable to many is : “Let Ωn represent all the information available in the universe at time n. Suppose that at time n optimum forecasts are made of *Xn+1* using all of the information in Ωn, and also using all of this information apart from the past and present values *Yn-j*, *j*≥0, of the series *Yt*,. If the first forecast, using all the information, is superior to the second, than the series *Yt*, has some special information about *Xt*, not available elsewhere, and *Yt*, is said to cause *Xt*.” (Ashley, Granger et al. 1980)

According to Freeman (1983), for the most simple bivariate case, Granger causality can be operationalized in the following way: Consider the process 〔X_t, Y_t〕, which we will assume to be jointly covariance stationary. Denote by $\overline{X_t}$ and $\overline{Y_t}$ all past values of X and Y, respectively. Let all past and present values of these two variables be represented as $\overline{\overline{X_t}}$ and $\overline{\overline{Y_t}}$. Define $\sigma^2(X_t \mid Z)$ as the minimum predictive error variance of X_t given Z, where Z is composed of the sets 〔$\overline{X_t}, \overline{Y_t}, \overline{\overline{X_t}}, \overline{\overline{Y_t}}$〕. Then there are four possibilities:

1. : Y causes X: $\sigma^2(X_t \mid \overline{Y_t}, \overline{X_t}) < \sigma^2(X_t \mid \overline{X_t})$.
2. : Y causes X instantaneously: $\sigma^2(X_t \mid \overline{\overline{Y_t}}, \overline{X_t}) < \sigma^2(X_t \mid \overline{Y_t}, \overline{X_t})$.
3. : Feedback: $\sigma^2(X_t \mid \overline{X_t}, \overline{Y_t}) < \sigma^2(X_t \mid \overline{X_t})$, and

   $\sigma^2(Y_t \mid \overline{Y_t}, \overline{X_t}) < \sigma^2(Y_t \mid \overline{Y_t})$.
4. : Independence: X and Y are not causally related:

   $\sigma^2(X_t \mid \overline{Y_t}, \overline{\overline{Y_t}}) = \sigma^2(X_t \mid \overline{X_t}, \overline{Y_t}) = \sigma^2(X_t \mid \overline{X_t})$, and

   $\sigma^2(Y_t \mid \overline{Y_t}, \overline{\overline{X_t}}) = \sigma^2(Y_t \mid \overline{Y_t}, \overline{X_t}) = \sigma^2(Y_t \mid \overline{Y_t})$.

For instance, in case I the minimum predictive error variance for X_t is smaller when the past values of Y, $\overline{Y_t}$, are included than when the minimum predictive error variance is calculated solely on the basis of $\overline{X_t}$. When the preceding result obtains and, at the same time, X Granger causes Y, we have feedback or case III. However, it must be certain that implicit in this formulation is the presumption that there are no omitted variables that are responsible for the variations in X and Y.

3.5.1 Approaches to test Granger Causality

Here we present two approaches of Granger causality test. The discussions of them for determining Granger causality applied in this research are reported in 3.5.1.1 and 3.5.1.2.

3.5.1.1 The "Direct Granger Method"

The reason to name this method as direct is that it assesses Granger causality in a direct way: by regressing each variable on lagged values of itself and others. When both series are deemed I(0), a VAR model in levels is used. When one of the series is found I(0) and the other one I(1), VAR is specified in the level of the I(0) variable and in the first difference of the I(1) variable. When both series are determined I(1) but not cointegrated, the proper model is VAR in terms of the first difference. Finally, when the series are cointegrated, we can use a vector error correction model (VECM) or, for a bivariate system, a VAR model in levels.

The direct approach is based on the following VAR system:

$$Y_t = \beta_0 + \sum_{j=1}^{J} \beta_j Y_{t-j} + \sum_{k=1}^{k} \gamma_k X_{t-k} + u_t, \tag{19}$$

Where Y_t are stationary (or can be made stationary by differencing), β_0 is a constant term, β_j and γ_k are coefficients of exogenous variables, and u_t are white noise error terms.

We can then simply use an F-test (Wald test) or the like to examine the null hypothesis - $\gamma_k = 0$ by regressing each variable on lagged values of itself and the other. This method produces results sensitive to the choice of lags J and K; insufficient lags yield auto-correlated errors (and incorrect test statistics), while too many lags reduce the power of the test. This approach also allows for a determination of the causal direction of the relationships, since we can also estimate the "reverse" model:

$$X_t = \beta_0 + \sum_{j=1}^{J} \beta_j X_{t-j} + \sum_{k=1}^{k} \gamma_k Y_{t-k} + u_t \tag{20}$$

Also, it is important to remember that Granger causality testing should take place in the context of a fully-specified model. If the model isn't well specified, "spurious" relationships (Granger and Newbold 1974) may be found, despite the fact of no actual (conditional) relationship between the variables.

3.5.1.2 The Toda and Yamamoto Granger Causality Test

As the direct Granger causality test mentioned in 3.5.1.1 relies heavily on the results of pre-testing of unit root and cointegration. There are chances incorrect conclusions drawn from preliminary analyses or pretest biases might be carried over onto the causality test.

As a result, in order to avoid the pre-test bias, we present the Toda and Yamamoto approach as followings. Like the name suggests, it is proposed by Toda and Yamamoto (1995). In fact, it's a modified Wald (MWald) test for linear restrictions on some parameters of an augmented VAR (mlag + d) in levels, where d is the maximum order of integration that we suspect might occur in the process. In the bivariate case, this model without deterministic terms can be written as follows, (Konya 2004)

$$y_t = \alpha_1 + \sum_{i=1}^{mlag} \beta_{1i} y_{t-i} + \sum_{i=mlag+1}^{mlag+d} \beta_{1i} y_{t-i} + \sum_{i=1}^{mlag} \gamma_{1i} x_{t-i} + \sum_{i=mlag+1}^{mlag+d} \gamma_{1i} x_{t-i} + \varepsilon_{1t} \quad (21)$$

$$x_t = \alpha_2 + \sum_{i=1}^{mlag} \beta_{2i} y_{t-i} + \sum_{i=mlag+1}^{mlag+d} \beta_{2i} y_{t-i} + \sum_{i=1}^{mlag} \gamma_{2i} x_{t-i} + \sum_{i=mlag+1}^{mlag+d} \gamma_{2i} x_{t-i} + \varepsilon_{2t} \quad (22)$$

where the most important is that VAR model can be cointegrated or non-cointegrated. The variables in the VAR may be either stationary or non-stationary. The testing procedure explained by Sun and Ma (2004) is given as follows.

"Suppose the lag length is chosen as q by the SIC and the maximum order of the integrated time series is one. We estimate a VAR with q+1 order and then only apply the Wald test on the coefficients of the variables with lags up to q to conduct the Grager causality test". (Lutkepohl and Burda 1997)

Except the advantage of being free from the pre-test bias, there is one more advantage of this MWald method based on the study of Zapata and Rambaldi (1997). They perform Monte Carlo experiments on bivariate and trivariate models, and get the results showing that the surplus lag test has excellent finite sample properties for both cointegrated and non-cointegrate VAR models.

3.6 IMPULSE REPONSE FUNCTION

Impulse Response Function (IRF) traces the effect of an innovation in one variable on the others. For example, let Y_t be a k-dimensional vector series generated by

$$Y_t = A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + U_t \tag{23}$$

$$Y_t = \Phi(B) U_t = \sum_{i=1}^{\infty} \Phi_i U_{t-i} \tag{24}$$

$$I = (I - A_1 B - A_2 B^2 - \ldots - A_p B^p)\Phi(B) \tag{25}$$

where $cov(U_t) = \Sigma$, Φ_i is the MA coefficients measuring the impulse response. In a detailed and exact way, $\Phi_{jk,i}$ represents the response of variable j to a unit impulse in variable k occurring i^{th} period ago. As Σ is usually non-diagonal, it is impossible to shock one variable with other variables fixed. Some kind of transformation is needed. Cholesky decomposition is the most popular one which we shall turn to now. Let P be a lower triangular matrix such that $\Sigma = PP'$, then Eq. (24) can be rewritten as

$$Y_t = \sum_{i=0}^{\infty} \theta_i \omega_{t-i} \tag{26}$$

where $\theta_i = \Phi_i\omega_t = P^{-1}U_t$ and $E(\omega_t\omega_t')=I$. Let D be a diagonal matrix with same diagonals with P and $W = PD^{-1}$, $\Lambda = DD'$. After some manipulations, we obtain

$$Y_t = B_0Y_t + B_1Y_{t-1} + \cdot\cdot\cdot + B_pY_{t-p} + V_t \tag{27}$$

where $B_0= I_k - W^{-1}$, $W = PD^{-1}$, $B_i = W^{-1}A_i$. Obviously, B_0 is a lower triangular matrix with 0 diagonals. In other words, Cholesky decomposition imposes a recursive causal structure from the top variables to the bottom variables but not the other way around.

For a K-dimensional stationary VAR(p) process, $\varphi_{jk,i} = 0$, for $j \neq k$, i=1,2,… is equivalent to $\varphi_{jk,i}$=0, for i=1,…, $p(K$-1). That is to say if the first $pK-p$ responses of variable j to an impulse in variable k is zero, then all the following responses are all zero. (Lutkepohl 2005) And variable k does not cause variable j if and only if $\Phi_{jk,i}$ =0, i=1, 2, ….

CHPATER 4 DATA COLLECTION AND ANALYSIS

4.1 THE DATA

This section discusses and analyzes the time series variables to be utilized in the later chapter. In this study, the monthly historical gas price data is obtained from the prices offered by CPC, Corporation, as it enjoys a 78% & 77% market share respectively (EpochTimes Taiwan 2008) in the supply of 95 lead-free gasoline and premium diesel gasoline.

A country's GDP, which generally reflects the development of national economy, is chosen as the second index of a factor affecting traffic volume. We collect the quarterly real GDP data published by Directorate General of Budget, Accounting and Statistics, Executive Yuan, R.O.C. The data has been adjusted by Consumer Price Index (CPI) of 2006 and converted to monthly basis using it as a measurement of ability to support a car's carrying cost.

One might expect the impact of gas price and GDP on traffic volume to be more significant when they are calculated in real terms. Therefore the gas price time series data are computed by dividing the nominal price by the ratio of 2006 CPI announced by Directorate General of Budget, Accounting and Statistics, Executive Yuan, R.O.C. to real terms (100 in 2006) in order to eliminate the influence of the inflations.

The original data of National Freeway No. 1, 3, and 5 monthly toll station traffic volumes are taken from Taiwan Area National Freeway Bureau, MOTC. Based on the preliminary data the traffic of each station is categorized into 5 clusters according to geographical locations. We obtained traffic volumes in four areas – northern, central, southern, and I-Lan area plus the one throughout the island.

The period of each variable computed in this study falls between 2004:01 to 2009:06, yielding a total of 66 monthly observations for each vehicle type. The toll traffic volume in I-Lan area, on the other hand, is taken from the period between 2006:09 to 2009:06 as it opened its service in 2006. Table 4.1 contains a list of the variables analyzed in this study.

Table 4.1 Variable Denotation and Definition

Denotation	Description	Sample Period
R95P	real 95 lead-free gas price (NT$ per liter, price adjusted based on 2006 Taiwan Consumer Price Index)	2004:01~2009:06
RDSP	real premium diesel price (NT$ per liter, price adjusted based on 2006 Taiwan Consumer Price Index)	2004:01~2009:06
RGDP	real gross domestic product (million NT$, seasonally adjusted at 2006 price)	2004:01~2009:06
SVN	small vehicle traffic volume of Freeway No. 1 & 3 toll stations around northern area	2004:01~2009:06

Table 4.1 Variable Denotation and Definition (continued)

Denotation	Description	Sample Period
SVC	small vehicle traffic volume of Freeway No. 1 & 3 toll stations around central area	2004:01~2009:06
SVS	small vehicle traffic volume of Freeway No. 1 & 3 toll stations around southern area	2004:01~2009:06
SVI	small vehicle traffic volume of Freeway No. 5 toll stations around I-Lan area	2006:09~2009:06
SVT	small vehicle traffic volume of Freeway No. 1 & 3 toll stations nationwide	2004:01~2009:06
TBN	truck and bus traffic volume of Freeway No. 1 & 3 toll stations around northern area	2004:01~2009:06
TBC	truck and bus traffic volume of Freeway No. 1 & 3 toll stations around central area	2004:01~2009:06
TBS	truck and bus traffic volume of Freeway No. 1 & 3 toll stations around southern area	2004:01~2009:06
TBI	truck and bus traffic volume of Freeway No. 5 toll stations around I-Lan area	2004:01~2009:06
TBT	truck and bus traffic volume of Freeway No. 1 & 3 toll station Nationwide	2004:01~2009:06
TLN	trailer traffic volume of Freeway No. 1 & 3 toll stations around northern area	2004:01~2009:06

Table 4.1 Variable Denotation and Definition (continued)

Denotation	Description	Sample Period
TLC	trailer traffic volume of Freeway No. 1 & 3 toll stations around central area	2004:01~2009:06
TLS	trailer traffic volume of Freeway No. 1 & 3 toll stations around southern area	2004:01~2009:06
TLI	trailer traffic volume of Freeway No. 5 toll stations around I-Lan area	2006:09~2009:06
TLT	trailer traffic volume of Freeway No. 1 & 3 toll stations nationwide	2004:01~2009:06
RES_RDSP	residual of real premium diesel price	
RES_TBI	residual of truck & bus traffic volume of Freeway No. 5 toll station around I-Lan area	
RES_RGDP	residual of real gross domestic product	

4.2 DESCRIPTIVE STATISTICS

The paper tries to combine the techniques with two sophisticated statistical software packages - SAS 9.2 and Eviews for all the statistical process used. However, a crucial step in the analysis of data is a careful description of the available data. Then, statistical analysis for main descriptive statistics and Pearson bivariate correlation coefficient are computed and displayed in table 4.2 and 4.3 respectively.

Table 4.2 Descriptive Statistics

Descriptive Statistics					
Variable	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
R959	66	25.39	3.82	15.63	34.25
RDSP	66	21.35	4.21	12.97	31.03
RGDP	66	1,017,799	65,198	917,023	1,122,026
SVN	66	18,206,179	908,854	15,513,910	19,891,532
SVNC	66	12,281,964	1,231,119	10,121,177	16,355,816
SVS	66	8,133,256	772,033	6,915,548	10,825,047
SVI	34	1,202,919	187,257	410,612	1,544,377
SVT	66	38,621,399	2,579,823	33,066,436	45,607,522
TBN	66	1,540,940	139,409	1,139,485	1,768,748
TBC	66	1,863,349	156,411	1,448,542	2,077,951
TBS	66	1,087,580	84,691	872,074	1,206,342
TBI	34	20,099	17,464	7	46,067
TBT	66	4,491,869	367,292	3,460,101	5,017,023
TLN	66	979,678	125,251	586,084	1,117,653
TLC	66	1,180,233	97,445	912,912	1,376,501
TLS	66	1,022,807	94,047	747,690	1,207,865
TLI	34	87.38	29.92	0	133
TLT	66	3,182,718	296,036	2,301,427	3,688,515

Notes:
STD DEV stands for standard deviation.
Price for R95P and RDSP is at NTD per liter.
RGDP is measured in million NTD.
Toll traffic volume is counted per car each month.

Table 4.2 indicates means, standard deviation, minimum and maximum value of each variable. For instance, the highest real 95 unleaded gas price is NTD 34.25 per liter as opposed to NTD 15.63 per liter the lowest. The price difference between them is equilibrant to 119 percent of fluctuation during the observed period.

The maximum real premium diesel price is NTD 31.03 which is over 2 times higher than the minimum real premium diesel price – NTD 12.79 per liter. As to the real GDP, it reaches its historical high – 1122 billon NTD and drops to the historical low 917 billion NTD, accounting for a 22% difference during the study period.

