1. Introduction

Owing to the fact that Taiwan owns very finite domestic energy resources and relies on imports for most of its energy requirements, the recent hike in global raw material prices has a negative impact on Taiwan's economy in the form of a surge in import prices and the rising inflationary pressure. Particularly, the soaring raw material prices have eaten into already emaciated profit margins in the manufacturing sector and put renewed pressure on majority of companies, which might inevitably pass these additional costs on the end customers. Consumer price index (CPI) is one of the major indices to measure the average price of consumer goods and services purchased by households and it will be used as our observed variable in this work.

The first oil embargo launched by the Organization of Petroleum Exporting Countries (OPEC) in the early 1970s has triggered the disputations on macroeconomic effects. Recently the direct effects of oil price shocks including both input-cost and income effects are still widely discussed. As far as the input-cost effect is concerned, higher energy cost diminishes usage of oil, in turn reducing productivity of capital and labor. While as for the income effect, higher cost of imported oil lowers disposable income of Taiwan's households. To sum up, oil price shocks have overall impacts on economies in the world.

From an empirical point of view, quite a few of studies verify that oil price fluctuations have influenced inflation (Hamilton, 1983, 1996, 2003; Mork, 1989, 1994; Hooker, 1996, 2002). Lee and Ni (2002) utilize identified VAR models to study the effects of oil price shocks on demand and supply side in various industries. They point out that for oil-intensive industries possessing a large cost share in energy (such as petroleum refinery and industrial chemicals) oil price shocks effectively reduce supply, while for other industries (especially the automobile industry) the main influence of oil price shocks is on the demand side. For possible non-linear relationships, Cuñado and de Gracia (2003) adopt different transformation of oil price data to investigate the impact of oil prices on inflation and industrial production indexes for numerous European countries using quarterly data for the period 1960-1999. They emphasize that oil prices have lasting effects on inflation and short run but asymmetric effects on production rates.

While increases in oil prices have received considerable attention around the world, the prices of metals, non-metals and other raw materials have risen much more rapidly over the past year. The cyclical fluctuation of metal prices and the relation with macroeconomic variables interest some researchers to throw themselves to the related works. For example, Slade (1991) selects all commodities traded on the London Metal Exchange (LME) in 1986 as her variables to find out why exchange pricing behaves more variably than producer pricing.[1] Achouch et al. (1999) take the aluminum, copper, tin, lead and zinc prices into consideration to study the interaction with the business cycle.

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[1] At that time, all of the commodities traded on the LME include aluminum, copper, lead, nickel, silver, and zinc. The data are on monthly frequency.

With regard to the steel industry, it produces a tremendous variety of products and is reckoned as relevant to the concern between the raw material suppliers and other industrial demanders in the economic system. Also, the intermittent increases in steel prices have sometimes been considered to be the most strategy impulse factor in the inflationary process. Evans and Walton (1997) adopt some uncomplicated pictorial techniques plus a structural time-series model to shed light on the time series properties of UK crude steel consumption. After removing several distinct outliers, they claim that steel consumption possesses a pretty regular seasonal pattern as well as a stochastic business cycle. Ghosh's (2006) empirical result in India suggests that a long-run equilibrium relationship between steel consumption and economic growth exists but proves the presence of unidirectional Granger causality running from GDP growth to steel consumption.

Copper, falling behind with the production of iron and aluminum, owns the third greatest yield in the whole world. With copper's excellent physical and chemical characteristic, it is widely used in such industries as electronic, electric, electric engineering, machinery, ornaments, etc. According to the report released by the International Copper Study Group (ICSG), world refined copper usage growth in 2007 was primarily driven by China, where the outward usage boosts by 37%, meanwhile, the net import volume increases by 157% to approximately 1.3 million tons. The volatility of price is mainly based on the cyclical use in building construction and related to political instability in copper-producing countries (e.g., Chile, Congo, and Zambia). To forecast future copper prices, Bracker and Smith (2003) find that GARCH-type models can give a more precise prediction than random-walk models. Comparing to asymmetric EGARCH, GJR-GARCH, and AGARCH models, the symmetric GARCH model relatively performs well.

