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

Yu-Chiun CHIOU [a], Shu-Chin YANG [b], Jin-Li HU [c]

[a,b] *Institute of Traffic and Transportation, National Chiao Tung University, 4F, 118 Sec.1, Chung Hsiao W. Rd., Taipei, 10012, Taiwan*
[a] *E-mail: ycchiou@mail.nctu.edu.tw*
[b] *E-mail: h.yang@adbglobal.com*
[c] *Institute of Business and Management, National Chiao Tung University, 4F, 118 Sec.1, Chung Hsiao W. Rd., Taipei, 10012, Taiwan*
[c] *E-mail: jinlihu@gmail.com*

**Abstract**: It is well acknowledged that gas price negatively affects traffic volume while GDP may have the contrary effect. To gain in-depth understandings of such relationships, this paper collects monthly time series data of freeway traffic, gas price and GDP of Taiwan to examine short- and long-term causal relationships by Granger causality test and cointegration test, respectively. Results show that gas price Granger causes large-vehicle (truck and bus) and trailer traffic, but not small-vehicle traffic. However, there is no statistically significant finding on long-term equilibrium relationship neither between gas price and freeway traffic nor between GDP and freeway traffic.

*Keywords*: Gas price, Cointegration, Granger causality.

## 1. INTRODUCTION

The gas price remarkably fluctuates in recent years. In June 2008, it reached its peak of US$ 139.36 per barrel. This is far beyond the price of $15.77 per barrel in 1998. Although gas price has dropped since its peak, the recent fluctuation of global gas price seems not reaching the end yet. Krugman (2008) still predicts, “Oil non-bubble and we are heading into an era of increasingly scarce, costly oil.” Similar to what Krugman forecasts that high gas price is not a past history, Greenspan (2008) predicts that we are facing a long term energy shortage. Both of them regard high gas price is an ongoing and unavoidable trend.

Soaring gas price triggers the global economy downturn and affects the policy makers of various governments, as well as alters ordinary people’s ways of life. With no exception, drivers around the world also suffer from the surge of gas price. Their driving behaviors have also dramatically changed such 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. Some of them even switch to public transportations to combat the ever-rising gas price. We present a summary of exiting studies for a better picture of the relationship between gas prices and car usage.

In America, the Federal Highway Administration of the States (FHWA, 2009) reported that at the time the gas price was rising the domestic travel on all roads and streets in Oct. 2008 decreased by 3.5% comparing to it was in the same month in 2007 when the gas price was at lower level. In Taiwan the Liberty Times revealed a similar finding that when gas price had around 12.7% sharp increase up to NT$ 34.6 per liter at the end of May in 2008 from NT$ 30.7 in November 2007, the freeway traffic volume decreased around ninety thousand, an equivalent of 11% drop for the same period last year. Those statistics from America and Taiwan point out that there is a negative correlation between gas price and traffic volume.

Not only gas price, GDP is also assumed as one of the elements affecting the numbers of vehicle's ownership and usage. Alfresson (2002) finds that historically GDP and energy consumption have been highly correlated. Wu (2006) also indicates that the ownership of vehicles and growth of its usage are related to the increasing of GDP. She further 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 running from GDP of the number to registered car in Taiwan while in Japan the 2 variables are independent. Lu *et al*. (2008) utilizes Grey relation analysis (GRA) to evaluate the relative influence of the gas price, GDP, the number of motor vehicles and the vehicle kilometers of travel (VKT) per energy increase in Taiwan. Their findings show 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. Jou and Sun (2008) show that gas price has a negative effect on road users; however, the magnitude of the effect is larger to commuters than to non-commuters. Chiou *et al*. (2009) also confirm that the gas price is one of key factors affecting drivers in choosing cars and motorcycles ownership, type and usage based on questionnaire survey and estimated Logit models.

Based on an assumption that higher driving cost would lead to less traffic, Taiwan government recently proposed an introduction of green tax as a means 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.

