國立交通大學

經營管理研究所

博 士 論 文

No. 130

國際能源價格衝擊對台灣總體經濟活動之影響

Effects of International Energy Price Shocks on Macroeconomic Activities in Taiwan

研 究 生：葉芳瑜

指導教授：胡均立　教授

中 華 民 國 九十九 年 六 月

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中華民國 九十九 年 六 月

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中文摘要

台灣為一能源有限且能源進口依存度高達 99.32 %的海島型經濟體。隨著國際能源價格不斷攀高，國際能源價格的變動對台灣總體經濟活動之影響將值得深入研究。本論文利用線性與非對稱的架構去評估國際能源價格(原油、煤炭、天然氣)與台灣總體經濟變數(工業生產指數、股價、利率、失業率、進口值與出口值等)之間的關係。利用 Tsay (1998) 所提出的多變量門檻模型結合非對稱動態調整過程加以分析，以能源價格變動當作一個門檻變數區分為能源價格上漲與下跌狀態，檢視在不同狀態下國際能源價格衝擊對台灣總體經濟活動的影響，進一步利用衝擊反應分析與變異數分解去評估能源價格波動對台灣總體經濟之衝擊。研究結果顯示：(1)油價的最適門檻值 2.48%，其次為天然氣價格門檻值 0.87%，最小為煤價門檻值 0.22%；(2)當油價大於門檻值時，油價對於工業生產值上的解釋能力更甚於利率；(3)當天然氣價格小於門檻值時，天然氣價格分別在股價與失業率上面都具有較大的解釋能力；(4)煤價衝擊與天然氣價格衝擊均對於台灣總體經濟活動而言具有延遲的負面影響。

關鍵詞：能源價格衝擊、總體經濟活動、多變量門檻誤差修正模型、衝擊反應分析、變異數分解

Effects of International Energy Price Shocks on Macroeconomic Activities in Taiwan

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Abstract

Taiwan is an island with limited domestic energy resources and its imported energy ratio is over 99.32%. As international energy prices keep rising, the impacts of this on Taiwan's economic activities have been an important issue of research. This paper applies a linear and asymmetric model to estimate the effects of international energy price shocks (including oil, coal, and natural gas prices) on Taiwan's macroeconomic activity (such as industrial production, stock price, interest rate, unemployment rate, imports and exports). We apply a multivariate threshold error correction model by Tsay (1998) to analyze the empirical data. By separating energy price changes into the decrease and increase, the energy price change as a threshold variable can analyze different impacts of energy price changes and their shock on industrial production. The variance decomposition and the impulse response functions are also employed to analyze the short-run dynamics of the variables. The preliminary findings are: (1) The optimal threshold levels are that the highest level is oil price at 2.48%, the next highest is natural gas price at 0.87%, and the lowest level is coal price at 0.22%. (2) If the change is above the threshold levels, then a change in oil price explains industrial production better than the interest rate. (3) If the change is below the threshold levels, then it appears that the change in natural gas price better explains stock prices and the unemployment rate than the interest rate. (4) Both oil price shock and natural gas shock have a delayed negative impact on macroeconomic activities.

Keywords: Energy Price Shocks; Macroeconomic Activity; Multivariate Threshold Error Correction (MVTEC) Model; Impulse Response Analysis; Variance Decomposition

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Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

1.1 Research Background

Energy price shocks are generally acknowledged to have important effects on both the economic activity and macroeconomic policy of industrial countries. Huge and sudden rises in energy prices increase inflation and reduce real money balances with negative effects on consumption and output. Among the most acute supply shocks hitting the world economies since World War II are sharp increases in the price of oil and other energy products. Figure 1.1 shows the annual average energy price (oil price, natural gas price, and coal price) from 1983 to 2009.