It is well known that the aluminum market has been long time controlled by a few transnational smelting companies who have the power to set list prices, which are disclosed openly and transparently. Nevertheless, the monopolizers most likely present changeful but secret discounts on these.[2] Therefore, the list prices exhibited on the market are eventually not in line with the actual transaction prices and this type of price variability may lead to a cost imposition on producers, consumers and stockholders (Radetzki, 1990). Focusing on the non-ferrous metals industry, Figuerola-Ferretti and Gilbert (2001) extend Slade's (1991) sample to reexamine the results, supporting that exchange prices are more mutable than producer prices.

The carbon dioxide (CO2) reduction requirement by the Kyoto Protocol forces many countries to dig into developing biomass energy despite the debate of the potential of biomass energy and the evaluation of effect. Corn and soybean are the iconic crops used for the substitution of current traditional energy for producing bio-energy to be refined as an alternative source of energy that is both effectively and ecologically sustainable. Therefore,

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[2] Aluminum trading started on the London Metal Exchange (LME) in 1978. The Comex division of NYMEX launched an unsuccessful contract in the mid-80s and re-launched another trading in 1999.

the cost of producing alcohol will depend on those agricultural commodities. However, due to the bottleneck that these crops fail to be produced dramatically in short time and the strong economic growth in emerging markets, combined with tight global grain supplies, resulted in near-record prices for corn, soybeans, and other food and feed grains in 2007. Higher corn prices propel farmers to enlarge corn acreage to gain more profit at the expense of other crops, such as soybeans and cotton, raising their prices as well. On the other hand, it is also quite arduous to capture the regularity of agricultural commodities by the reason of weather, political intervention, substitution effect between agricultural products, and the seasonal factor, etc. Lee's (2003) contribution reveals that when the importer imports corn with the corn import price uncertainty increases, the corn surpasses the soybean in import quantity and consumer surplus, but when importing soybean with the uncertainty of corn import price increases, the soybean import quantity and consumer surplus will be more than the condition with decided corn import price.

Past studies mainly focus on the relationship between energy consumption and economic growth. Cheng and Lai (1997) follow Hsiao's (1981) version of Granger causality approach to explore the causality between energy consumption and economic growth for Taiwan during the period 1955-1993. They find a causal linkage running from GDP to energy consumption without feedback. Hondroyiannis et al. (2002) explore the linkage between energy consumption, economic growth and consumer price index (CPI) for Greece for the time span of 1960-1996. In this work, a long-run relationship among them and a bi-directional causality between energy consumption and economic growth are found, yet less empirical work has been undertaken to investigate the dynamic relationship between internal consumer price level and international commodity prices. The objective of this study is to examine cointegration and Granger causality between CPI and import raw material prices indices in Taiwan in bivariate vector autoregression (VAR) framework.

2. Methodologies

2.1 Unit Root Tests

We first test for stationarity of each variable by employing two conventional unit root test techniques: the augmented Dickey-Fuller (1981) (ADF) and the Phillips-Perron (1988) (PP) tests. The three differencing AR models of ADF are expressed as follows:

$$\text{Model 1:} \quad \Delta Y_t = \gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{1}$$

$$\text{Model 2:} \quad \Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{2}$$

$$\text{Model 3:} \quad \Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{3}$$

where Δ is the difference operator; t denotes time t; and $\gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i}$ is an augmented part of ADF test and the optimal lag length can be decided by minimizing Akaike's information criterion (AIC) or Schwarz's Bayesian information criterion (SBC). Model (1) is defined as a pure random walk with lag terms, model (2) is a random walk with drift and model (3) is a random walk with drift around a stochastic trend. The null hypothesis and alternative hypothesis for the ADF test are H_0: $\gamma = 0$ and H_1: $-2 < \gamma < 0$.

Even though the ADF test with long lag terms is thought to be superior to the others (Schwert, 1989),[3] this paper also performs the PP test which is robust in the presence of serial

[3] Ayat and Burridge (2000) also argue that the ADF approach with lag length selected via an information criterion is simple to implement and performs well in most cases.

correlation and heteroscedasticity. If the series are tested to be non-stationary in levels and become stationary when first differenced, then they are said to be integrated of order one and cointegration approaches are supposed to be applied to study the possible long-run relationships among the variables, which are required to realize the real behavior of the variables.

2.2 Cointegration

According to Engle and Granger (1987), if each element of a vector of time series x_t first becomes stationary after differencing, but a linear combination $\alpha' x_t$ is already stationary, the time series x_t are regarded as co-integrated with co-integrating vector α. The 'spurious problem' (Granger and Newbold, 1974) is the first task to be ruled out and the more powerful Johansen (1988) multivariate maximum likelihood cointegration test is scheduled to investigate the common stochastic trend among variables.