Apparently the relationship between gas price/GDP and car usage play a significant role in this proposal. However, even though there are evidences that there is a correlation among said three variables, it does not mean correlation equal causation. We cannot 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. The policy makers require a clear picture of the effects of gas price and GDP on traffic volume in making relevant energy guidelines or regulations. With an aim to unveil the mystery of the effects, this paper uses various time series methods with consideration of time lag factor to examine the effects of gas price and GDP on freeway traffic respectively for policy maker a better reference on a successful green tax policy making to achieve certain levels of environmental protection.

The rest of this paper is organized as follows. Section 2 briefly introduces the methodology backgrounds used in this study. The data collection and analysis of three time series data of gas price, GDP and traffic volume are presented in Section 3. The empirical tested results are given in Section 4. Finally, the concluding remarks and suggestions for future studies are followed.

## 2. METHODOLOGY

This section is divided into five parts to present the methodologies adopted in this paper. The methodologies of unit root, cointegration, vector autoregression model, Granger causality, and impulse response function are discussed as follows, respectively.

### 2.1. Unit Root

When the data-generating process (DGP) is non-stationary or so called with unit root, the often use of ordinary least squares (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.

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.

The augmented Dickey-Fuller (ADF) test can be expressed in the following three forms:

1) Model with intercept and trend

$$\Delta Y_t = \mu + \gamma Y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta Y_{t-j} + \beta t + \omega_t \tag{1}$$

2) Model with intercept but without trend

$$\Delta Y_t = \mu + \gamma Y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta Y_{t-j} + \omega_t \tag{2}$$

3) Model without intercept and without trend

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta Y_{t-j} + \omega_t \tag{3}$$

where,

$\Delta$ :first difference operator,
$Y_t$ :the predictor variable,
$\mu$ :the drift term,
$t$ :the time trend,
$p$ :the largest lag length used, and
$\omega_t$ :error term.

The null hypothesis:

$H_0$: $\gamma=0$ (unit root, non-stationary)

$H_1$: $\gamma\neq0$ (without unit root, stationary)

If the null hypothesis - $H_0$ (with unit root) is rejected, it's concluded that the rejection of the tested variable existing unit root, i.e. stationary series.

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

$$Y_t = \alpha Y_{t-1} + \mu_t \tag{4}$$

2) type with single mean

$$Y_t = \mu + \alpha Y_{t-1} + \mu_t \tag{5}$$

3) type with constant and time trend term

$$Y_t = \mu + \alpha Y_{t-1} + \delta t + \mu_t \tag{6}$$

where,

$\mu_t$ : 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 potentially suffers severe finite sample power (De Jong, 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 $\mu_t$ are negative, and therefore, are more sensitive to model misspecification (the order of autoregressive and moving average components). 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 is the reason why the ADF and PP tests continue to be the most widely used unit root tests.

## 2.2. Cointegration

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 definition of cointegration is a stationary 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 (*k* order integrated 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) Engle and Granger (1987) also indicate that if two or more variables are cointegrated, they may diverge substantially from equilibrium in the short term but they must obey an equilibrium relationship in the long run.

One way to test for cointegration is a residual based test named Engle and Granger Two-Step Procedure. Given two variables of interest, the first step of the Engle-Granger procedure involves the estimation of the following statistic cointegrating regression:

$$Y_t = d_t + \beta X_t + \varepsilon_t \quad \text{for } t=1,\ 2,\ \ldots,\ T \tag{7}$$

where,

$d_t$ : a deterministic term which may be either an intercept ($\alpha$) or an intercept plus linear trend ($\alpha+\beta t$).

First, it is to test the variables for their order of integration. 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 Eq.(7) using a Dickey-Fuller test as below.

$$\Delta b_t^2 = (\rho - 1) b_{t-1}^2 + v_t \tag{8}$$

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

Another approach named maximum likelihood (ML) method proposed by Johansen (1988, 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

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots. + A_n Y_{t-n} + \varepsilon_t \tag{9}$$

where,

$Y_t$ : lag length $n$ $(p \times 1)$ vector endogenous variable.