It can also be inferred from the same table that traffic volumes during the study period also fluctuate, ranging from around 19.8 million cars the highest to 15.5 million the lowest, as was shown in the small vehicle traffic volume in the northern area.

Table 4.3 Pearson Correlation Coefficients

Pearson Correlation Coefficients Prob > |r| under H0: Rho=0						
		SVN	**SVC**	**SVS**	**SVI**	**SVT**
R95P	**r**	0.17974	-0.29531	-0.2852	-0.16296	-0.34702
	Sig.	0.1487	0.0161	0.0203	0.1911	0.0444
RGDP	**r**	-0.292	-0.29436	-0.25372	-0.31927	0.04603
	Sig.	0.0174	0.0164	0.0398	0.009	0.796
		TBN	**TBC**	**TBS**	**TBI**	**TBT**
RDSP	**r**	0.24127	-0.15705	-0.08756	-0.28845	0.00451
	Sig.	0.051	0.2079	0.4845	0.098	0.9713
RGDP	**r**	-0.18325	-0.55185	-0.41785	-0.05206	-0.40091
	Sig.	0.1408	<.0001	0.0005	0.77	0.0009
		TLN	**TLC**	**TLS**	**TLI**	**TLT**
RDSP	**r**	0.481	0.71687	0.61227	0.21118	0.63399
	Sig.	<.0001	<.0001	<.0001	0.2381	<.0001
RGDP	**r**	-0.03492	0.53829	0.31798	0.26812	0.26343
	Sig.	0.7807	<.0001	0.0093	0.1314	0.0326

In statistics, Pearson's correlation (typically denoted by *r)* is used to find a degree of linear relationship between at least two continuous variables. The value for a Pearson's can fall between 0.00 (no correlation) and 1.00 (perfect correlation). A correlation coefficient of thirty pairs of data used in this study is taken into account. Two pieces of information are provided in each cell - the Pearson correlation coefficients and the statistically significance in Table 4.3, which illustrates the direction and strength of association between variables.

After a careful observation, we maintain that in most cases, the coefficients are rather weak and not statistically significant to stand at the 0.05 level, as measured by the t-statistics. It can be assumed that traffic is insensitive to changes in the gas price or GDP. Although there are still exceptions in four out of thirty cases, three pairs of cases showing strong and positive relationships between “gas price and trailer traffic volume in central Taiwan”, “gas price and trailer traffic volume in southern Taiwan”, “gas price and trailer traffic in nationwide” and between “GDP and trailer traffic volume in central Taiwan”. The only case which reflects a strong but negative relationship between “GDP and traffic volume of truck and bus” is in central Taiwan.

Figure 4.1 to 4.6 demonstrate a clear picture of traffic volume trends from 2004:01 ~ 2009:06. From Figure 4.1 and 4.2, it can be seen that small vehicle volumes do not vary considerably during the study periods. The yearly high is often in each February; presumably it is because of the winter vocation and Chinese Lunar New Year holidays which bring more cars on the road.

In general, people are less likely to give up on using cars due to the increasing gas price. Similar phenomena could be observed when comparing the variation between traffic volume and GDP. However, a sharp drop in gasoline price in Jan. 2009 did produce some small noticeable impacts on the increasing small vehicle traffic be it in northern, central or southern area.

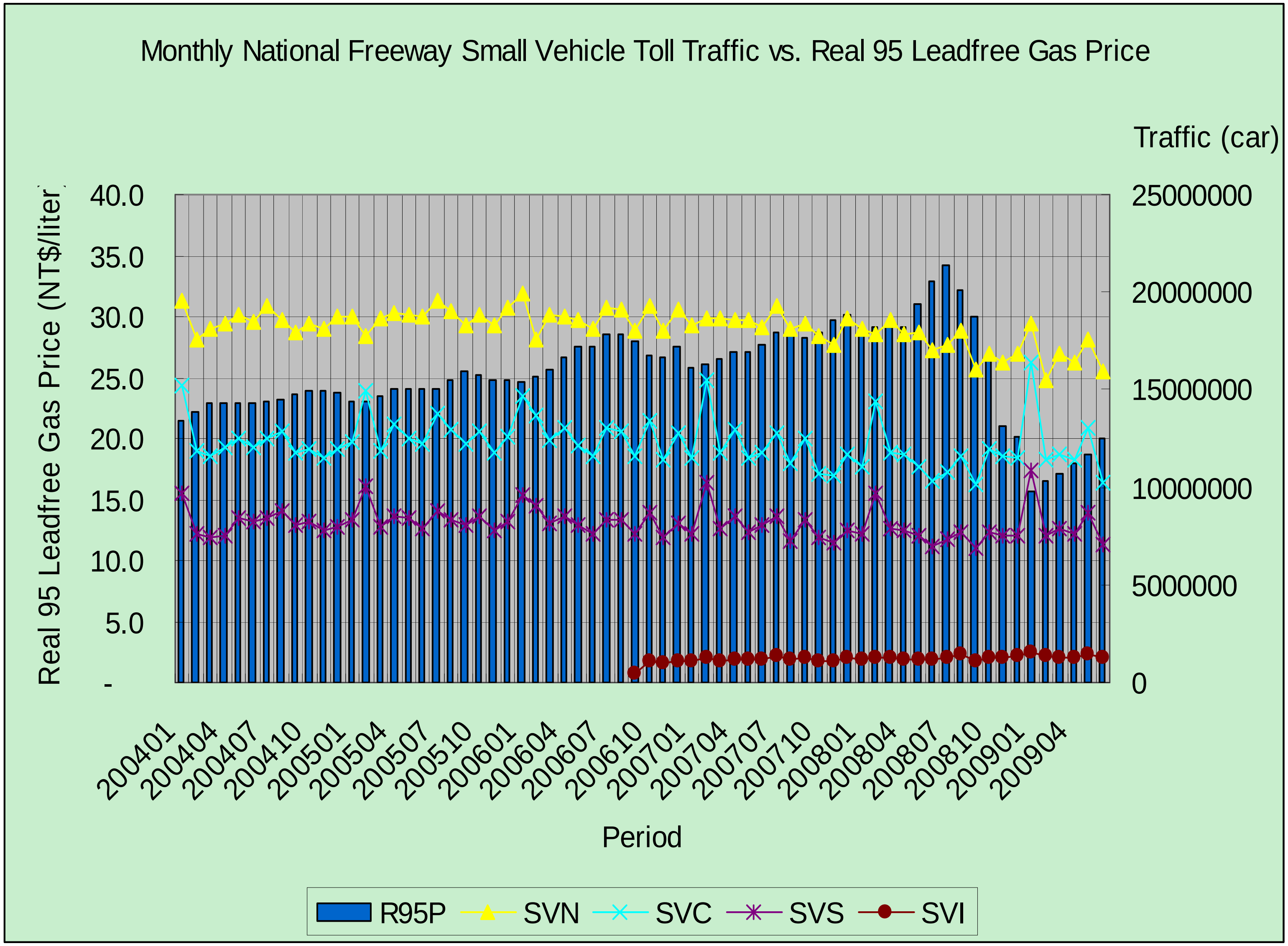


Figure 4.1 Monthly National Freeway Small Vehicle Toll Traffic vs. Real 95 Leadfree Gas Price

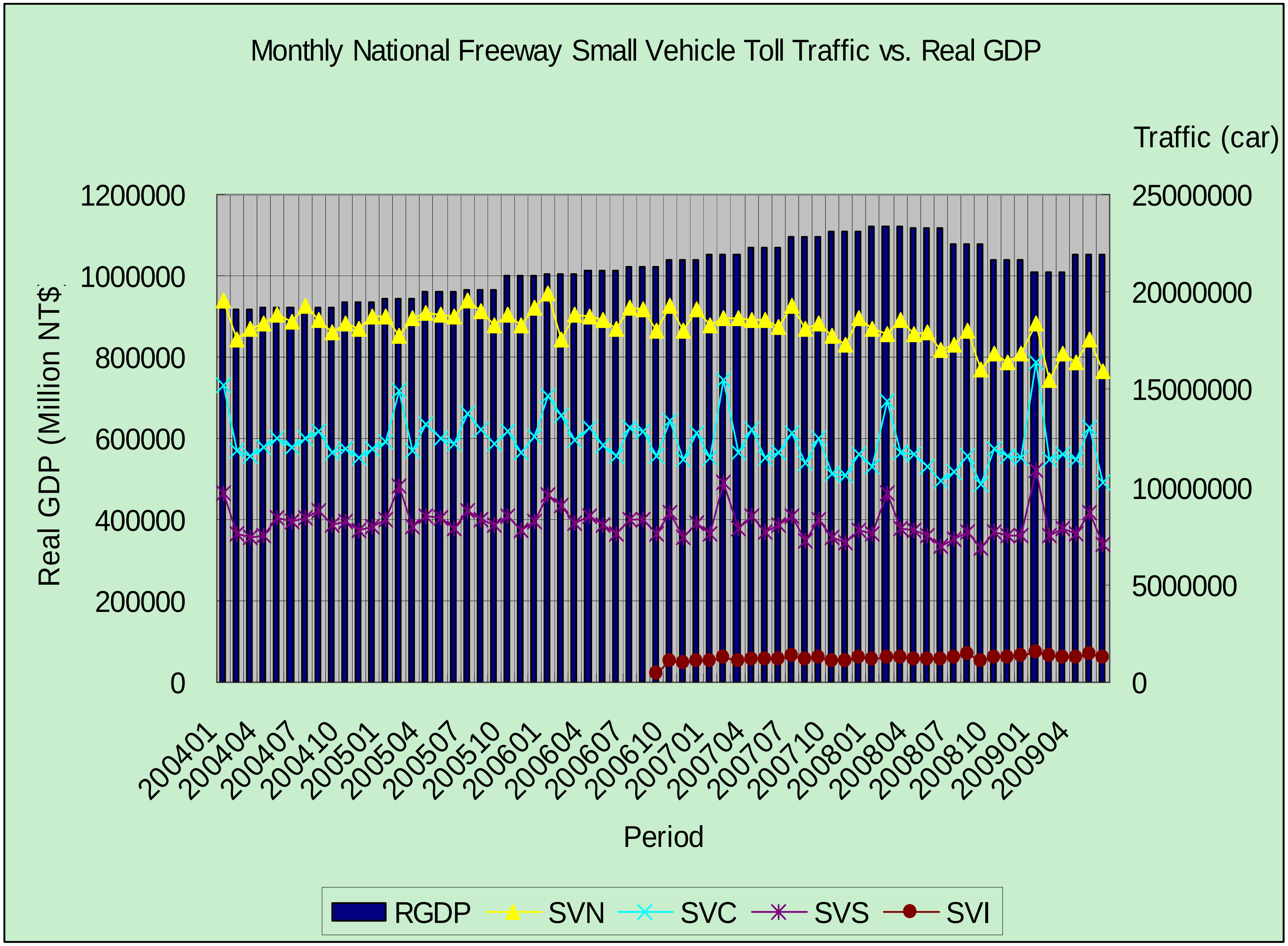


Figure 4.2 Monthly National Freeway Small Vehicle Toll Traffic vs. Real GDP

Figure 4.3 and 4.4 show the relationship of “truck and bus traffic volume” vs. ‘”real premium diesel price” and vs. “real GDP” respectively. Like small vehicle traffic volumes illustrated in Figure 4.1 and 4.2, we observe the truck and bus traffic volume often drops in February each year. We assume this considerable low period of traffic drop stems from the same reason for small vehicle traffic mentioned earlier.

Except the big effect of holiday season in February which brings fewer truck and bus on the road, based on Figure 4.3, and 4.4 the traffic volumes of truck and bus stay quite stable. There is no neither remarkable growth nor decline in volume during the study periods. Out of our expectation, when the gas price rocked to the highest price – NT$ 31.03 per liter in July 2008, the truck and bus traffic volume did not sink but instead it rose 2% till 8%.

The bar graph in Figure 4.4 demonstrates GDP remains stable during the period of Jan. 2004 to Jun. 2009. Even though there are small numbers of up and down in GDP, the truck and bus traffic volume seems not dancing with its fluctuations. It implies the impact of GDP on the traffic is not conspicuous.

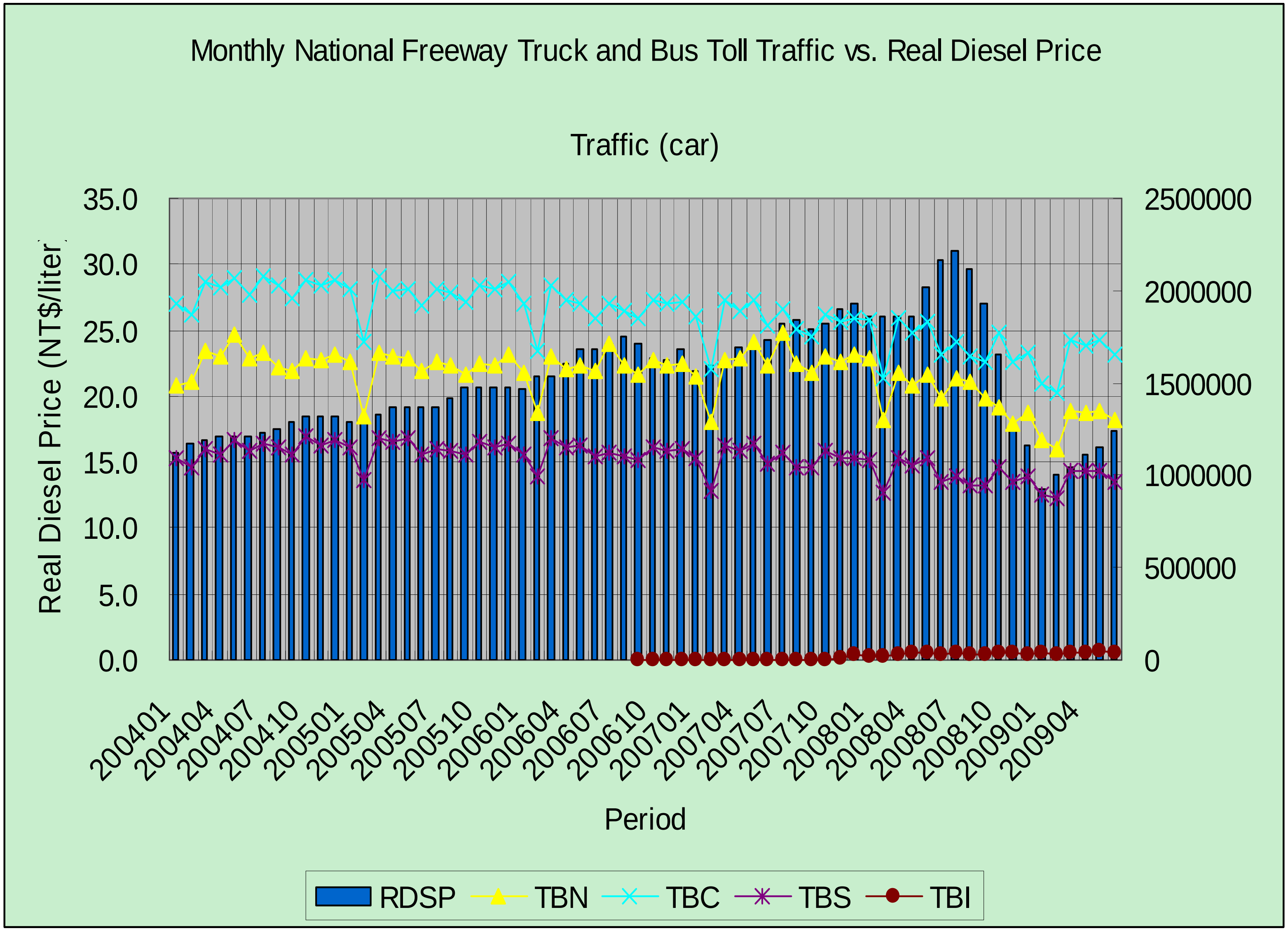


Figure 4.3 Monthly National Freeway Truck and Bus Toll Traffic vs. Real Diesel Price