Following Johansen (1988) and let Y_t be a k×1 matrix, the VAR representation of general form can be set up:

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 \Delta Y_{t-2} + \ldots + A_p \Delta Y_{t-p} + \varepsilon_t \tag{4}$$

$$\varepsilon_t \sim \text{i.i.d. } N(0\,,\,\sigma^2)$$

In order to apply the Johansen test, the VAR model above needs to be rewritten in error correction form:

$$\Delta Y_t = A_0 + \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-2} + \Gamma_2 \Delta Y_{t-3} + \ldots + \Gamma_{t-p} \Delta Y_{t-p-1} + \varepsilon_t \qquad (5)$$

where Δ is the first difference operator, and ΠY_{t-1} is termed as the equilibrium error or error correction. Here $\Pi = \sum_{i=1}^{p} A_i - I$, $\Gamma_i = \sum_{j=1}^{i} A_j - I$.

The parameter matrix r (Π) will be further marked, that the rank r of this matrix r (Π), where (0 < r < p), will determine the number of cointegrating vectors in the VAR system. According to the property of the matrix r (Π), three cases are possible.

1. Rank (Π) = p
2. Rank (Π) = 0
3. Rank (Π) = $r < p$

In the first case, Π is full rank and Y_t is a stationary series, i.e., $Y_t \sim I(0)$, and we may directly estimate the VAR model with Y_t. In the second case, none is stationary, i.e., $Y_t \sim I(1)$, and there is no cointegration. And estimating the VAR model using ΔY_t is suggested. Under the condition of last case, say the reduced rank, the matrix Π can be decomposed as Π $= \alpha\beta'$, where α is known as the speed of adjustment vector; β is the cointegrating vector, and both α and β are p × r matrices.

The number of cointegrating vectors can be judged by determining the significance of the characteristic roots of Π. There are two test statistics for cointegration under the Johansen approach, which are formulated as:

$$\lambda_{trace}(r) = -2\ln(\theta) = -T\sum_{i=r+1}^{n}\ln\left(1-\hat{\lambda}_i\right) \tag{6}$$

and

$$\lambda_{\max}(r, r+1) = -2\ln(\theta, r \mid r+1) = -T\ln\left(1-\hat{\lambda}_{r+1}\right) \tag{7}$$

where r is the number of cointegrating vectors under the null hypothesis; T is the total number of observations; and $\hat{\lambda}_i$ is the estimated value for the ith ordered eigenvalue from the Π matrix. If both test statistics are greater than the critical value, we reject the null hypothesis that there are r cointegrating vectors in favor of the alternative that there are $r + 1$ (for λ_{trace}) or more than r (for $\lambda_{\max}$) stationary relationships between the relevant variables. The Schwartz Bayesian information criterion (SBC) is again used to select the optimal number of lag length.

2.3 Granger's Causality Test

If the predication of the current value of Y_t is improved by including past values of X_t, then it is supposed that the variable X_t Granger-causes Y_t. 'Predictability' is thus the main concept of evaluating the causality between variables. The causal relationship between the CPI and the import raw material price indices in Taiwan will be detected by Hsiao's (1981) version of Granger causality test. If two variables are tested to be stationary, the standard form of the Granger's causality approach can be expressed as follows:

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{P} \alpha_i \Delta Y_{t-i} + u_{1t} \tag{8}$$

Hsiao's procedure involves two steps. The first step is to calculate the sum of squared errors (SSE) for Eq. (8) where $i = 1, 2, ..., P$. The FPE(*p*) considering the lag terms will then be obtained in the following equation:

$$\text{FPE}(p) = \frac{\text{SSE}}{T - p - 1}(1 + \frac{p+1}{T}) \tag{9}$$

where *T* is the total number of observations, *p* is the order of lags altering from 1 to *P*, and *SSE* is the sum of squared errors. The minimum FPE is decided by the corresponding SSE and p^*, which is expressed as FPE(p^*) to make a comparison in the next step. In the second step, the focus will be shifted to the following equation:

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{P} \alpha_i \Delta Y_{t-i} + \sum_{j=1}^{Q} \beta_j \Delta X_{t-j} + u_{2t} \tag{10}$$