The VAR model of the first difference can be re-written as follows:

$$\Delta Y_t = \sum_{j=1}^{n-1} \pi_j \Delta Y_{t-j} + \pi Y_{t-n} + \varepsilon_t \tag{10}$$

where,

$\pi_j$ : a short term adjusting coefficient to describe short-term relationship, $\pi$ 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 $\pi$

decides the number of cointegrated vector. $\pi$ has three kinds of styles:

1) $rank(\pi) = n$, then $\pi$ is full rank. It means all of variables are stationary series in the regression ($Y_t$)
2) $rank(\pi) = 0$, then $\pi$ is null rank. It means variables do not exist cointegrated relationship.
3) $0 < rank(\pi) = r < n$, then some of variables exist $r$ cointegrated vector.

Johansen approach has used rank of $\pi$ 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 Eqs. (11) and (12) respectively.

1) Trace test:

$H_0 : rank(\pi) \le r$(at most r integrated vector)

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

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i) \tag{11}$$

where,

$T$ : sample size,

$\hat{\lambda}_i$ : estimated of characteristic root.

If test rejects $H_0$ that means variables exist at least $r$+1 long term cointegrated relationship.

2) Maximum eigenvalue test:

$H_0 : rank(\pi) \le r$(at most r integrated vector)

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

$$\lambda_{\max}(r, r+1) = -T \ln(1-\hat{\lambda}_{r+1}) \tag{12}$$

If the null hypothesis is accepted, it means variables have $r$ cointegrated vector. The method is starting to test from the hypothesis that 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.

## 2.3. 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, 2, ..., $T$) 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:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + e_t \tag{13}$$

where,

$Y_t$ : a $k$×1 vector of endogenous variables,

$c$ : a $k$×1 vector of constants (intercept),

$A_1, \ldots, A_P$ : matrices of coefficients to be estimated, and

$e_t$ : a $k$×1 vector of error terms that may be contemporaneously correlated but are uncorrelated 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:

1) All the variables are $I(0)$ (stationary): one is in the standard case, i.e. a VAR in level.
2) All the variables are $I(d)$ (non-stationary) with $d$ >0:
   a) 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.
   b) 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 value of Akaike, Schwarze-Bayesian, or other information criteria.

## 2.4. Granger Causality

Here we present two approaches of Granger causality test: The first one is called 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. Lastly, when the series are cointegrated, we can use a vector error correction (VECM) model or, for a bivariate system, a VAR model in levels.

The direct approach is based on the following VAR system:

$$Y_t = \beta_0 + \sum_{j=1}^{J} \beta_j Y_{t-j} + \sum_{k=1}^{K} \gamma_k X_{t-k} + u_t \tag{14}$$

where,

$Y_t$ : stationary (or can be made stationary by differencing),
$\beta_0$ : a constant term,
$\beta_j$ and $\gamma_k$ : coefficients of exogenous variables, and
$u_t$ : 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:

$$X_t = \beta_0 + \sum_{j=1}^{J} \beta_j X_{t-j} + \sum_{k=1}^{K} \gamma_k Y_{t-k} + u_t \tag{15}$$

Moreover, the Granger causality testing should take place in the context of a fully-specified model. If the model is not well specified, the spurious relation pointed out by Granger and Newbold (1974) may be found, despite of the fact that no actual (conditional) relationship exists between these variables.