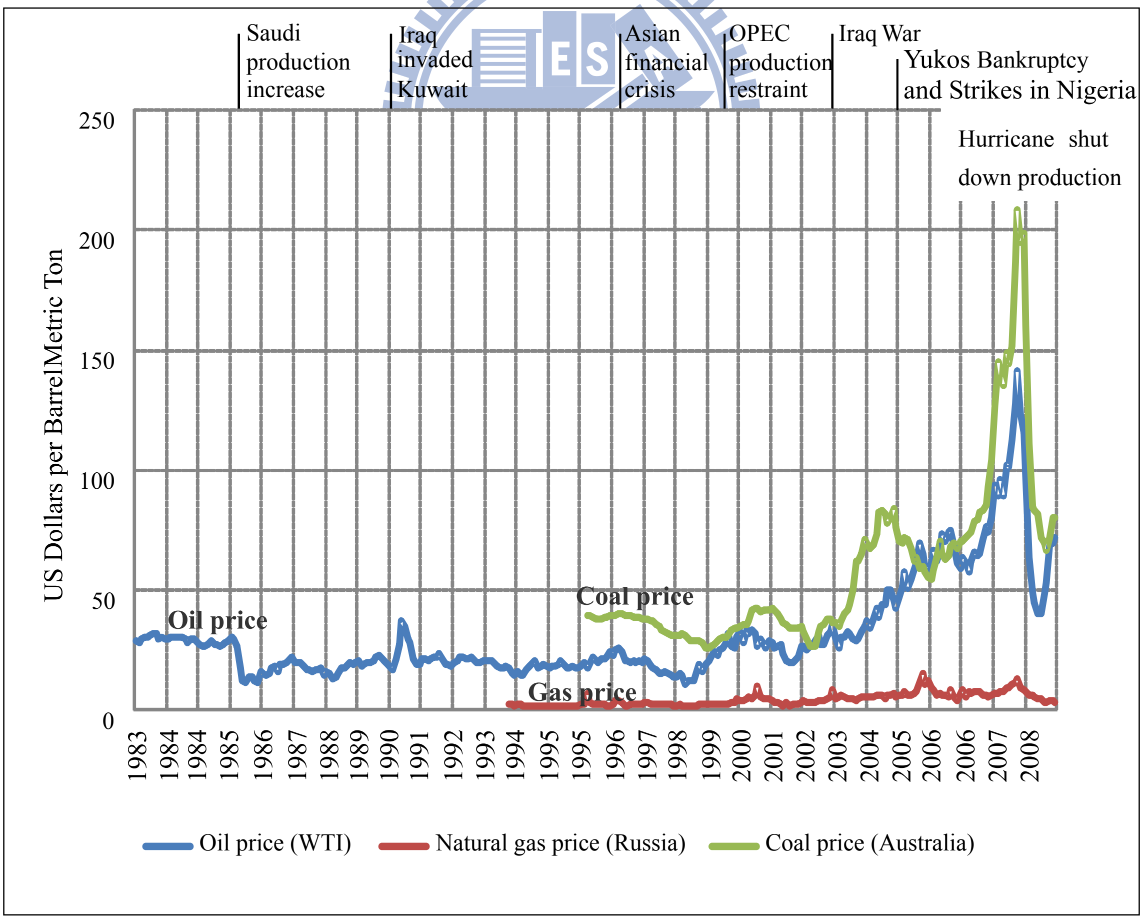

Figure 1.1 World Marketed Energy Price, 1983-2009

Since the 1970s, oil price in the world market has experienced fluctuations including sharp rises during the first and second oil crises. During the periods of 1973-1974 and 1978-1979, when the Organization of Petroleum Exporting Countries (OECD) first imposed an oil embargo and the Iranian revolution disrupted oil supplies, the prices of a barrel of oil increased from $3.4 to $30. In 1990, prices rapidly rose from $16 to $26 after the Gulf War. Finally, due to a decline from the Asian financial crisis in 1999, prices fell from $20.28 to $11.13. Since 2000, oil prices have continued an upward trend with repeated fluctuations. In particular, oil price volatility in the crude oil market has risen during 2004 to 2008. By March 13, 2008, the oil price had spiked to a historical high of $110.21 per barrel (West Texas Intermediate (WTI) spot). Recently, the WTI oil future prices averaged $76 per barrel in October 2009 on the New York Mercantile Exchange (NYMEX). This is an increase of just over 8 percent for this month. EIA (2009) estimates that the January 2010 WTI futures contract consistent with this volatility was $61 per barrel at the lower limit and $104 per barrel at the upper limit for the 95 percent confidence interval.

Higher prices of oil driving demand for other energy have made natural gas and coal more competitive (see Figure 1.2). From 1986 to 1999, natural gas prices averaged $1.87 per million cubic feet (mcf), with a standard deviation of $0.24 per year (Kliesen, 2006). Since 2001, natural gas prices began to rise noticeably. Natural gas prices in both real and nominal dollars were at record-high levels by 2005. In 2008, natural gas prices averaged approximately $9 per mcf. Because price-setting is based on production costs and applications for rate increases move slowly through the bureaucratic process, natural gas volatility is quite small. On average, natural gas price variability is 3%-4%.