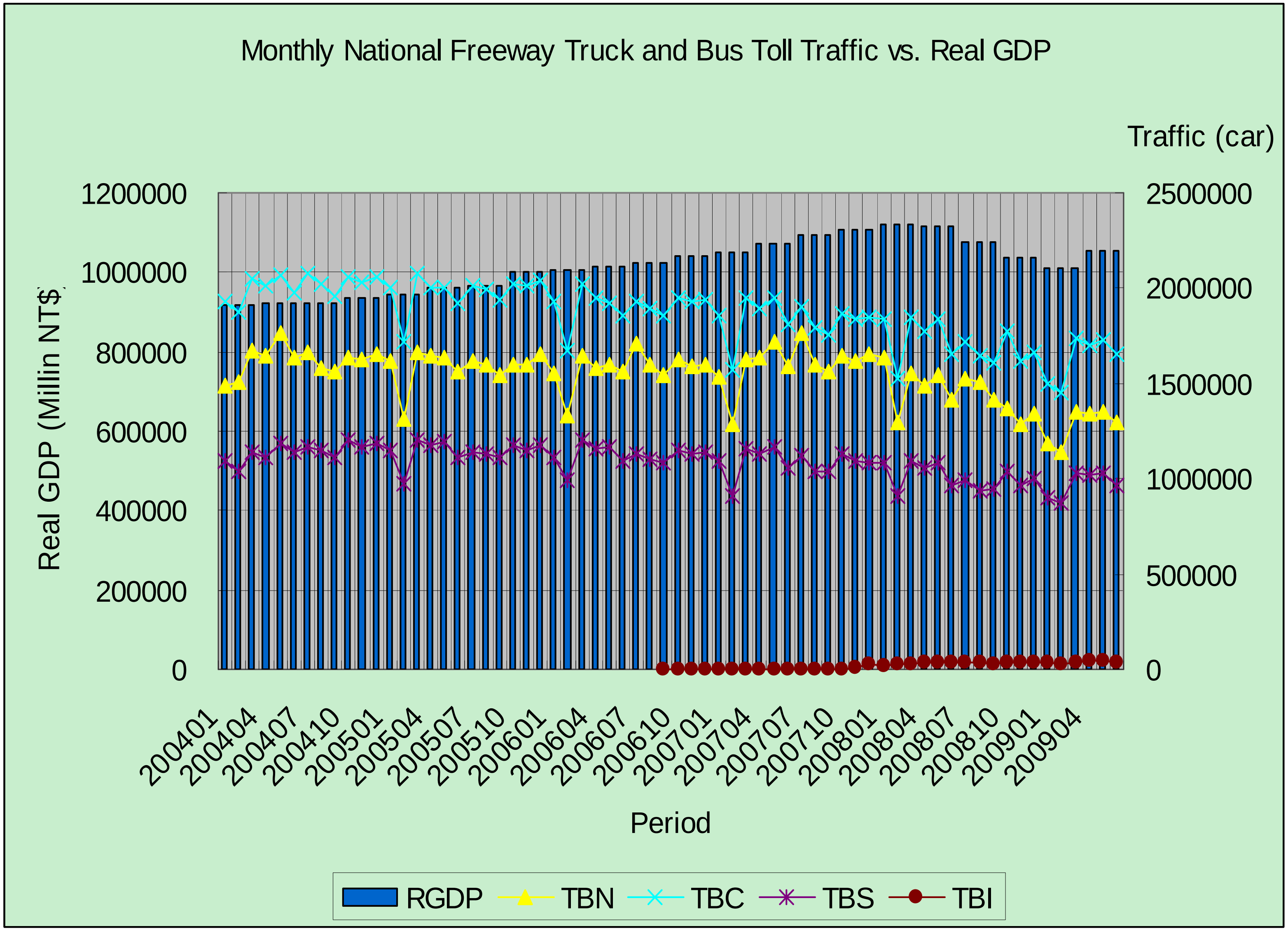


Figure 4.4 Monthly National Freeway Truck and Bus Toll Traffic vs. Real GDP

Based on Figure 4.5 and 4.6, again we notice an opposite phenomena of the lowest truck and bus traffic volume in each February to the traffic volume of small vehicle in the same period. The major reason to this situation can be regarded that it's usage of this type of vehicles is often for business purpose and in addition that February is always with less working in a year. Comparing the volume in February with the one in previous month in the same year, the fluctuation percentages are around 19, 14 and 21 in 2005, 2006 and 2007 in order of year. Aside from this significant decreasing in volume, the rest in other months before July 2008, one month right after the peak gas price in the study period, remain relatively constant.

Another note-worthy point is the trailer traffic, not counting the holiday month, does not return to its normal volume of traffic. Between the periods of September 2008 to till June 2009, it seems the trailer drivers continue to drive less even though the gas price returns to its stable level several months ago. The reasons behind this situation can be deduced that gas price depresses highway toll traffic much longer than the fluctuation period of itself. The GDP stays rather stable (bar chart of Figure 4.6) during this period of time seems to suggest that it does not play as a significant role of causing this depression of toll trailer traffic. Hence, it's very likely there can be other factors leading to this phenomenon, which requires further study.

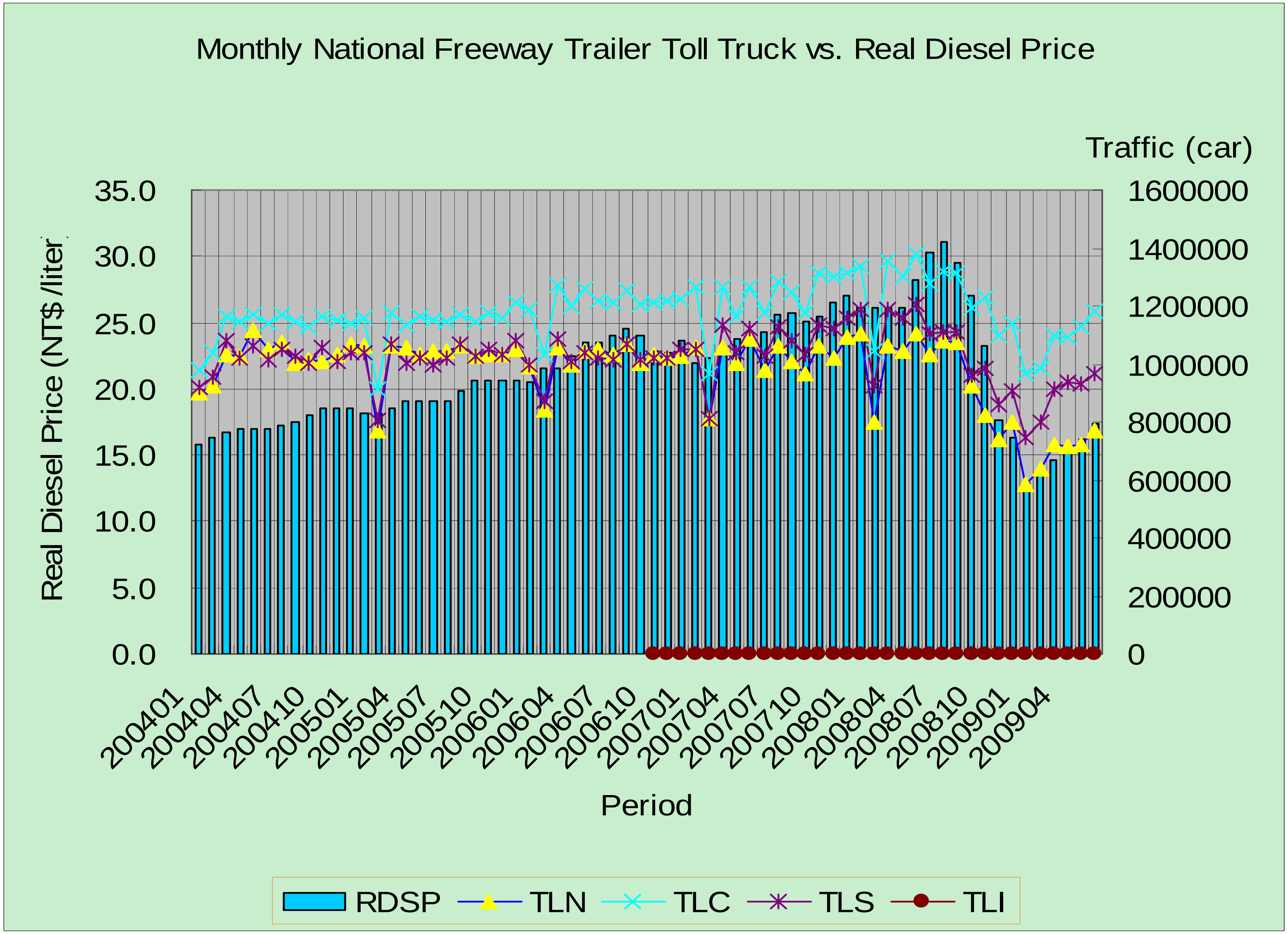


Figure 4.5 Monthly National Freeway Trailer Toll Traffic vs. Real Diesel Price

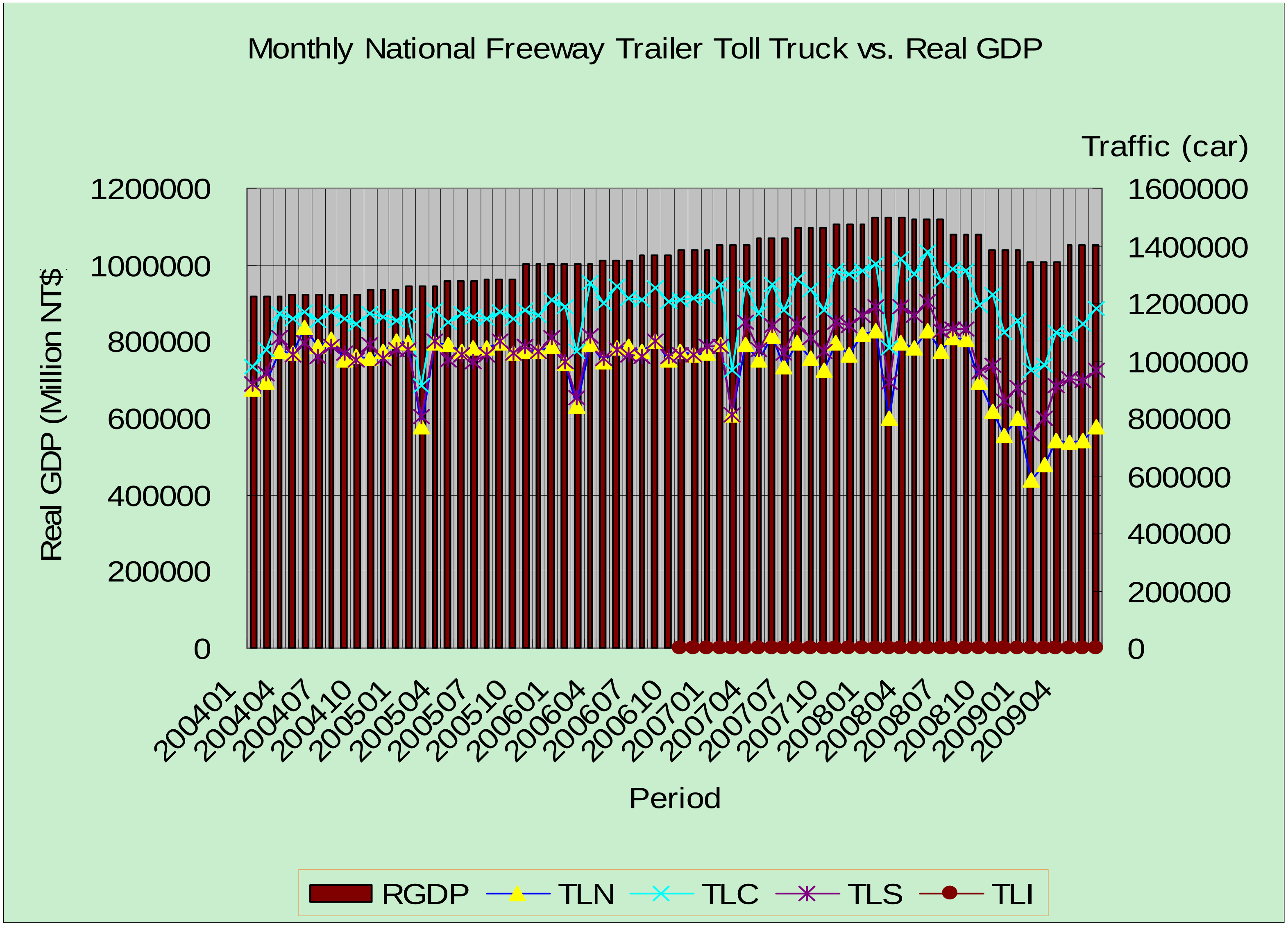


Figure 4.6 Monthly National Freeway Trailer Toll Traffic vs. Real GDP

CHPATER 5 EMPIRICAL RESUTLS

In this chapter, we present empirical results tested in the study. Figure 5.1 demonstrates the analytical process of statistics tests on time series applied in this study. It begins with unit root, cointegration, then Granger causality and finally impulse response functions prior to the final conclusion.

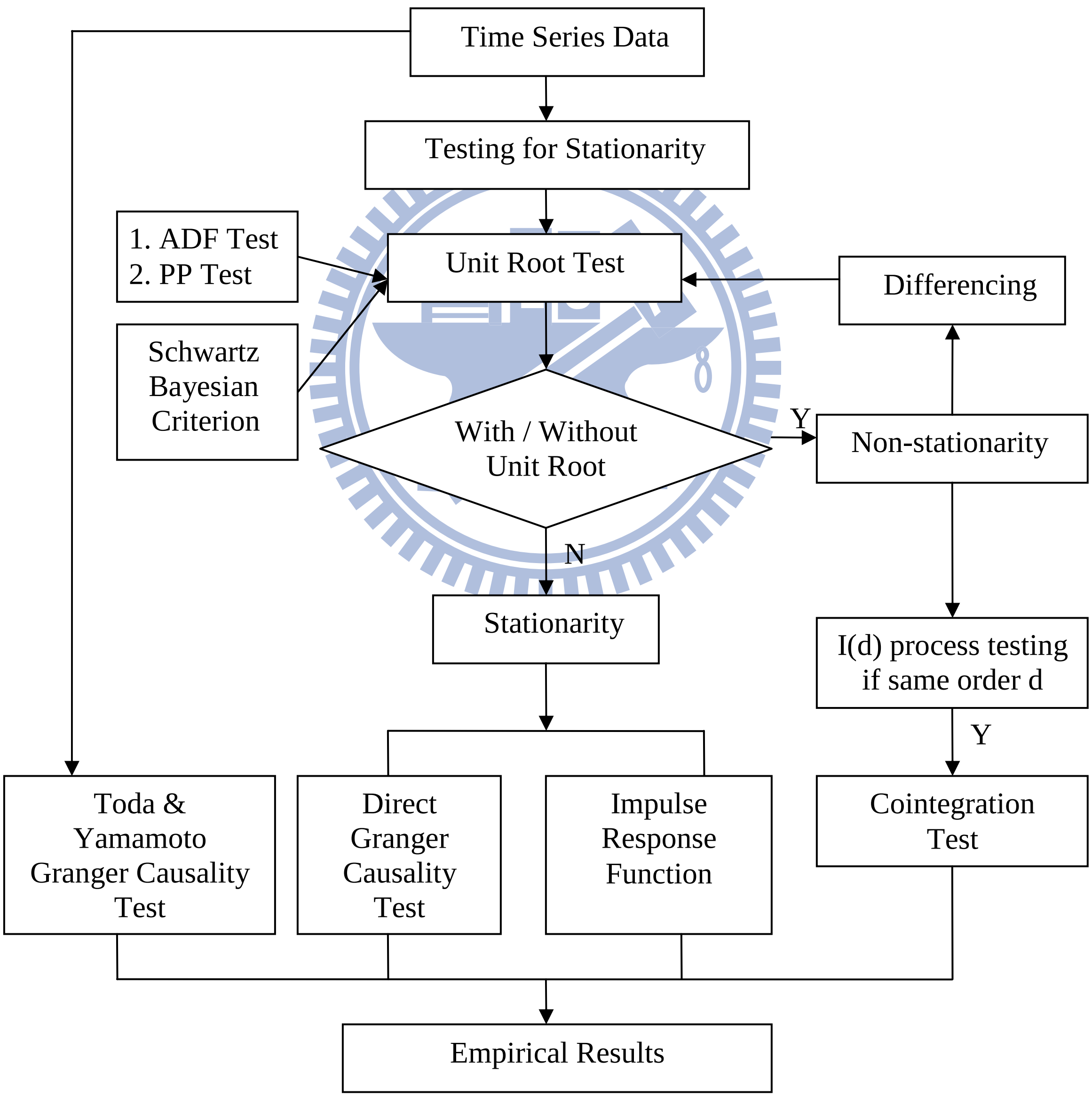


Figure 5.1 Analytical Procedure for Testing Granger Causality

5.1 UNIT ROOT TESTS

In this section, we examine whether the series under investigation are stationary. We do this by applying the ADF & PP unit root test by using the SAS software package.