As the direct Granger causality test 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 is 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):

$$Y_t = \alpha_1 + \sum_{j=1}^{mlag} \beta_{1j} Y_{t-j} + \sum_{j=mlag+1}^{mlag+d} \beta_{1j} Y_{t-j} + \sum_{k=1}^{mlag} \gamma_{1k} X_{t-k} + \sum_{k=mlag+1}^{mlag+d} \gamma_{1k} X_{t-k} + \varepsilon_{1t} \tag{16}$$

$$X_t = \alpha_2 + \sum_{j=1}^{mlag} \beta_{2j} Y_{t-j} + \sum_{j=mlag+1}^{mlag+d} \beta_{2j} Y_{t-j} + \sum_{k=1}^{mlag} \gamma_{2k} X_{t-k} + \sum_{k=mlag+1}^{mlag+d} \gamma_{2k} X_{t-k} + \varepsilon_{2t} \tag{17}$$

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 Granger causality test." (See also Lutkepohl and Burda, 1997)

Except for 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.

## 2.5. Impulse-Response 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

$$Y_t = A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + U_t \tag{18}$$

$$Y_t = \Phi(B) U_t = \sum_{i=1}^{\infty} \Phi_i U_{t-i} \tag{19}$$

$$I = (I - A_1 B - A_2 B^2 - \ldots - A_p B^p)\Phi(B) \tag{20}$$

where,

$cov(U_t) = \Sigma$ and

$\Phi_i$ : 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 $\Sigma$ 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. (19) can be rewritten as

$$Y_t = \sum_{i=0}^{\infty} \theta_i \omega_{t-i} \tag{21}$$

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

$$Y_t = B_0 Y_t + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + V_t \qquad (22)$$

where,

$B_0 = I_k - W^{-1}$,

$W = PD^{-1}$, and

$B_i = W^{-1} A_i$.

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, ….

## 3. DATA SOURCES AND VARIABLES

To obtain reliable traffic data for analysis, this study collects the traffic volume data at mainline toll stations along the freeways in Taiwan. Three representative freeways are chosen for study: No.1 and No.3 (from north to south) and No.5 (from west-north to east-north). To compare the effects of gas price and GDP on freeway traffic of different geographical areas and vehicle types. The traffic data is further divided by areas: nationwide, northern, central, southern and I-Lan (east-northern) and by vehicle types: small vehicles (passenger car and light duty truck), large vehicles (bus and heavy duty truck), and trailers, making a total of 15 series of traffic.

There are two petroleum corporations in Taiwan -- Chinese Petroleum Corporation (CPC) and Formosa Petrochemical Corporation (FPC). The gas prices of these two corporations might be slightly different. However, since CPC enjoys 78% and 77% market shares in the supply of #95 lead-free gasoline (95LFG) and premium diesel gasoline (PDG), respectively, the historical gas price data is obtained from the prices offered by CPC. It is worth to mention that both types of fuels are major energies for small vehicles (95LFG), large vehicles (PDG) and trailers (PDG). In addition, to eliminate the influence of the inflations, only the real gas price time series data are used in this study, which are obtained by dividing the nominal gas prices of 95LFG and PDG by CPI (Consumer price index). The real prices of these two gasolines are represented by R95P and RDSP, respectively.

Except for gas price, GDP generally reflects the development of national economy. It is believed that the more rapid growth in economy, the more trips will be generated. Based on this, GDP is chosen as the second factor of affecting freeway traffic volumes. Again, the real GDP (RGDP) data is collected and used for the following investigation.

All of above-mentioned time series data are collected during the time period of January 2004 to June 2009, yielding a total of 66 monthly observations, except for the traffic data of I-Lan area containing from September 2006 to June 2009, since it opened its service since September 2006. Gas price in Taiwan was under strict control (almost remained unchanged) prior to 2004. Therefore, it is meaningless to examine their relationships prior to 2004.

Table 1 gives the definitions and descriptive statistics of these variables. Table 2 presents the correlation coefficients of R95P (RDSP) and RGDP with fifteen traffic data. As noted from Table 2, gas price and RGDP exhibit rather different effects on freeway traffic in different areas and vehicle types. Some of tested results are even against general expectations that gas price has negative effect while GDP has positive effect on freeway traffic. For instance, RDSP has a significantly positive effect on trailer traffic in four areas and RGDP has a significantly negative effect on small-vehicle traffic in four areas. In addition, nearly a half of the correlation coefficients are not significantly tested, showing that traffic is insensitive to changes in the gas price or GDP.