From the above equation, Y_t is defined as a controlled variable, with the order of lags set at p^* from Eq. (9), and X_t as a manipulated variable. According to Eq. (10), we estimate the *SSE* of Y_t by altering the lag order of X_t from 1 to *Q* and decide the order producing the smallest FPE, which denotes as q^*. Finally, the corresponding two-dimensional FPE is of the form:

$$\text{FPE}(p^*, q) = \frac{\text{SSE}(p^*, q)}{T - p^* - q - 1}(1 + \frac{p^* + q + 1}{T}) \tag{11}$$

where *q* is known as the lag order of series X_t altering from 1 to *Q*; and p^* is the optimum number of lags estimated in the preceding step. Summing up the above, we may draw the conclusion that series X_t Granger-causes series Y_t, if FPE(p*, q*) is smaller than FPE(p*).

2.4 The Vector Autoregression Model (VAR)

Since many economic empirical works are traditionally established according to the prior knowledge, it is hard to settle the proper causality and the endogenous- exogenous relationship between variables until the vector autoregression model (VAR) unfolded by Sims (1980). The VAR model treats every variable as been endogenous and expresses their interaction relationship with multiple regression equations rather than one regression equation. The general mathematic form of VAR model is given by:

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i Y_{t-i} + \varepsilon_t \tag{12}$$

$$E(\varepsilon_t \varepsilon_s) = 0 \;;\; E(\varepsilon_t \varepsilon_t') = \Sigma \neq 0$$

where Y_t is a n × 1 vector of variables; β_i is n × n matrices of coefficients; α is n × 1 vector of intercept terms; and ε_t is a n × 1 vector of disturbances, i.e., the process of one-step-ahead forecast errors.

To make sure that the error terms are all white noise, AIC will be used to select the optimal lag length. If the common stochastic trend among non-stationary variables does not exist, the VAR model in first difference will be applied to carry out the analysis, which is described as follows:

$$\Delta Y_t = \alpha + \sum_{i=1}^{m} \beta_i \Delta Y_{t-i} + \varepsilon_t \qquad (13)$$

2.5 Impulse-Response Analysis with VAR

To better comprehend the dynamic response pattern in the VAR model, we further employ the impulse responses to trace out the responsiveness of the dependent variables to shocks to each of the variables. By utilizing the Wold's decomposition theorem, the VAR model can be transformed into the form of Moving Average (MA), that is, each variable can be expressed as a linear combination of current value and previous values of a white noise error term. The process is as follows:

$$Y_t - \sum_{i=1}^{m} \beta_i Y_{t-i} = \alpha + \varepsilon_t$$

$$(1-\beta_1 L - \beta_2 L^2 - \ldots - \beta_m L^m) Y_t = \alpha + \varepsilon_t$$

$$Y_t = (1-\beta_1 L - \beta_2 L^2 - \ldots - \beta_m L^m)^{-1}\alpha + (1-\beta_1 L - \beta_2 L^2 - \ldots - \beta_m L^m)^{-1}\varepsilon_t$$

$$Y_t = \alpha' + \sum_{i=0}^{\infty} C_i \varepsilon_{t-i} \qquad (14)$$

where L is the lag operator; α' is n×1 vector of constants; C_i is n×n matrices; and C_0 = I is an unit matrix.

Typically, the estimated VAR residuals are deemed contemporaneously correlated. In order to dissect the effects of innovations in one variable uncontaminated by contemporaneous innovations in other variables, one workable implementation to achieve this goal is to apply the Choleski decomposition to generate triangular orthogonalization matrices. Eq. (12) ensures the following equation:

$$Y_t = \alpha' + \sum_{i=0}^{\infty} C_i K K^{-1} \varepsilon_{t-i}$$

Let $C_i^*=C_iK$ and $e_{t-i} = K^{-1}\varepsilon_{t-i}$. The above equation can be re-expressed as:

$$Y_t = \alpha^t + \sum_{i=0}^{\infty} C_i^* e_{t-i} \tag{15}$$

where C_i^* is an impact multiplier and e_{t-i}s are neither autocorrelated nor contemporaneously correlated.

In this way, each variable can be transformed into the function of innovations and these matrices multiplied by the estimated VAR model create uncorrelated residuals, which help to observe how the coefficients change when the objective variable receive spontaneous shocks from other variables.