Here we follow the ADF testing procedure suggested by Dolado, Jenkison et al. (1990) and Nieh and Wang (2005), who regard the most suitable exam order of estimated model of unit root test is Model (3) → Model (2) → Model (1). It means Model (3) with the factors of time trend and constant is tested firstly. If time trend and constant appear insignificant, the Model (2) which contains only constant and no trend will then be estimated subsequently. If constant remains insignificant, it means Model (1) – the pure random walk is the most suitable. The output for this test is given in the table 5.1.

Table 5.1 Results of Unit-Root Tests in Levels

Variable	**ADF**			**PP**		
	Model (1)	**Model (2)**	**Model (3)**	**Model (1)**	**Model (2)**	**Model (3)**
R95P(3)	**-0.40**	**-2.69**	**-2.57**	**-0.37**	**-1.84**	**-1.60**
RDSP(2)	**-0.38**	**-2.84**	**-2.95**	**-0.23**	**-1.80**	**-1.40**
RGDP(1)	**1.28**	**-1.51**	**-0.79**	**1.29**	**-1.47**	**-0.84**
SVN(2)	**-0.66**	**-0.94**	**-2.59**	**-0.95**	**-4.60*** **	**-6.66*** **
SVC(0)	**-0.93**	**-8.35*** **	**-8.76*** **	**-0.93**	**-8.35*** **	**-8.76*** **
SVS(0)	**-0.84**	**-8.61*** **	**-8.91*** **	**-0.84**	**-8.61*** **	**-8.91*** **
SVI(5)	**1.41**	**-1.39**	**-2.18**	**0.50**	**-6.29*** **	**-9.74*** **
SVT(0)	**-0.76**	**-7.53*** **	**-8.75*** **	**-0.76**	**-7.53*** **	**-8.75*** **

Table 5.1 Results of Unit-Root Tests in Levels (continued)

Variable	ADF Model (1)	ADF Model (2)	ADF Model (3)	PP Model (1)	PP Model (2)	PP Model (3)
TBN(1)	**-0.47**	**-2.41**	**-3.85****	**-0.47**	**-3.78*****	**-5.42*****
TBC(1)	**-0.48**	**-2.18**	**-6.19*****	**-0.54**	**-3.56*****	**-8.07*****
TBS(5)	**-1.33**	**0.02**	**-2.64**	**-0.56**	**-4.92*****	**-7.27*****
TBI(1)	**0.48**	**-0.83**	**-1.98**	**0.45**	**-0.86**	**-2.15**
TBT(1)	**-0.45**	**-2.38**	**-5.22*****	**-0.50**	**-3.91*****	**-7.12*****
TLN(2)	**-0.69**	**-1.37**	**-2.20**	**-0.48**	**-3.38****	**-4.37*****
TLC(2)	**-0.02**	**-2.67**	**-2.61**	**0.11**	**-5.89*****	**-6.00*****
TLS(2)	**-0.35**	**-2.32**	**-2.33**	**-0.17**	**-5.35*****	**-5.35*****
TLI(5)	**-0.80**	**-1.41**	**-1.50**	**-0.55**	**-4.39*****	**-4.20****
TLT(2)	**-0.38**	**-2.21**	**-2.33**	**-0.18**	**-5.12*****	**-5.21*****

Notes:
Null Hypothesis: variable has a unit root
Model 1: no intercepts; no trends
Model 2: unrestricted intercepts; no trends
Model 3: unrestricted intercepts and trends
**Significant at the 5% level.
***Significant at the 1% level.
( ): Lag Length – based on minimum BIC value

Table 5.1 provides the unit root test for the null hypothesis. There are four variables - real 95 lead-free gas price, real premium diesel price, real GDP and truck and bus traffic in I-Lan area all failing to reject the null hypothesis of series with unit root both by ADF and PP test at 5% significance level. Hence, they are regarded as non-stationary and further differencing of the data is required to eliminate the unit root from the data-generating process. Beside the mentioned four variables with unit root, the statistics for traffic volumes of small vehicle and “truck and bus” around northern and central area as well as nationwide all consistently reject the null hypothesis and therefore no unit root is present no matter tested by ADF or PP.

An intriguing result reveals here. We obtain eight conflicting outputs computed by ADF and PP test; such as the results of the small vehicle traffic in northern and I-Lan area, truck and bus traffic in southern area plus the trailer traffic in all five areas. As there is an overwhelming proof that unit-root tests suffers from low power. Further more, “Dickey and Fuller’s (1981) unit root test is derided by some scholars as “yes man”; namely the level term which standard is uneasily to be refused by unit root test. (Chou and Nieh 2005; Nieh and Wang 2005) In order to avoid the problem of over differencing, and in addition that ACF plots displayed in Figure 7.1 suggest the stationary series of all the traffic time series giving the confidence vote to support us taking the results of PP test instead of ADF.

When we take the first difference on the series with unit root in level and run the similar regressions again as a next step, the statistics reported in the Table 5.2 illustrates that the four variables all reject the null hypothesis of a series with unit root. In consequence, they become stationary after the first-difference and it may suggest that there is no need for second difference.

Table 5.2 Results of Unit-Root Tests in First Difference

Variable	ADF			PP		
	Model(1)	Model(2)	Model(3)	Model(1)	Model(2)	Model(3)
R95P(1)	**-3.20*****	**-3.18****	**-3.14**	**-4.72*****	**-4.68*****	**-4.71*****
RDSP(1)	**-3.22*****	**-3.19****	**-3.82****	**-4.10*****	**-4.07*****	**-4.25*****
RGDP(0)	**-7.94*****	**-8.11*****	**-8.25*****	**-7.94*****	**-8.11*****	**-8.25*****
TBI(0)	**-5.49*****	**-5.75*****	**-5.63*****	**-5.49*****	**-5.75*****	**-5.63*****

Notes:
Null Hypothesis: variable has a unit root
Model 1: no intercepts; no trends
Model 2: unrestricted intercepts; no trends
Model 3: unrestricted intercepts and trends
**Significant at the 5% level.
***Significant at the 1% level.
( ): Lag Length – based on minimum BIC value

5.2 COINTEGRATION TESTS

As indicated earlier, a cointegration is a linear combination of 2 variables - X and Y or more series which are non-stationary, then the series are said to be cointegrated. In other words, if they are I(k) series and may be co-integrated becoming stable process of I (k-b, b>=1), it is called the I(k) series are cointegrated. (Engle and Granger 1987; Yang 2009).

Due to the fact that there are only four variables – real 95 unleaded gas price, real premium diesel price, real GDP plus truck and bus traffic in I-Lan area are integrated with the same first order denoted as I (1) while the rest interested variables are stationary series denoted as I (0), there are only those I (1) variables with the possibility of cointegration. The next step is to test for cointegration using The Engle-Granger two-step method and Johansen Cointegration Test to investigate the pairwise long haul relationship between the variables. In addition, as R95P is no related to TBI, we do not incorporate it in the cointegration tests in this section.

Based on 5% significance level, the results stated in Table 5.3, 5.4 and 5.5 suggest that there is no evidence of co-integration neither between "real premium diesel price and truck & bus toll traffic around I-Lan area", nor between "real GDP and truck and bus toll traffic around I-Lan area". In general, it means gas prices, traffic volume and GDP follow a random walk i.e. there is no co-integration among them.

Table 5.3 Results of Cointegration

by The Engle-Granger Two-Step Method

	ADF			PP		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
Residual Series						
RES_RDSP vs. RES_TBI(1)	**-1.27**	**-1.25**	**-1.45**	**-1.16**	**-1.13**	**-1.48**
RES_RGDP vs. RES_TBI(1)	**-0.99**	**-0.93**	**-1.91**	**-0.99**	**-0.94**	**-2.01**

Note:
Null Hypothesis: no co-integration.
** / *** denotes rejection of the hypothesis of no cointegration at 0.05 / 0.01 level
Model 1: no intercepts; no trends
Model 2: unrestricted intercepts; no trends
Model 3: unrestricted intercepts and trends
**Significant at the 5% level.
***Significant at the 1% level.
( ): Lag Length – based on minimum BIC value

Table 5.4 Results of Cointegration by Johansen Cointegration Test for RDSP & TBI

Hypothesized No. of CE(s)	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
Model 1: No intercept or trend in CE or test VAR			
Rank			
None	**4.878986**	12.32090	0.5845
At most 1	0.750952	4.129906	0.4440
Model 2: Intercept (no trend) in CE – no intercept in VAR			
None	17.27634	20.26184	0.1225
At most 1	1.973673	9.164546	0.7829
Model 3: Intercept (no trend) in CE and test VAR			
None	14.77125	15.49471	0.0641
At most 1	0.425293	3.841466	0.5143
Model 4: Intercept and trend in CE – no trend in VAR			
None	20.75717	25.87211	0.1900
At most 1	3.875177	12.51798	0.7601
Model 5: Intercept and trend in CE – linear trend in VAR			
None	18.45332	18.39771	0.0491
At most 1	2.917143	3.841466	0.0876

Note:
Null Hypothesis: no cointegration
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values
The model selection follows Nieh and Lee (2001) decision procedure, diagnosing models one by one from model 1 to Model 2 till 5 until the model that cannot be rejected for the null.
Lag Length: 2 (based on minimum BIC value)

Table 5.5 Results of Cointegration by Johansen Cointegration Test for RGDP & TBI

Hypothesized No. of CE(s)	Trace Statistic	0.05 Critical Value	Prob.**
Model 1: No intercept or trend in CE or test VAR			
Rank			
None	**11.84749**	12.32090	0.0599
At most 1	1.597247	4.129906	0.2421
Model 2: Intercept (no trend) in CE – no intercept in VAR			
None	16.81955	20.26184	0.1394
At most 1	5.478079	9.164546	0.2350
Model 3: Intercept (no trend) in CE and test VAR			
None	14.58612	15.49471	0.0682
At most 1	3.588777	3.841466	0.0582
Model 4: Intercept and trend in CE – no trend in VAR			
None	25.80001	25.87211	0.0510
At most 1	4.388566	12.51798	0.6854
Model 5: Intercept and trend in CE – linear trend in VAR			
None	20.71972	18.39771	0.0233
At most 1	2.584900	3.841466	0.1079

Note:
Null Hypothesis: no cointegration
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values
The model selection follows Nieh and Lee's (2001) decision procedure, diagnosing models one by one from model 1 to Model 2 till 5 until the model that cannot be rejected for the null.
Lag Length: 1 (based on minimum BIC value)

5.3 GRANGER CAUSALITY TESTS

As the two different cointegration tests in chapter 5.2 show no evidence of a long run relationship between the corresponding variables, an error correction model (ECM) based causality tests are not appropriate (Toda and Phillips 1994) to be used in this study. We conduct causality tests using Granger approach - vector auto-regression model (VAR) on stationary series (in level or after being d time(s) differenced) for each of the two pairs between "gas price and freeway traffic" and "GPD and freeway traffic".

A caveat from SAS that Granger causality test is very sensitive to the choice of lag length and to the methods employed in dealing with any non-stationary of the time series.(Inc. 2008) Hence, in order to re-enforce the Granger-causality test results, we apply both approaches, except the Wald test but also Toda and Yamamoto procedure (denoted MWald Test).

It has been shown that using non-stationary data in causality tests may yield spurious causality result (Granger and Newbold 1974). Therefore, before applying the indirect approach, we categorize the stationary variables (in level form or after differencing) in pairs and perform the indirect Granger causality technique to test for the bivariate causation.

Secondly, we use the MWald based on the results of unit root test in 5.1 assuming that the maximal order of intergration is one, i.e. d=1. For each pair of variables, the preferred mlag value was same as indirect approach selected on the basis of SBC statistics from

VAR (mlag) estimated by OLS over the same sample. As a result, the lag length for MWald test is determined as mlag+1.

The results on the Wald test as well as MWald of Granger causality at 5% significant level are indicated in the Table 5.6 Granger causality test infers the direction of causality, which is summarized in the following Table 5.7

Table 5.6 Results of Granger Causality Tests

Null Hypothesis	Wald Test	MWald Test
1. R95P & SVN (3/3)		
R95P does not Granger cause SVN	**6.83**	**5.17**
SVN does not Granger cause R95P	**10.45****	**8.00****
2. R95P & SVC (2/4)		
R95P does not Granger cause SVC	**2.66**	**4.32**
SVC does not Granger cause R95P	**14.91*****	**9.14**
3. R95P & SVS (2/4)		
R95P does not Granger cause SVS	**2.23**	**5.54**
SVS does not Granger cause R95P	**16.89*****	**11.40****
4. R95P & SVI (1/3)		
R95P does not Granger cause SVI	**0.03**	**2.70**
SVI does not Granger cause R95P	**0.05**	**2.83**
5. R95P & SVT (2/4)		
R95P does not Granger cause SVT	**0.89**	**3.18**
SVT does not Granger cause R95P	**13.02*****	**10.54****
6. RDSP & TBN (1/3)		
RDSP does not Granger cause TBN	**11.69*****	**12.84*****
TBN does not Granger cause RDSP	**0.09**	**0.45**
7. RDSP & TBC (1/3)		
RDSP does not Granger cause TBC	**7.04****	**7.82****
TBC does not Granger cause RDSP	**0.71**	**1.62**
8. RDSP & TBS (5/5)		
RDSP does not Granger cause TBS	**5.39**	**12.91****
TBS does not Granger cause RDSP	**10.75**	**2.54**
9. RDSP & TBI (1/3)		
RDSP does not Granger cause TBI	**1.13**	**6.03**
TBI does not Granger cause RDSP	**0.25**	**2.59**
10. RDSP & TBT (1/3)		
RDSP does not Granger cause TBT	**8.31*****	**9.08****
TBT does not Granger cause RDSP	**0.04**	**0.97**

Table 5.6 Results of Granger Causality Tests (continued)