Table 1. Descriptive statistics and definitions of all variables

| Variable | N | Mean | Std | Definitions |
|---|---|---|---|---|
| R95P | 66 | 25.39 | 3.82 | Real price of #95 lead-free gasoline. |
| RDSP | 66 | 21.35 | 4.21 | Real price of premium diesel gasoline. |
| RGDP | 66 | 1,017,799 | 65,198 | Real gross domestic product. |
| SVN | 66 | 18,206,179 | 908,854 | Small-vehicle traffic of Freeway No.1 and 3 in northern area. |
| SVC | 66 | 12,281,964 | 1,231,119 | Small-vehicle traffic of Freeway No.1 and 3 in central area. |
| SVS | 66 | 8,133,256 | 772,033 | Small-vehicle traffic of Freeway No.1 and 3 in southern area. |
| SVI | 34 | 1,202,919 | 187,257 | Small-vehicle traffic of Freeway No.5 in I-Lan area. |
| SVT | 66 | 38,621,399 | 2,579,823 | Small-vehicle traffic of Freeway No.1 and 3 nationwide. |
| TBN | 66 | 1,540,940 | 139,409 | Large-vehicle traffic of Freeway No.1 and 3 in northern area. |
| TBC | 66 | 1,863,349 | 156,411 | Large-vehicle traffic of Freeway No.1 and 3 in central area. |
| TBS | 66 | 1,087,580 | 84,691 | Large-vehicle traffic of Freeway No.1 and 3 in southern area. |
| TBI | 34 | 20,099 | 17,464 | Large-vehicle traffic of Freeway No.5 in I-Lan area. |
| TBT | 66 | 4,491,869 | 367,292 | Large-vehicle traffic of Freeway No.1 and 3 nationwide. |
| TLN | 66 | 979,678 | 125,251 | Trailer traffic of Freeway No.1 and 3 in northern area. |
| TLC | 66 | 1,180,233 | 97,445 | Trailer traffic of Freeway No.1 and 3 in central area. |
| TLS | 66 | 1,022,807 | 94,047 | Trailer traffic of Freeway No.1 and 3 in southern area. |
| TLI | 34 | 87.38 | 29.92 | Trailer traffic of Freeway No.5 in I-Lan area. |
| TLT | 66 | 3,182,718 | 296,036 | Trailer traffic of Freeway No. 1 and 3 nationwide. |

Note: Std stands for standard deviation. Prices for R95P and RDSP are at NT$ per liter. RGDP is measured in NT$ millions. Traffic is measured in vehicle/month.

Table 2. Correlation analysis of traffic with gas price and GDP

| | | | | | | |
|---|---|---|---|---|---|---|
| *R95P and RGDP vs. small-vehicle traffic* | | | | | | |
| | | SVN | SVC | SVS | SVI | SVT |
| R95P | *r* | 0.180 | -0.295 | -0.285 | -0.163 | -0.347 |
| | *p-value* | 0.149 | 0.016* | 0.020* | 0.191 | 0.044* |
| RGDP | *r* | -0.292 | -0.294 | -0.254 | -0.319 | 0.046 |
| | *p-value* | 0.017* | 0.016* | 0.040* | 0.009* | 0.796 |
| *RDSP and RGDP vs. large-vehicle traffic* | | | | | | |
| | | TBN | TBC | TBS | TBI | TBT |
| RDSP | *r* | 0.241 | -0.157 | -0.088 | -0.288 | 0.005 |
| | *p-value* | 0.051 | 0.208 | 0.485 | 0.098 | 0.971 |
| RGDP | *r* | -0.183 | -0.552 | -0.418 | -0.052 | -0.401 |
| | *p-value* | 0.141 | <.0001* | 0.001* | 0.770 | 0.001* |
| *RDSP and RGDP vs. trailer traffic* | | | | | | |
| | | TLN | TLC | TLS | TLI | TLT |
| RDSP | *r* | 0.481 | 0.717 | 0.612 | 0.211 | 0.634 |
| | *p-value* | <.0001* | <.0001* | <.0001* | 0.238 | <.0001* |
| RGDP | *r* | -0.035 | 0.538 | 0.318 | 0.268 | 0.263 |
| | *p-value* | 0.781 | <.0001* | 0.009* | 0.131 | 0.033* |

* denotes significance at the 5% level.