3. Empirical results

3.1 Data Sources and Descriptions

This study employs various time series methodologies to fully investigate the dynamic relationships between import raw material price indices and Taiwan's consumer price index. All of the import commodity price indices considered in this study include crude oil, steel, copper, aluminum, corn, soybean, and their related products. Monthly data are selected. The sample period runs from 1991:1to 2007:12, total 204 accounts of each variable are collected.

The data are mainly collected from the National Statistics Database set up by the

Directorate-General of Budget, Accounting and Statistics, Executive Yuan in Taiwan. All variables are in logarithmic form and seasonal adjustment is considered.[4] The trends of these variables and descriptive statistics for every import commodity price index are showed in Fig. 1 and Table 1. It is vivid to see that CPI, crude oil, steel, copper, aluminum, corn and soybean price indices are at or near record heights in 2007.

[Figure 1 inserts here.]

[Table 1 inserts here.]

3.2 Unit Root tests

Given the importance of unit root testing to avoid the problem of spurious regressions, the augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests of stationarity are applied to each series. As shown in Table 2, the series of CPI and all import commodity price indices, after logarithmic transformation and seasonal adjustments, are non-stationary in levels and become stationary after first differencing; i.e., they are I (1) variables. Therefore, the cointegration test can be rational employed for the long-run equilibrium relationship.

[Table 2 inserts here.]

3.3 Cointegration tests

[4] The seasonal adjustment is carried out by using the X11 procedure, which is first developed by the U.S. Bureau of Census.

Since that all the variables are integrated of the same order, the next step is to test for cointegration using the Johansen's multivariate maximum likelihood procedure, which has been shown to be superior to Engle and Granger's residual-based approach. Among other things, the Johansen approach is capable of detecting multiple cointegration relationships.

The test results are summarized in Table 3, where *r* represents the number of cointegrating vectors. These results imply that the null hypothesis of no cointegration relationships is not rejected against the alternative of one cointegrating relationship at the 1% level for every pairwise comparison.

Both the trace test and the maximum eigenvalue test indicate that the null hypothesis of no cointegration relationships is not rejected against the alternative of one cointegrating relationship at the 1% level for every pairwise comparison.

[Table 3 inserts here.]

3.4 Granger's causality tests

The prerequisite to apply the standard Granger's causality test requires that the series of variables to be stationary. According to the results of unit root tests, the initial form of the series fails to conform to the condition of covariance stationarity. Therefore, before conducting the Granger's test, all variables are needed to be transformed into first difference form for our further analysis.

Since Taiwan is arguably a small open economy system, it fails to dominate international raw material prices. In this analysis, we consider only the unidirectional Granger's causal linkage running from import commodity price index to CPI. The results of Granger's causality test between CPI and all the import commodity price indices are presented in Table 4.

As shown in Table 4, it reveals that for the oil equation, since $4.73\times10^{-5} > 4.72\times10^{-5}$, we cannot reject the hypothesis that oil price index Granger-causes CPI. This means that the inclusion of past values of oil price index in the CPI equation provides a better explanation of current values of CPI than when excluded. Similarly, since $4.73\times10^{-5} > 4.69\times10^{-5}$ in the corn equation, we can get equivalent conclusion that import corn price index Granger-causes CPI. Thus, a growth in import crude oil price index and import corn price index is found to be responsible for a higher level of CPI.

[Table 4 inserts here.]

3.5 Impulse-Response Simulations

In table 5 the optimal lag order of the VAR model is determined as 1 on the basis of SBC. We do not choose VAR(8) as our optimal model until consider the elimination of autocorrelation of residual and compare the LR test value with chi-square value. On the other hand, the ordering of the variables in the impulse-response analysis might probably be crucial enough to give a different outcome. Hence, the ordering variables has been tried to check that an equal outcome is displayed. Fig.2 shows the impulse-response paths of CPI up to 20 months after a one standard deviation shock stimulated from every import commodity price index. From the test results, the CPI tends to have positive responses to the shock of every import commodity price index at initial period, with the exceptions of copper and aluminum price index. On the whole, the CPI fluctuates up and down around the pre-shock level and becomes stable gradually.

[Fig. 2 inserts here.]