Null Hypothesis	Wald Test	MWald Test
11. RDSP & TLN (1/3)		
RDSP does not Granger cause TLN	**13.45***	**22.12***
TLN does not Granger cause RDSP	**0.78**	**1.24**
12. RDSP & TLC (2/3)		
RDSP does not Granger cause TLC	**16.46***	**48.17***
TLC does not Granger cause RDSP	**4.22**	**1.04**
13. RDSP & TLS (2/3)		
RDSP does not Granger cause TLS	**20.10***	**27.02***
TLS does not Granger cause RDSP	**2.31**	**1.62**
14. RDSP & TLI (1/3)		
RDSP does not Granger cause TLI	**0.04**	**1.68**
TLI does not Granger cause RDSP	**0.00**	**0.81**
15. RDSP & TLT (2/3)		
RDSP does not Granger cause TLT	**20.99***	**28.67***
TLT does not Granger cause RDSP	**3.57**	**1.21**
16. RGDP & SVN (2/3)		
RGDP does not Granger cause SVN	**1.97**	**5.53**
SVN does not Granger cause RGDP	**4.92**	**12.08***
17. RGDP & SVC (1/2)		
RGDP does not Granger cause SVC	**1.22**	**4.43**
SVC does not Granger cause RGDP	**0.82**	**0.85**
18. RGDP & SVS (1/2)		
RGDP does not Granger cause SVS	**1.59**	**4.88**
SVS does not Granger cause RGDP	**0.91**	**0.88**
19. RGDP & SVI (1/2)		
RGDP does not Granger cause SVI	**0.21**	**0.98**
SVI does not Granger cause RGDP	**0.15**	**0.56**
20. RGDP & SVT (3/2)		
RGDP does not Granger cause SVT	**1.79**	**5.55**
SVT does not Granger cause RGDP	**15.72***	**1.23**
21. RGDP & TBN (3/2)		
RGDP does not Granger cause TBN	**5.44**	**2.05**
TBN does not Granger cause RGDP	**4.28**	**3.78**
22. RGDP & TBC (1/3)		
RGDP does not Granger cause TBC	**0.59**	**7.96**
TBC does not Granger cause RGDP	**4.51**	**4.01**
23. RGDP & TBS (1/3)		
RGDP does not Granger cause TBS	**0.89**	**8.25**
TBS does not Granger cause RGDP	**5.02**	**3.97**
24. RGDP & TBI (1/2)		
RGDP does not Granger cause TBI	**1.01**	**1.82**
TBI does not Granger cause RGDP	**6.47**	**14.40***

Table 5.6 Results of Granger Causality Tests (continued)

Null Hypothesis	Wald Test	MWald Test
25. RGDP & TBT (1/2)		
RGDP does not Granger cause TBT	**0.45**	**5.79**
TBT does not Granger cause RGDP	**3.93****	**4.12**
26. RGDP & TLN (3/5)		
RGDP does not Granger cause TLN	**12.05*****	**13.45****
TLN does not Granger cause RGDP	**7.14**	**7.82**
27. RGDP & TLC (3/5)		
RGDP does not Granger cause TLC	**6.61**	**14.38****
TLC does not Granger cause RGDP	**13.53*****	**11.24****
28. RGDP & TLS (3/5)		
RGDP does not Granger cause TLS	**7.74**	**12.27****
TLS does not Granger cause RGDP	**14.34* ****	**13.06****
29. RGDP & TLI (0/2)		
RGDP does not Granger cause TLI	**n/a**	**1.49**
TLI does not Granger cause RGDP	**n/a**	**3.40**
30. RGDP & TLT (3/5)		
RGDP does not Granger cause TLT	**10.14****	**13.17****
TLT does not Granger cause RGDP	**12.35*****	**10.38**

Notes:
Null Hypothesis: no Granger-cause
**Significant at the 5% level.
***Significant at the 1% level.
** / *** denotes rejection of the null hypothesis
(/): (Lag Length for Wald Test / Lag Length for MWald Test) – both based on minimum AICC (corrected Akaike's information criterion) value.

Table 5.7 Summaries of Granger Causality Test Results

Variable	Wald Test	MWald Test	Variable
R95P	←	←	**SVN**
R95P	←	×	**SVC**
R95P	←	←	**SVS**
R95P	×	×	**SVI**
R95P	←	←	**SVT**
RDSP	→	→	**TBN**
RDSP	→	→	**TBC**
RDSP	×	→	**TBS**

Table 5.7 Summaries of Granger Causality Test Results (continued)

Variable	Wald Test	MWald Test	Variable
RDSP	×	×	TBI
RDSP	→	→	TBT
RDSP	→	→	TLN
RDSP	→	→	TLC
RDSP	→	→	TLS
RDSP	×	×	TLI
RDSP	→	→	TLT
RGDP	×	←	SVN
RGDP	×	×	SVC
RGDP	×	×	SVS
RGDP	×	×	SVI
RGDP	←	×	SVT
RGDP	×	×	TBN
RGDP	←	→	TBC
RGDP	←	→	TBS
RGDP	←	←	TBI
RGDP	←	×	TBT
RGDP	→	→	TLN
RGDP	←	↔	TLC
RGDP	←	↔	TLS
RGDP	×	×	TLI
RGDP	↔	→	TLT

Notes:

× denotes absence of any Granger causality

→ / ← denotes one way Granger causality running direction

↔ denotes feedback Granger causality relationship

Before we start to go into details to demonstrate the results, there is one thing must be highlighted in advance. As gas prices in Taiwan were under strict control by the government prior to May 2008 which is in part of our study, we would regard any Granger causality direction running from traffic to gas prices as a typical result of datadriven, ignoring any precedence from traffic volume to gas prices while focusing on the one way direction from gas prices to traffic volume only.

Table 5.7 indicates there is no lead or lag relation between “R95P and SVI”, “RDSP and TBI”, “RDSP and TLI”, “RGDP and SVC”, “RGDP and SVS”, “RGDP and SVI”, “RGDP and TBN” and “RGDP and TLI” supported by no significant statistics from both Granger causality tests. Meanwhile, there are consistent precedence relations, “from RDSP to TBN, TBC, TBT, TLN, TLC, TLS and TLT”, “from RGDP to TLN” as well as “from TBI to RGDP”.

Similar to unit root tests, we also encounter conflicting empirical results here. For instance, the inconsistent one way causality running direction between “R95P and SVC”, “RDSP and TBS”, and “RGDP and SVN, SVT, TBC, TBS, TBT, TLC, TLS, TLT” is found. Furthermore, MWald Test shows there are feedback relationship between “RGDP and TLC” and “RGDP and TLS” while they are unidirectional Granger causality conducted by Wald Test. The different outcomes conducted by Wald and MWald test require further study and hence, in this study we take those consistent results only.

5.4 IMPULSE RESPONSE ANALYSIS

The impulse response can be described as the impact of a shock in one variable on another variable. The application of theory and techniques of bivariate models for impulse response of toll traffic are applied to help understand at predicting the driver's behavior of vehicle usage on freeway. Before we try to provide the appropriate interpretation of the results, the situation of Taiwan gasoline market must be reviewed once again. As indicated in Granger Causality test, the retail gas prices in Taiwan are not under a free market mechanism, we will have to ignore the gas price response to shock in traffic volume. Instead, we will focus only in terms of the one way response of freeway traffic to the gas price shock and to GDP innovation.

Based on the vector autoregressive (VAR) model and the AICC (corrected Akaike's information criterion) minimum value for order selection as a measure of model fit, the impulse responses are calculated with up to 12 lags which is a time span of one year in our model. In figure 5.2~5.7, we plot the orthogonalized impulse response functions with two standard errors we obtain of a two variable VAR to capture the short-run volatility of freeway traffic volumes in response to one standard deviation of gas price shock or GDP innovation.

Besides, it is known that residuals from a VAR model are generally correlated and applying the Cholesky decomposition is equivalent to assuming recursive causal ordering from the top variable to the bottom variable. Changing the causal ordering of the variables could lead to different results of the impulse response analysis. As a consequence, only the consistent running direction of Granger causality testes by both Wald and MWald tests found in section 5.3 are discussed as follows.

We obtain positive feedbacks from Figure 5.3 - the impulse response of truck and bus traffic to premium diesel price in northern, central and I-Lan area. The response period is around 5 lags and the effect dies down gradually after that.

As to the aspect of impulse response of trailer traffic toward premium gas prices demonstrated in Table 5.4, in general, the traffic volumes in 3 geographic areas – northern, central and southern, as well as nationwide give a positive and around 10 periods of response in average. And there is no persistence of the effect of the impulse from premium diesel gas price.

In comparison to the effect of gas price and GDP on highway traffic respectively, Figures 5.5 shows positive response of traffic to real GDP for each vehicle types in most areas except in I-Lan area. Figure 5.6 indicates that the shock of GDP leads to less and shorter response in truck and bus freeway traffic. It suggests there is less correlation between GDP and truck and bus traffic volumes in Taiwan comparing the response of same traffic volumes to gas price. Also, it implies the fluctuations of GDP can not provide better forecast of the shock of the truck and bus than gas price does.

Figure 5.7 reveals a divergent result from 5.4 for the northern trailer traffic response to GDP innovation in comparison to the response to gas price shock. The steep curve indicates that there is a strong correlation between the freeway toll trailer traffic in northern area and GDP. The impact period is even prolonged to over 12 lags. It leads us to believe the shock of GDP may be able to help predict the fluctuation in the northern trailer traffic volume.

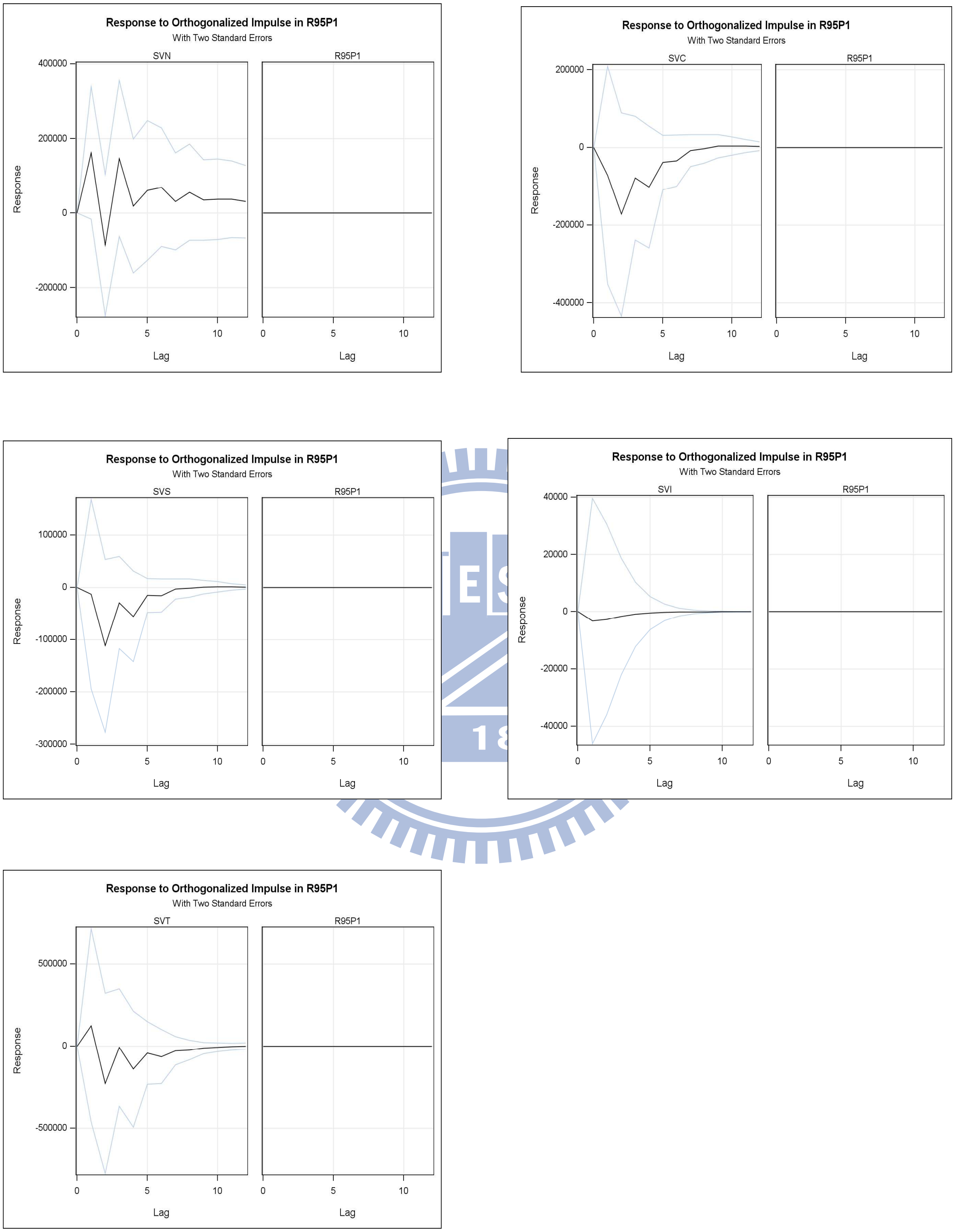


Figure 5.2 Plots of Small Vehicle Toll Traffic Impulse Response in 95 Lead-free Gas Price with Two Standard Errors

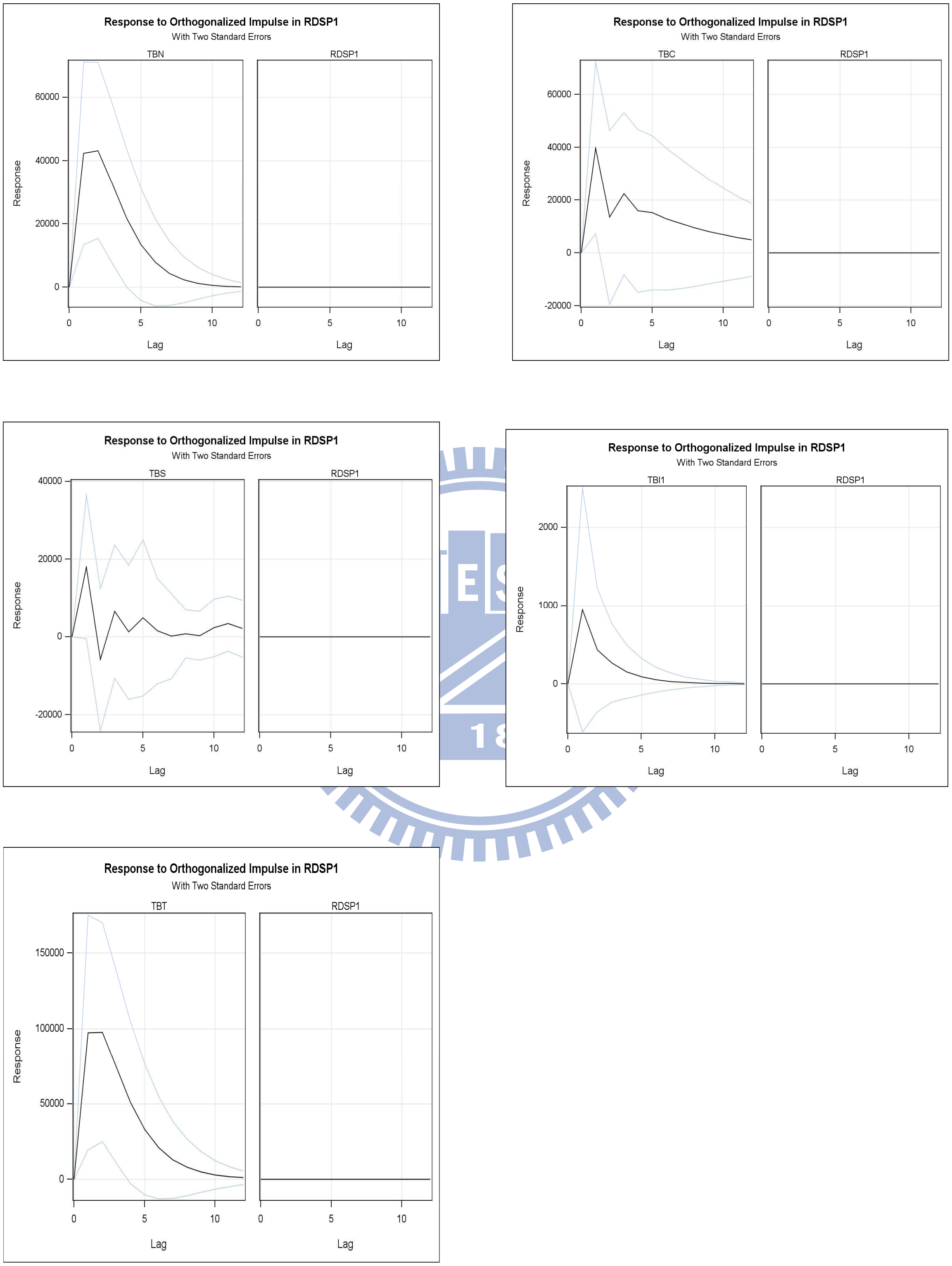


Figure 5.3 Plots of Truck and Bus Toll Traffic Impulse Response in Premium Diesel Gas Price with Two Standard Errors