## 4. RESULTS

### 4.1. Unit Root Tests

Here we follow the ADF testing procedure suggested by 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 3.

Table 3 provides the unit root tests for the null hypothesis of series with unit root. There are four variables - real 95 lead-free gas price, real premium diesel price, real GDP and large vehicle 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 large vehicle in 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.

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, large vehicle traffic in southern area plus the trailer traffic in all five areas. There is an overwhelming proof that unit-root tests suffers from low power. Furthermore, "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). Therefore, in order to avoid the problem of over differencing, we take the results of PP test instead of ADF.

Table 3. 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* |
| 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* |

Note: *: Significance at the 5% level. ( ): Lag length – based on minimum BIC value.
Model 1: no intercepts and no trends; Model 2: unrestricted intercepts and trends; Model 3: unrestricted intercepts and trends.

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 4 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 4. 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* |
| RTBI(0) | -5.49* | -5.75* | -5.63* | -5.49* | -5.75* | -5.63* |

Note: *: Significance at the 5% level. (  ): Lag length – based on minimum BIC value.
Model 1: no intercepts and no trends; Model 2: unrestricted intercepts and trends; Model 3: unrestricted intercepts and trends.

### 4.2. Cointegration Test

Due to the fact that there are only four variables – real 95 unleaded gas price, real premium diesel price, real GDP plus large vehicle 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 Tables 5, 6 and 7 suggest that there is no evidence of co-integration neither between "real premium diesel price and large vehicle toll traffic in I-Lan area", nor between "real GDP and large vehicle toll traffic in 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. Results of cointegration test by the Engle-Granger Two-step method

| Residual Series | ADF | | | PP | | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| 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: *: Significance at the 5% level. (  ): Lag length – based on minimum BIC value.
Model 1: no intercepts and no trends; Model 2: unrestricted intercepts and trends; Model 3: unrestricted intercepts and trends.

Table 6. Results of Johansen Cointegration Test for RDSP & TBI

| Hypothesized No. of CE(s) | Trace statistic | Critical value (α=0.05) | p-value |
|---|---|---|---|
| Model 1: No intercept or trend in CE or test VAR | | | |
| 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: * denotes rejection of the hypothesis at the 0.05 level.

Table 7. Results of Johansen Cointegration test for RGDP & TBI

| Hypothesized No. of CE(s) | Trace statistic | Critical value (α=0.05) | p-value |
|---|---|---|---|
| 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: * denotes rejection of the hypothesis at the 0.05 level.

### 4.3. Granger Causality Tests

As the two different cointegration tests in Subsection 4.2 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 paper. 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. 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 MWalt Test).

The results on the Wald test as well as MWald of Granger causality at the 5% significance level are indicated in the Table A1. Granger causality test infers the direction of causality, which is summarized in the following Table 8.

Table 8. Results of Granger causality test

| Variable | Wald test | MWald test | Variable |
|---|---|---|---|
| R95P | ← | ← | SVN |
| R95P | ← | × | SVC |
| R95P | ← | ← | SVS |
| R95P | × | × | SVI |
| R95P | ← | ← | SVT |
| RDSP | → | → | TBN |
| RDSP | → | → | TBC |
| RDSP | × | → | TBS |
| 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 direction; ↔ denotes feedback Granger causality relationship.