4. Conclusion

By applying techniques of co-integration and Hsiao's version of Granger causality, this study finds the absence of a long-run equilibrium relationship between CPI and import raw material price indices but establishes the presence of causal linkage between CPI and import crude oil price index and between CPI and import corn price index. Our findings support the prevailing view that the soaring oil price still dominates Taiwan's CPI level and has given rise to the inflationary force. Until now, oil prices have increased very sharply from a 25 year low of $11 per barrel in February 1999 to a peak of close to $100 per barrel in December 2007, which equips us with the justification to seek for an alternative energy as well. Lee et al. (1995) emphasize the volatility arguing that an oil shock tends to have a notable impact in an environment where oil prices have been steady than in an environment where oil price movement has been changeable. Their point of view gives us another contemplation in dealing with the current controversial issue about freezing the oil price.

Except for direct human consumption, corn is also used for animal feed and ethanol production. Given that livestock feed consists of a large amount of corn usage, a situation may be reasonably imaged that both higher feed costs stimulated by bio-energy demand and transportation costs caused by increasing oil price result in a more obvious impact on meat and poultry prices. In terms of the persistent development of renewable energy, finite and precious lands, along with high human resource cost, have hindered Taiwan from developing bio-energy crop in large numbers. The alternative route for Taiwan is to develop some feasible and inexhaustible resources, such as solar energy, hydropower and wind power to replace the traditionally mass-used and high-polluted energy step by step.

However, the above non-ferrous metals selected for this work can be recycled. High recycling rate in Taiwan expands the efficiency of use of the refuse metals and brings in energy savings. For this reason, we have slightly pressing intension to import more overseas, which also relatively moderates the pressure on the material-price-push-inflation. From our results, even though the recycled energy seems to have a limited relevance with Taiwan's consumer price index, from the financial point of view, the trends of raw material prices in the international community motivate investors to perform a preliminary hedge aiming at the depletable energy. Moreover, those countries having mass resources might benefit from the increases in the exported mineral resources and agricultural products prices, which also forms a good investment objective for them.

Intended research may probably lengthen the sample period or use daily data or different countries as variables by means of employing the GARCH-type model to capture the possible fluctuation of prices and this type of analysis of the long-term trend and variations in the price of raw materials may help improve the quality of decision and is expected to play a crucial role in policy formulation.

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Table 1

Summary of Descriptive Statistics for Every Import Commodity Price Index (1991-2007)

Variables	Oil	Steel	Copper	Aluminum	Corn	Soybean
Mean	43.49	68.44	44.01	68.76	92.91	98.86
Maximum	142.18	149.64	119.23	109.34	185.13	194.04
Minimum	15.51	48.41	26.07	51.06	66.50	69.53
Std. Dev.	27.70	22.19	23.70	13.90	21.26	20.63
Skewness	1.58	1.74	2.08	1.51	1.58	1.53
Kurtosis	4.61	5.47	6.16	4.51	5.58	6.53
Jarque-Bera	107.18	154.82	232.07	97.27	141.58	185.47

Note: 1. The year 2006 is taken as the base year.

Table 2

Results of Unit Root Tests

Variable		CPI	Oil	Steel	Copper	Aluminum	Corn	Soybean
Level								
ADF	T_u	-1.85	1.12	1.92	0.02	-0.13	-0.54	-0.60
	T_t	-2.36	-1.56	0.33	-1.04	-1.59	-0.83	-0.98
	T	2.08	1.80	1.77	1.03	0.87	0.86	0.97
PP	T_u	-2.85	0.91	2.27	0.35	-0.90	-0.53	-0.50
	T_t	-2.35	-1.73	0.54	-0.74	-2.10	-0.78	-0.87
	T	4.09	1.01	1.79	1.20	0.56	0.90	0.91
First Difference								
ADF	T_u	-2.89**	-13.03***	-7.83***	-9.40***	-12.75***	-8.59***	-8.89***
	T_t	-2.77	-13.22***	-8.57***	-9.59***	-12.83***	-8.73***	-9.00***
	T	-1.96**	-12.86***	-7.63***	-9.34***	-12.72***	-8.55***	-8.84***
PP	T_u	-17.77***	-13.03***	-7.79***	-9.46***	-13.66***	-8.80***	-8.89***
	T_t	-18.61***	-13.22***	-8.58***	-9.66***	-13.71***	-8.92***	-9.01***
	T	-16.39***	-12.87***	-7.54***	-9.28***	-13.67***	-8.76***	-8.84***

Note: 1. *** and ** represent significance at the 1% and 5% levels, respectively.