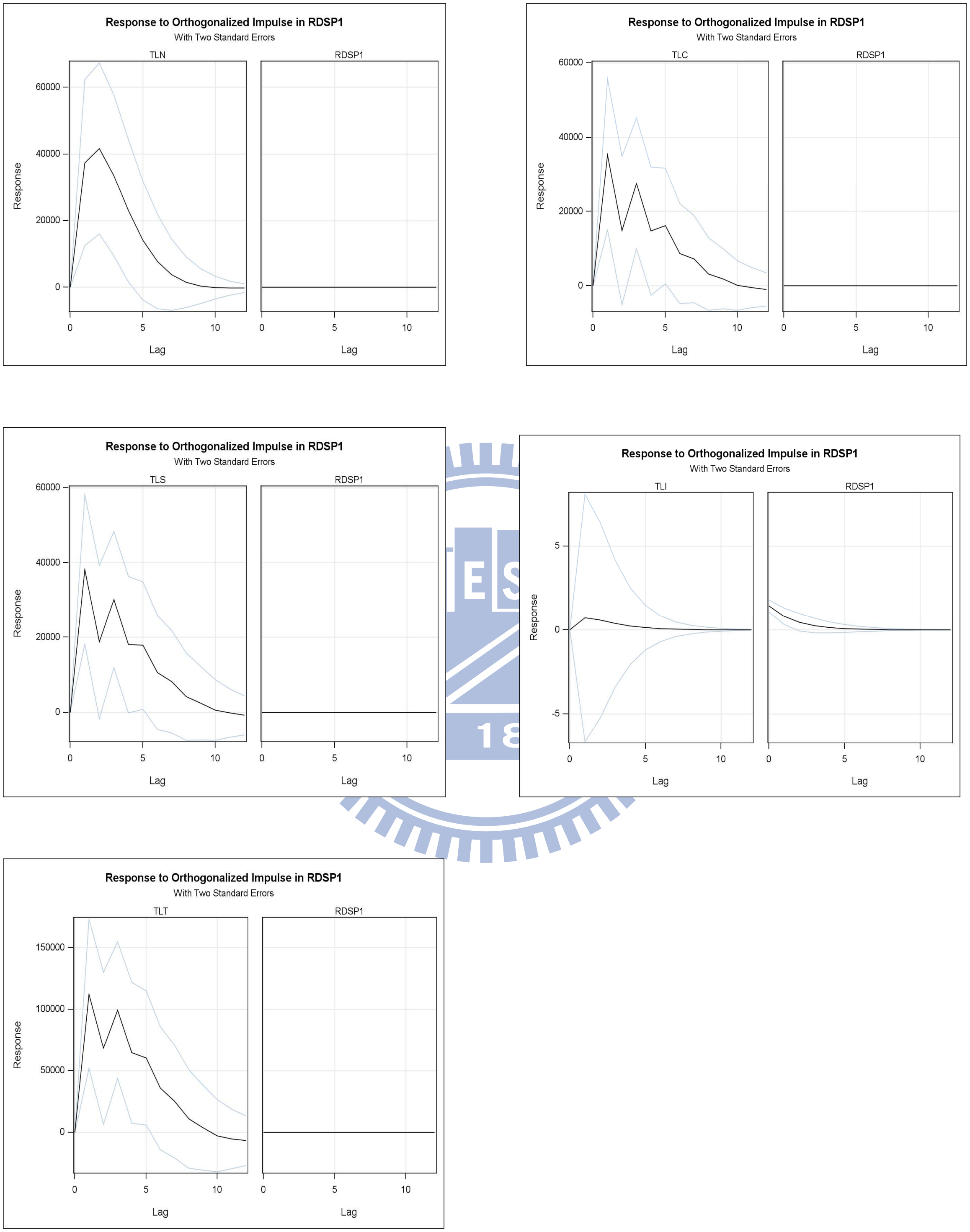
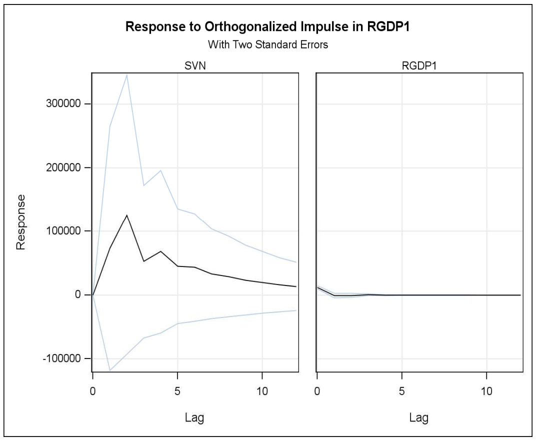
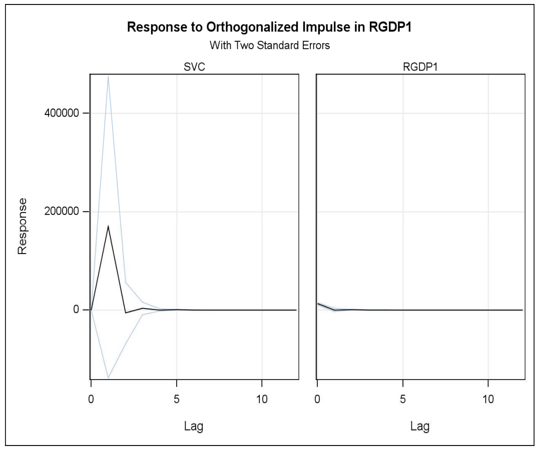
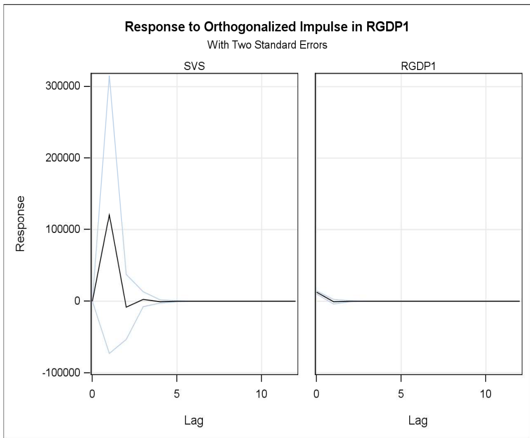
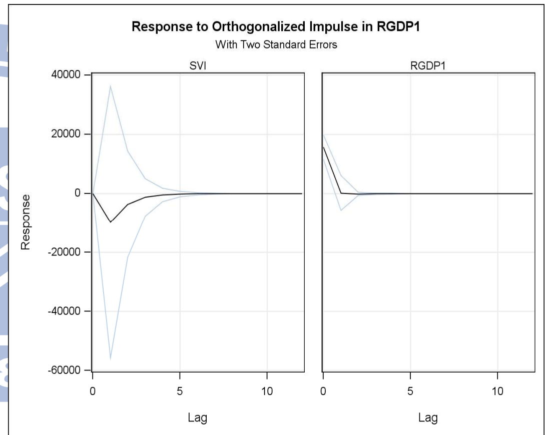


Figure 5.4 Plots of Trailer Toll Traffic Impulse Response in Premium Diesel Gas Price with Two Standard Errors









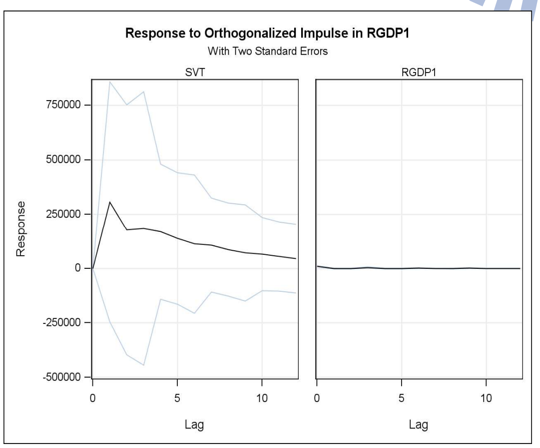


Figure 5.5 Plots of Small Vehicle Toll Traffic Impulse Response in GDP with Two Standard Errors

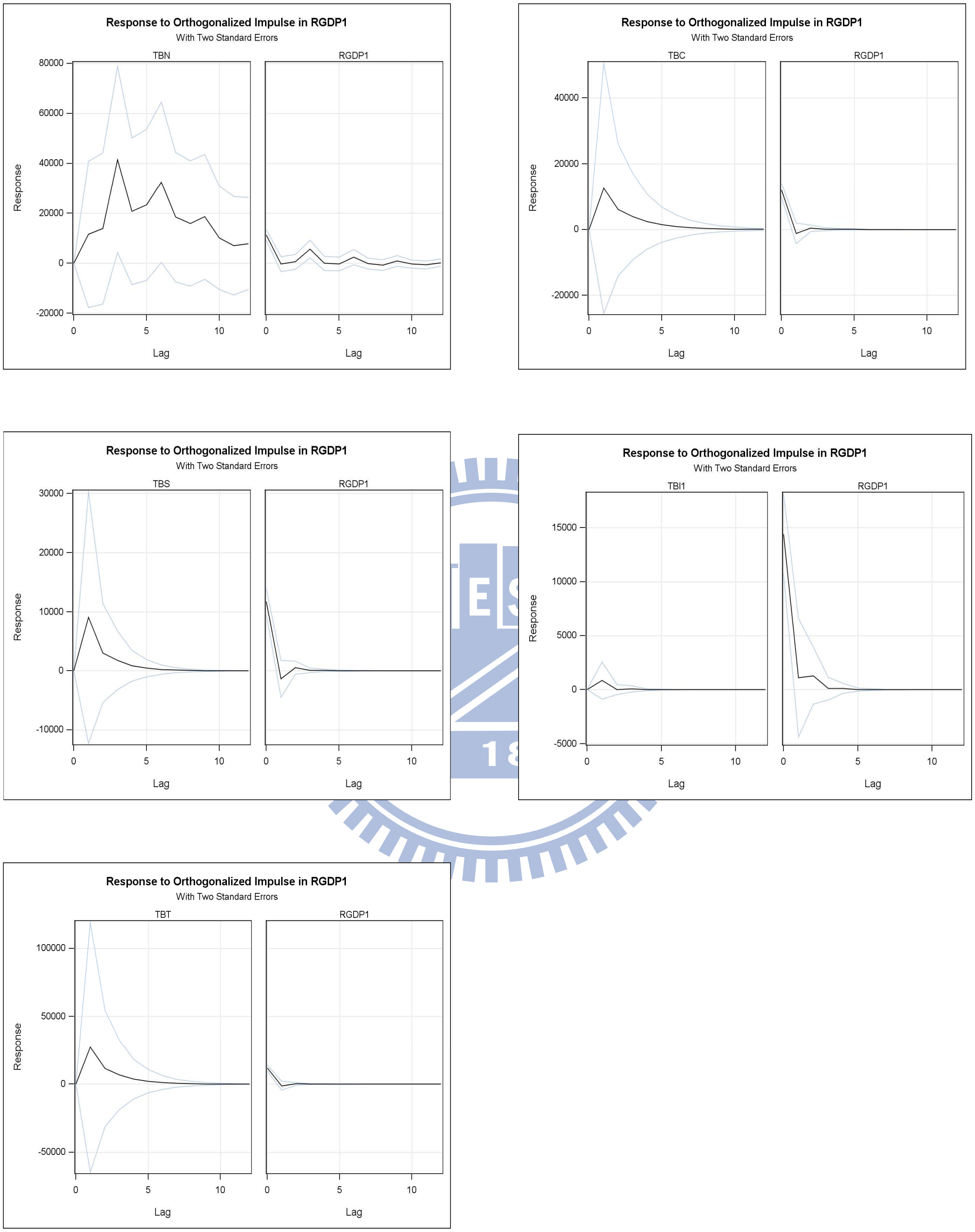


Figure 5.6 Plots of Truck and Bus Toll Traffic Impulse Response in GDP with Two Standard Errors

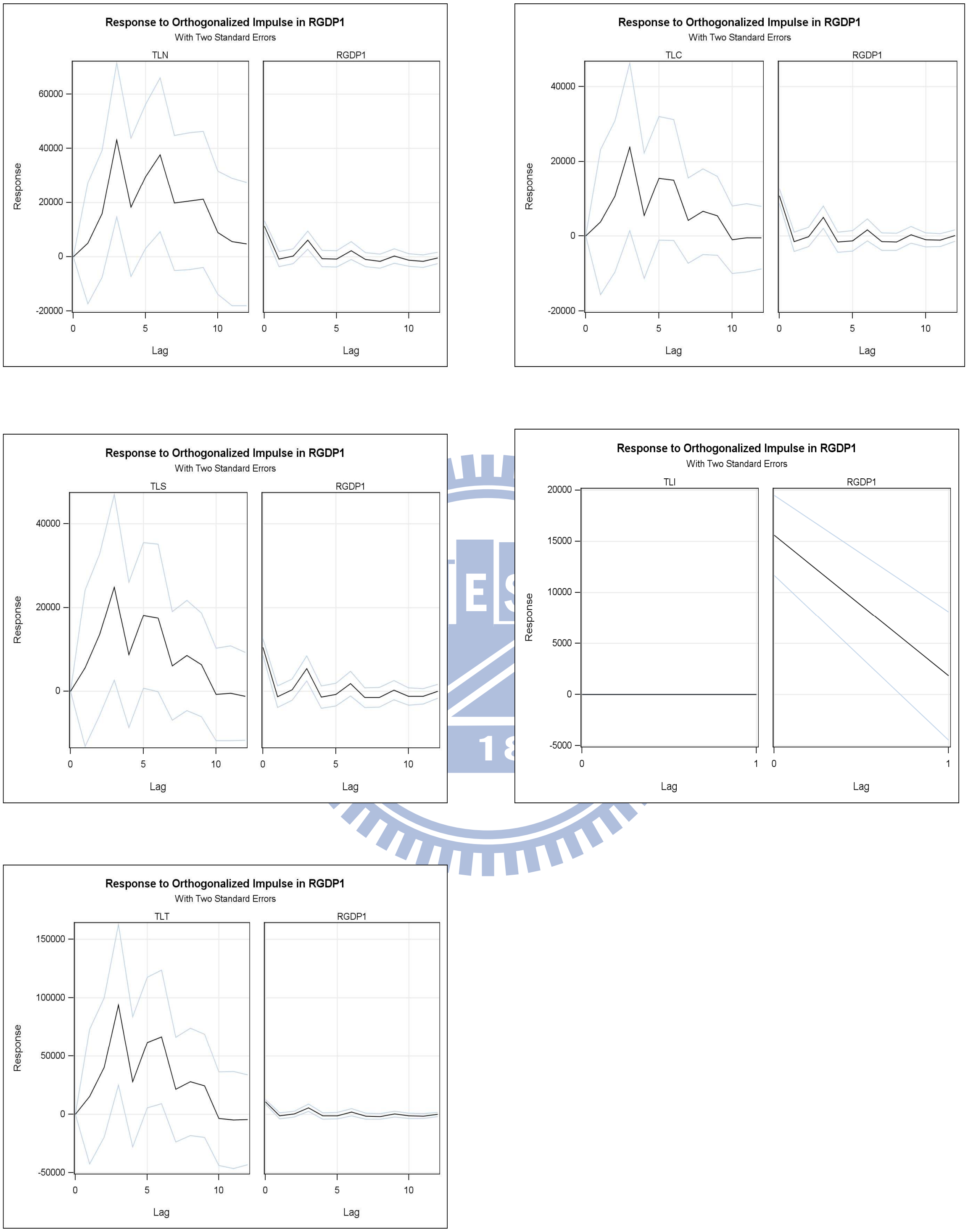


Figure 5.7 Plots of Trailer Toll Traffic Impulse Response in GDP with Two Standard Errors

CHPATER 6 CONCLUSIONS AND SUGGESTIONS

6.1 CONCLUSIONS

This study investigates the effects of gas price and GDP on freeway traffic. Our interest is focused on the empirical long run equilibrium relationship, the Granger causal effect for short term, and the impulse response between “gas price and traffic volume” as well as “GDP and traffic volume” in Taiwan by taking into account five and half years of gas prices, GDP and freeway traffic volume time series data over the period 2004:01 to 2009:06.