Prior to discuss the detailed 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 data-driven, ignoring any precedence from traffic volume to gas prices while focusing on the one way direction from gas prices to traffic volume only.

Table 8 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 paper we take those consistent results only.

In sum, 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 large vehicle’ 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 island-wide. However, there is no Granger causality found in traffic volume in I-Lan area neither between it and gas prices nor it with GDP, except one result that the large vehicle 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 makes the drivers of large vehicle as well as of the trailer less giving up the freeway use when the gas price shock and GDP innovation. Furthermore, based on 5% significance level, the results stated in Tables 5, 6 and 7 suggest that there is no evidence of co-integration neither between “real premium diesel price and large vehicle toll traffic in I-Lan area”, nor between “real GDP and large vehicle toll traffic in 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. 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. 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 makes the drivers of large vehicle as well as of the trailer less giving up the freeway use when the gas price shock and GDP innovation (it only takes one-third of travel time for the use of freeway in comparing to the use of alternative surface roads).

## 4.4. 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 ignore the gas price response to shock in the traffic volume. Instead, we will focus only in terms of the one way response of freeway traffic to the gas price shock and to the innovation.

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, in this section we present the plots of orthogonalized impulse response analysis based on the consistent running direction of Granger causality testes by both Wald and MWald tests found in Subsection 4.3 to capture the short-run volatility of freeway traffic volumes in response to one standard deviation of gas price shock or 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. Fig.1 depicts the results of orthogonalized impulse response functions with two standard errors we obtain.

The response of output to the shock in Fig.1 exhibits the fact that one standard deviation change of gas prices or GDP has a positive impact on toll freeway traffic. We obtain positive feedback from Fig.1 – 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. About the aspect of impulse response of trailer traffic toward premium gas prices, the trailer 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. As a whole, there is no persistent response and the effect fades out gradually around 10 periods later.

Figure 1 also reveals a divergent result for the northern trailer traffic response to GDP innovation in comparison to the response to the 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.