2. The numbers showed in this table represent t value. T_u, T_t, and T respectively denote test equation computed with intercept, with linear trend and intercept, and without intercept and linear trend. ADF and PP stand for augmented Dickey-Fuller and Phillips and Perron unit root tests with the same critical values at 5% are -2.86, -3.41, -1.94 and at 1% are -3.43, -3.96, -2.57, respectively.

Table 3

Determination of Cointegration Rank

Null Hypothesis	Eigenvalue	Trace Statistics	Max-Eigen Statistics	5% Critical Value
Oil & CPI (SBC= 12)				
$r = 0$	0.0282	5.4879	5.4630	12.3209
$r \leq 1$	0.0001	0.0249	0.0249	4.1299
Steel & CPI (SBC=13)				
$r = 0$	0.0037	7.4447	7.1646	12.3209
$r \leq 1$	0.0015	0.2801	0.2801	4.1299
Copper & CPI (SBC=12)				
$r = 0$	0.0455	9.5644	8.8889	12.3209
$r \leq 1$	0.0035	0.6755	0.6755	4.1299
Aluminum & CPI (SBC=12)				
$r = 0$	0.0406	9.4190	7.9225	12.3209
$r \leq 1$	0.0078	1.4966	1.4966	4.1299
Corn & CPI (SBC=12)				
$r = 0$	0.0499	11.3812	7.7853	12.3209
$r \leq 1$	0.0083	1.5959	1.5959	4.1299
Soybean & CPI (SBC=13)				
$r = 0$	0.0466	11.7109	9.0571	12.3209
$r \leq 1$	0.0139	2.6537	2.6537	4.1299

Note: 1. *r* denotes the number of cointegrating vectors: The critical values are for the 5% level of significance.

2. The lag lengths are selected on the basis of minimizing Schwartz Information Criteria (SBC).

Table 4

Granger Causality Tests

Regressions	Final Prediction Error
$\Delta CPI_t = \alpha_{11} + \sum_{i=1}^{2} \beta_{11i} \Delta CPI_{t-i} + u_{11t}$	4.73×10^{-5}
$\Delta CPI_t = \alpha_{11} + \sum_{i=1}^{2} \beta_{11i} \Delta CPI_{t-i} + \sum_{j=1}^{2} \beta_{12j} \Delta Oil_{t-j} + u_{12t}$	4.72×10^{-5}
$\Delta CPI_t = \alpha_{11} + \sum_{i=1}^{2} \beta_{11i} \Delta CPI_{t-i} + \sum_{j=1}^{1} \beta_{12j} \Delta Steel_{t-j} + u_{12t}$	4.81×10^{-5}
$\Delta CPI_t = \alpha_{11} + \sum_{i=1}^{2} \beta_{11i} \Delta CPI_{t-i} + \sum_{j=1}^{1} \beta_{12j} \Delta Copper_{t-j} + u_{12t}$	4.77×10^{-5}
$\Delta CPI_t = \alpha_{11} + \sum_{i=1}^{2} \beta_{11i} \Delta CPI_{t-i} + \sum_{j=1}^{1} \beta_{12j} \Delta Aluminum_{t-j} + u_{12t}$	4.75×10^{-5}
$\Delta CPI_t = \alpha_{11} + \sum_{i=1}^{2} \beta_{11i} \Delta CPI_{t-i} + \sum_{j=1}^{1} \beta_{12j} \Delta Corn_{t-j} + u_{12t}$	4.69×10^{-5}
$\Delta CPI_t = \alpha_{11} + \sum_{i=1}^{2} \beta_{11i} \Delta CPI_{t-i} + \sum_{j=1}^{3} \beta_{12j} \Delta Soybean_{t-j} + u_{12t}$	4.75×10^{-5}

Table 5

Lag Length Determination for VAR Model

Model	SBC	LR
VAR(1)	-30.7674	
VAR(2)	-29.8547	NA
VAR(3)	-28.8925	NA
VAR(4)	-27.9231	NA
VAR(5)	-26.9596	NA
VAR(6)	-25.8383	NA
VAR(7)	-24.8144	NA
VAR(8)	-23.9217	NA
VAR(9)	-23.1278	27.6640
VAR(10)	-22.3810	30.9624
$\chi^2(49) = 33.9385$		

Note: 1. SBC is the Schwarz information criterion, and LR is the likelihood ratio test statistic.