As different tests of unit-root, cointegration and Granger causality and also different model specifications can and often lead to contradicting results, making it unjustifiable to test for causality in merely a single model. With a view to avoid putting all our faith in a single method and to steer clear of the ambiguity, we apply two procedures for the tests of unit root, cointegration and Granger causality on the interested series. Based on this principle, the main findings of this research are indicated as follows.

First, regarding to the unit root test for series stationarity, same as some other researches, inconsistent results of ADF and PP test occur. In order not to lose important info in the original series and for avoiding over differncing, we take the results of PP unit root test, which suggest that most of the traffic series belonging to stationary structures are different from the four series with unit root – 95 lead free gas price, premium diesel price, GDP and truck and bus traffic volume in I-Lan area.

Secondly, in the aspect of long term relationship, we continue to conduct cointegration tests to exam the long term equilibrium relationship. Both results from the Engle-Granger Two-Step method and Johansen cointegration test present consistent outcome indicating no cointegration among the tested series. Therefore, it implies no c-integration between the variables.

Furthermore, as to the short run Granger causality, the study adopts Wald plus Toda and Yamamoto Granger causality tests to investigate the Granger causal effect. Similar to unit root tests, we once more, encounter some inconsistent results such as the Granger causality between the "GDP and Truck and Bus traffic" and the "GDP and Trailer traffic" in central, southern area and nationwide. This is believed that further study is required to determine the linkage between the variables.

As opposed to the said results, we also obtain some consistent outputs on the causality tests. For instance, there are same Granger causality results between "premium diesel price and the traffic volumes of truck and bus" as well as "premium diesel price and trailer traffic volumes" in most of areas. Taking trailer traffic volumes as an example, it demonstrates premium diesel price is precedence to trailer traffic in northern, central, south area and nationwide.

There is one intriguing finding. That is no Granger causality in traffic volume in I-Lan area neither between it and gas prices nor it with GDP. , except one result – truck and bus traffic in the same area takes precedence over GDP. The reasons behind this result can be regarded as the usage of small vehicle is for the purpose of tourist travels and the open to service of Sueshan Tunnel make the drivers of truck and bus as well as of the trailer less giving up the freeway use when the gas price shock and GDP innovation. Furthermore, it makes us believe both gas price and GDP may not be able to play as indicators in forecasting the traffic volume in I-Lan.

Finally, about the impulse response, overall it is contradictory to our expectation that one of the key components of the total costs of driving is the cost of gasoline and as such, rises in gasoline prices could potentially have a significant impact on driver behavior. It suggests the link between a gas price hike and a decline in toll road use is not that solid especially for the traffic volumes of truck and bus plus of trailer. In view of these phenomena, we may conclude that the usage of these two types of vehicles is mainly for commercial transportation purpose. The rising gas price did not have an impact on day to day business running.

In summary, as mentioned in previous chapters, gas price were under strict control by Taiwan government prior to May 2008, the linkage between gas prices and highway traffic may not be similar to what it is in other free markets. As a consequence, the findings such as ours must be used with caution especially when the market structure is changed. Also our results demonstrate it requires all things considered when the local government proposes possible policy implications on green tax imposition to reduce carbon dioxide emission. Finally, our observations in this study may be used as a reference for current and future government policies of pertaining to the decline in greenhouse gas emissions.

6.2 SUGGESTIONS

Even though our those empirical studies may be able to reinforce what was already known from previous work or bring a few new insights to this field, there are further researches enumerating as follows which can be considered to take on next research agenda.

1. extend sample period to improve power of test and avoid pretest biases.
2. apply more econometric methods to re-enforce the causal effect of our results.
3. incorporate more unobserved impact factors on car usage.
4. replace the monthly data with daily to observe the daily variation.
5. include the series of vehicle travel distance to improve our understanding of driver's travel behavior.
6. focus on the traffic in a smaller area such as Taipei municipal area for a better insight of the road use in downtown.
7. add Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, whose null hypothesis is series with no unit root different from ADF and PP test, to improve the accuracy of unit root test and to low the possibilities of pretest bias.
8. use Polynomial Distributed Lag Regression, PDL Reg to estimate regression models for time series data in which the effects of some of the regressor variables are distributed across time.
9. employ threshold regression model for further study of the effects of gas price innovations.

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APPENDIX

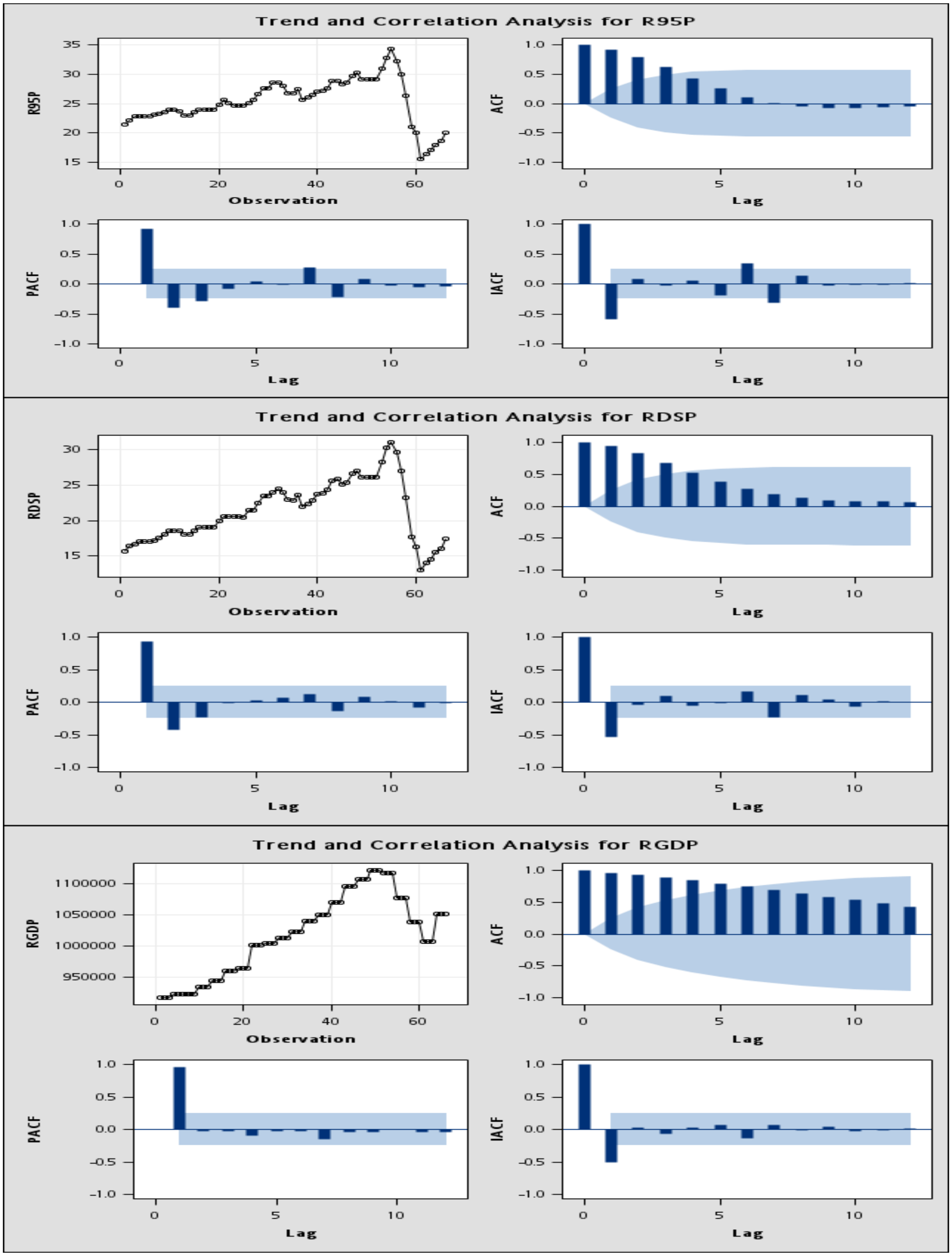


Figure 7.1 Plots of Trend and Correlation Analysis for Series in Levels

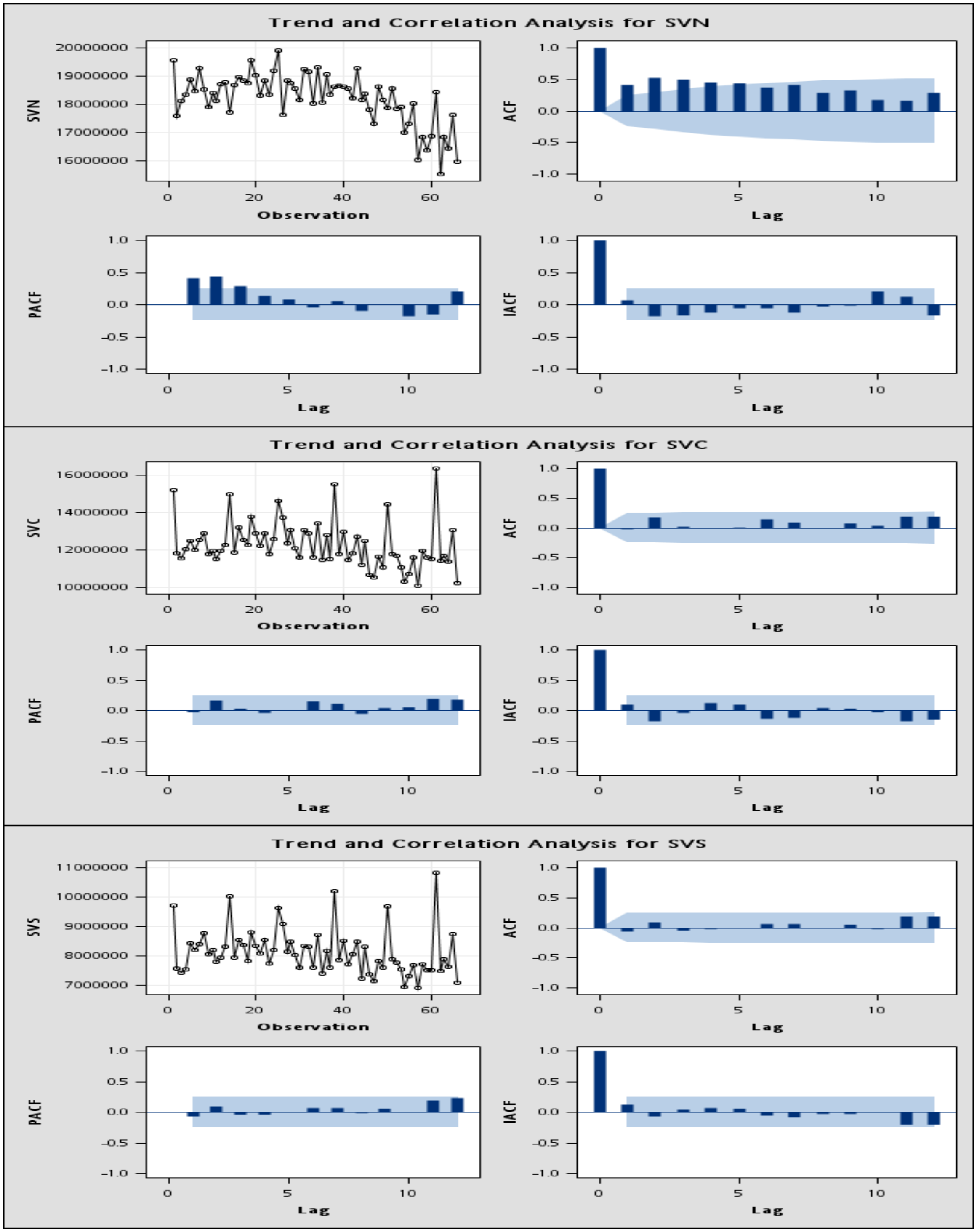
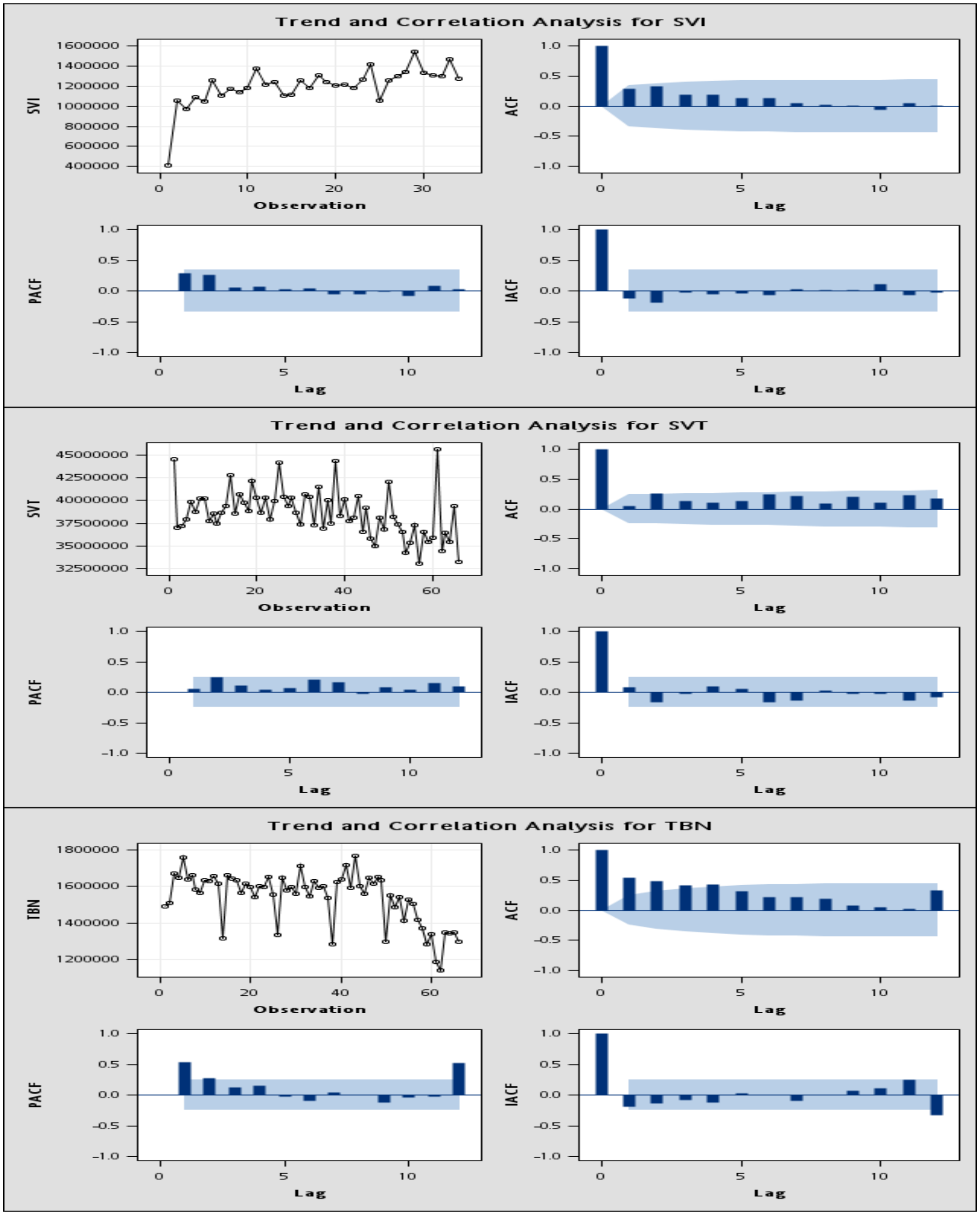