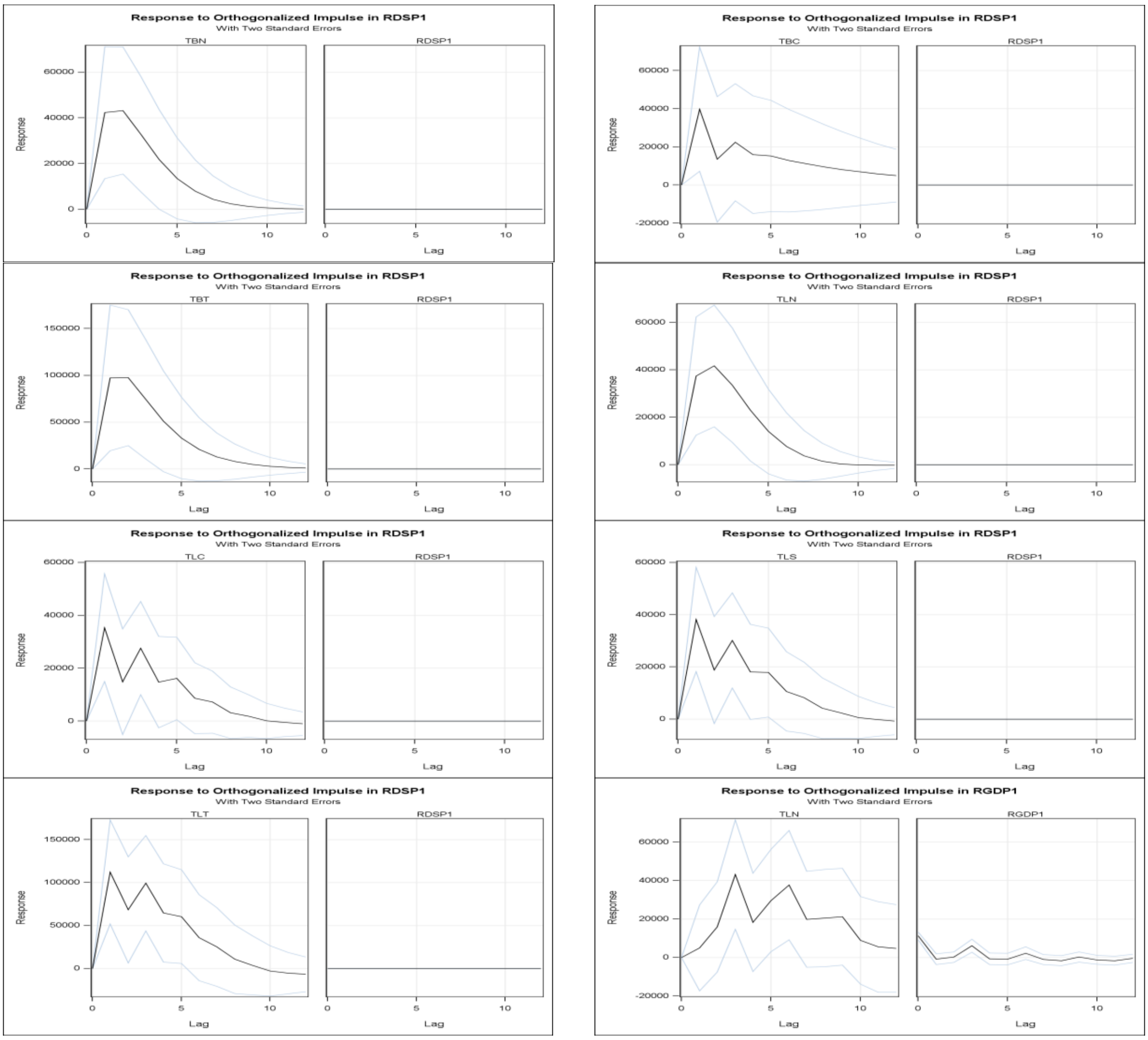


Figure1. Freeway traffic impulse and response to gas price and GDP

## 5. CONCLUSIONS

This paper investigates the effects of gas price and GDP on freeway traffic. Our interest has 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 gas prices, GDP and freeway traffic volume time series data over the period of five and a half years time from January 2004 to June 2009.

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 major findings of this research can be identified as follows:

Firstly, regarding to the unit root test for series stationarity, consistent with previous research inconsistent results of ADF and PP test occur. In order not to lose important info in the original series and for avoiding over differencing, 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 large vehicle 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 cointegration between the variables; none of long-term equilibrium relationship between gas price or GDP and freeway traffic in Taiwan has a statistically significant finding.

As to the short-term Granger causality, this paper adopts Direct Granger causality test and Toda-Yamamoto Granger causality test 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 large vehicle" 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 large vehicle' 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 island-wide.

There is no Granger causality found in traffic volume in I-Lan area neither between it and gas prices nor it with GDP, except one result that the large vehicle 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 makes the drivers of large vehicle as well as of the trailer less giving up the freeway use when the gas price shock and GDP innovation (it only takes one-third of travel time for the use of freeway in comparing to the use of alternative surface roads). Furthermore, based on 5% significance level, the results stated in Tables 5, 6 and 7 suggest that there is no evidence of co-integration neither between "real premium diesel price and large vehicle toll traffic in I-Lan area", nor between "real GDP and large vehicle toll traffic in 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. 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 the rises of gas price would potentially have a significant impact on driving choice 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 large vehicle and 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, our results demonstrate besides gas price and GDP, it requires all things considered when the local government would impose an excise levy on green taxes as a means to reduce carbon dioxide emissions. And another important note to readers as mentioned in previous chapters, Taiwan gas prices were under strict control by local 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. Our findings must be used with caution especially when the oil price market structure is changed.

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## APPENDICES

Table A1 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 |
| 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*** |
| 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. ( / ): Lag lengths for Wald test/MWald test–based on minimum AICC (corrected Akaike's information criterion) value.