2. The critical value of the chi-square distribution is at the 5% level.

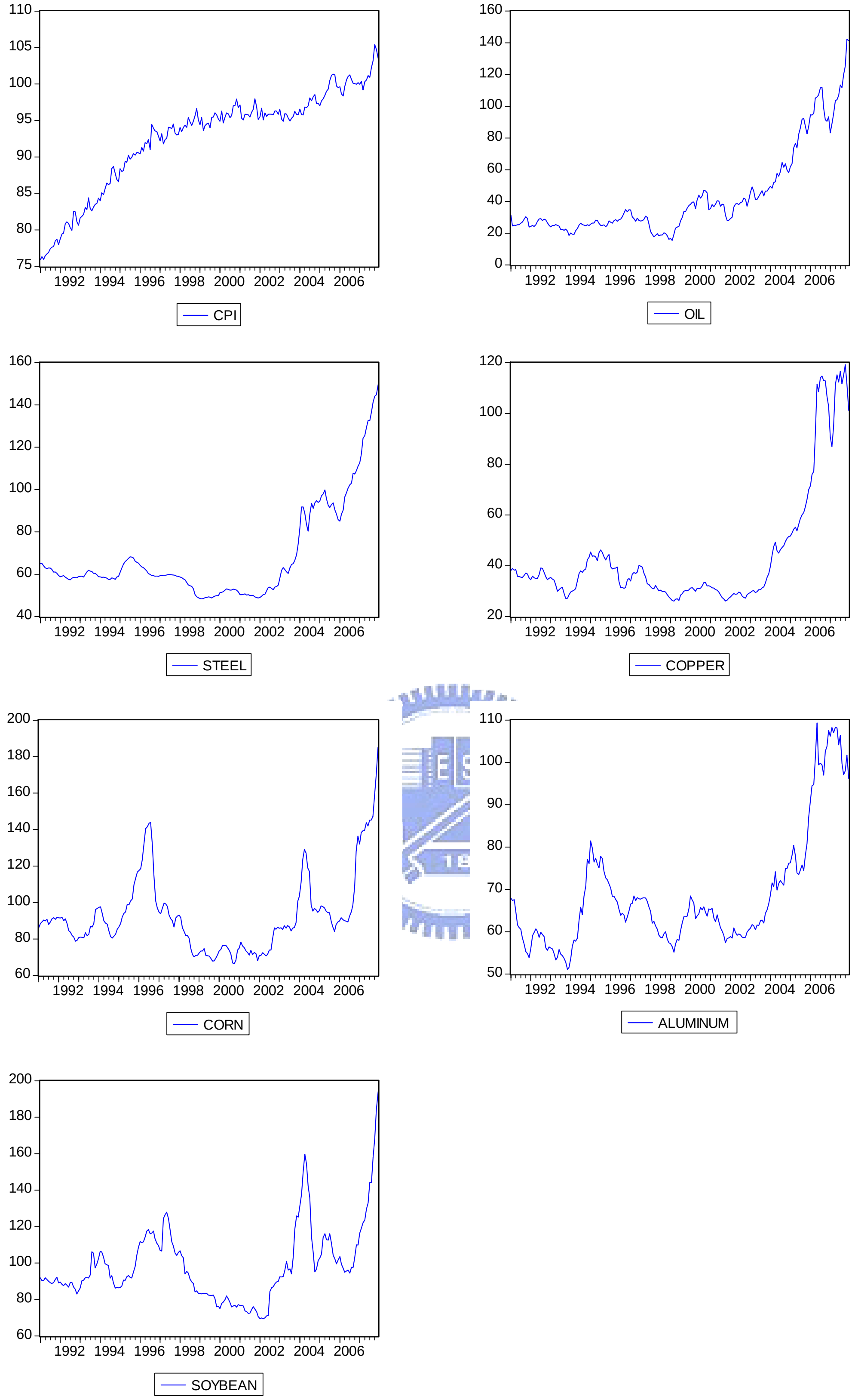

Fig. 1 Consumer Price Index and Import Raw Material Price Indices in Taiwan (1991-2007)

Fig. 2 Impulses and Responses of CPI to a Price Index Shock of Every Import Raw Material