Figure 7.1 Plots of Trend and Correlation Analysis for Series in Levels (continued)



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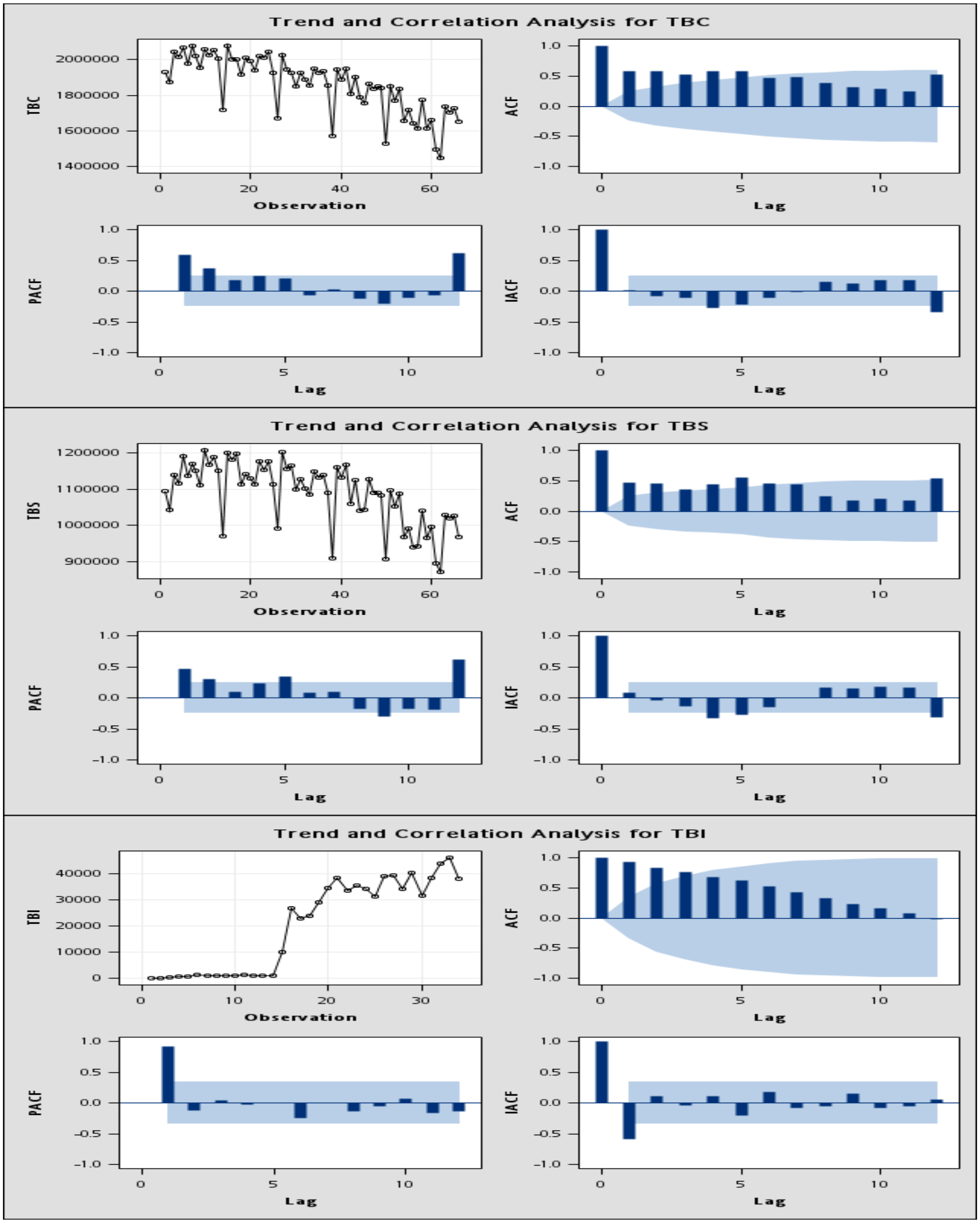

Figure 7.1 Plots of Trend and Correlation Analysis for Series in Levels (continued)

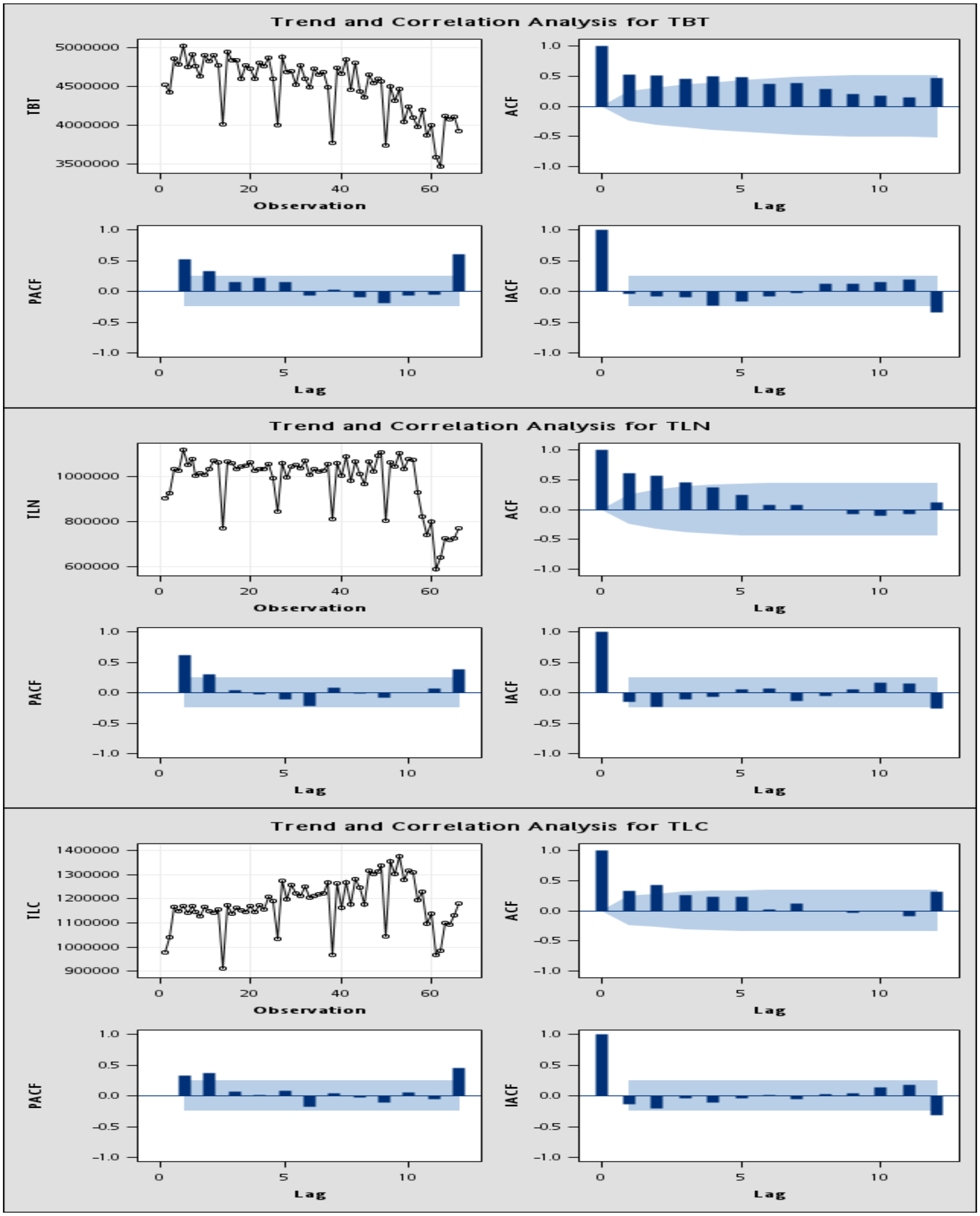

Figure 7.1 Plots of Trend and Correlation Analysis for Series in Levels (continued)

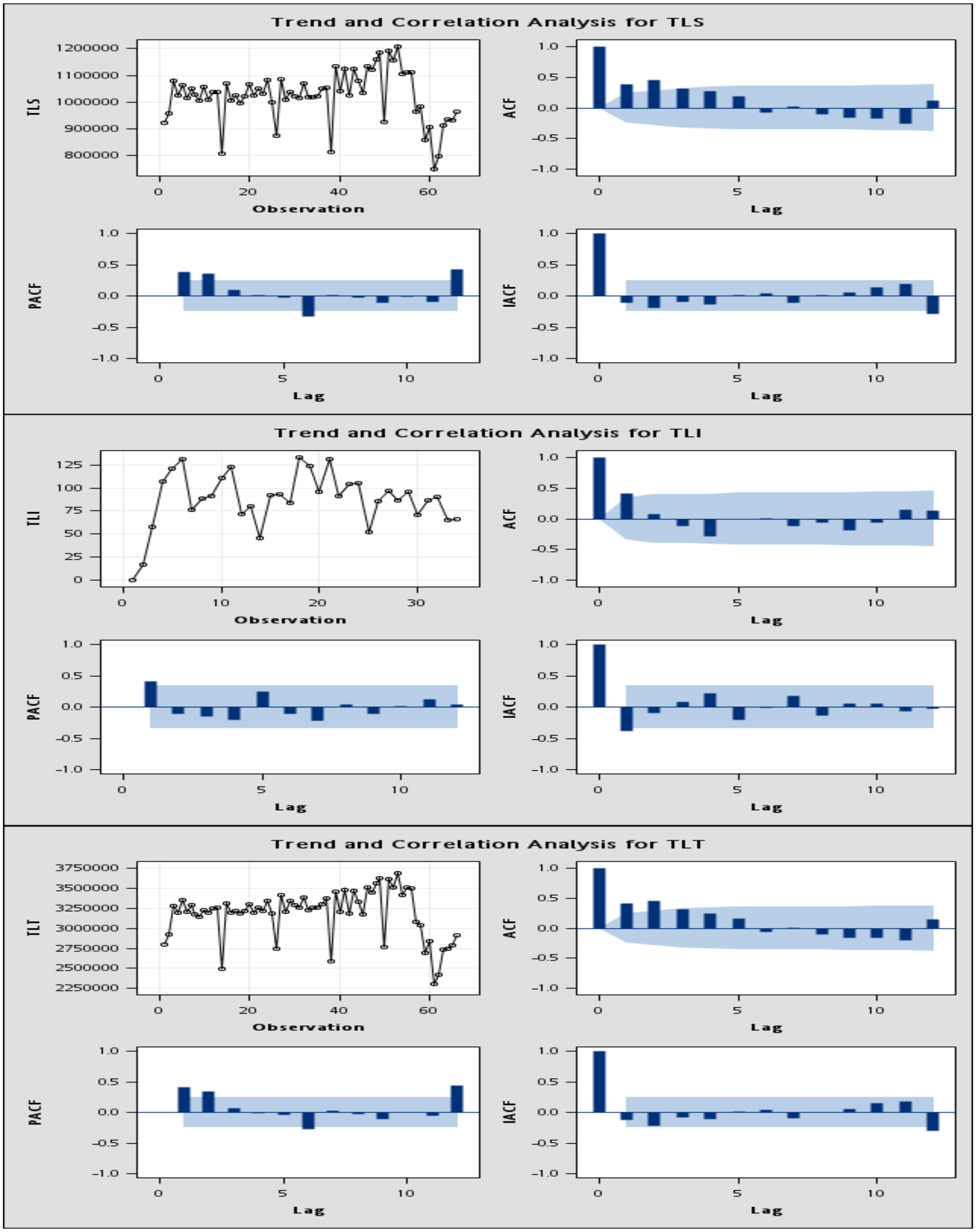

Figure 7.1 Plots of Trend and Correlation Analysis for Series in Levels (continued)

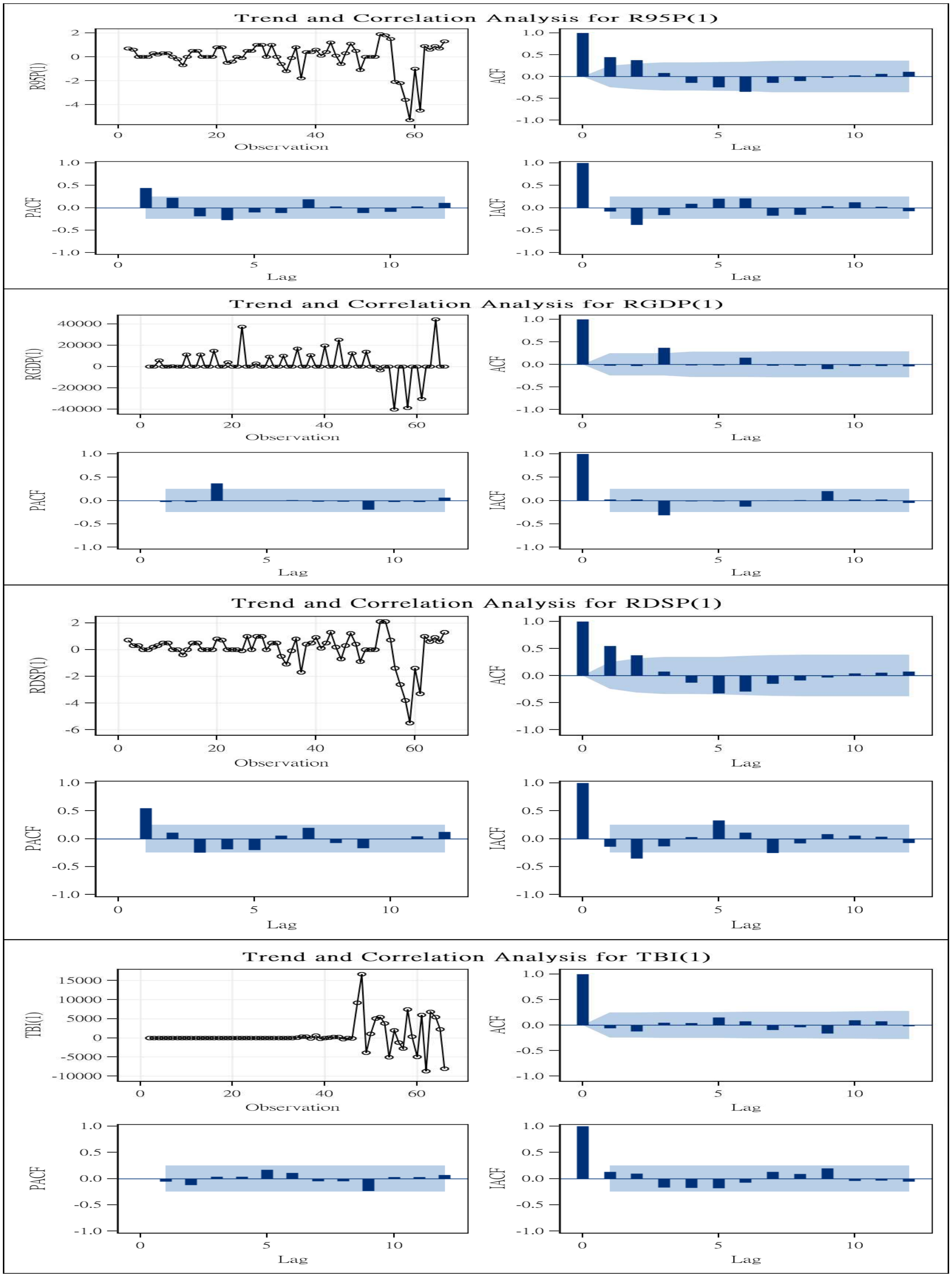

Figure 7.2 Plots of Trend and Correlation Analysis for Series in First Difference