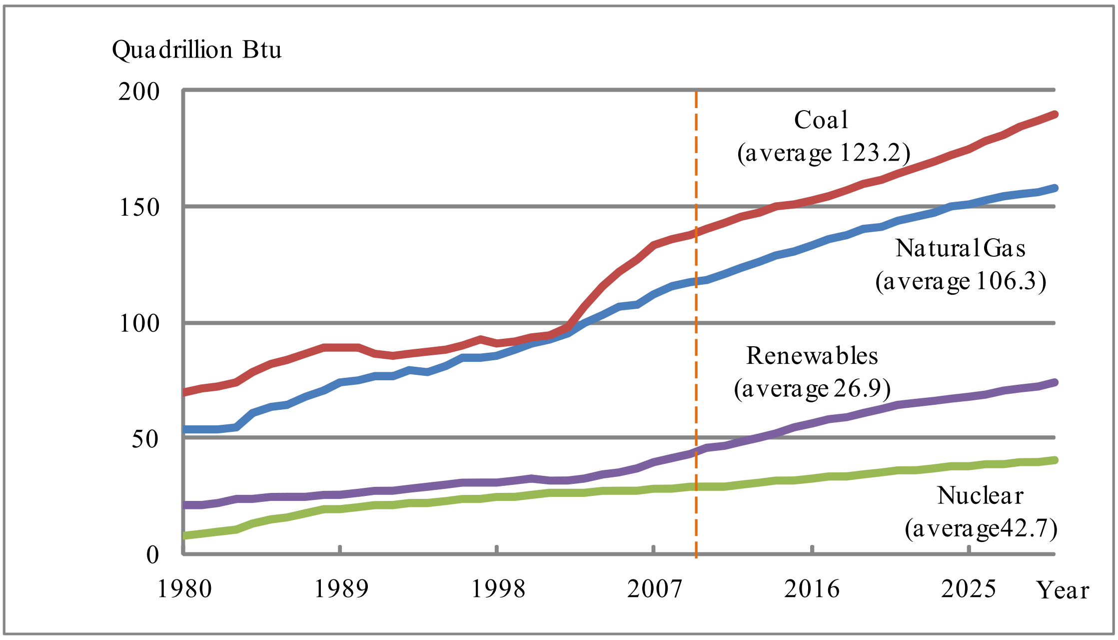

Figure 1.2 World Marketed Energy Use by Fuel Type, 1980-2030

Sources: Energy Information Administration, International Energy Annual 2006

Coal is similarly the primary factor for industrial revolution in the world. In 2006 coal was the world's fastest-growing used fuel with global consumption rising by 5% per annum. The monthly average coal price reached a record high of $208.55 per mcf in 2008. Coal prices saw severe fluctuations during 2003 to 2009.

At the regional level, oil is of particular importance to many Asian economies as most are net importers of this energy product. Because Taiwan is an island with limited indigenous energy resources and energy imports are over 99.32% in 2008, Taiwan has been identified as one of six Asian economies (including Japan, Philippines, Singapore, South Korea, Taiwan, and Thailand) that are considered to be easily subjected to world oil price fluctuation (Aoyama and Berard, 1998). Figure 1.3 illustrates the co-movement of Taiwan's domestic energy prices indices (including fuel oil, coal, natural gas, gasoline, and diesel oil) with fluctuations of the WTI oil price index since 1971. We observe that the former variables are linked to the latter's trend.

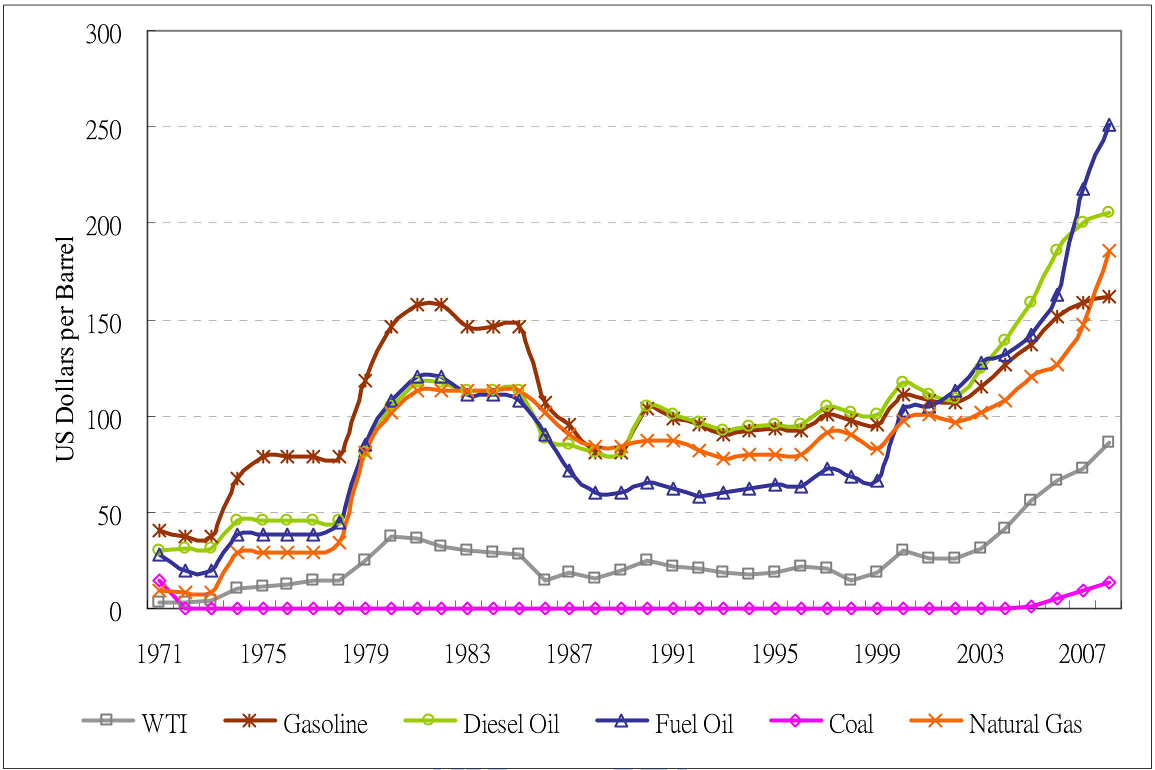

Figure 1.3 The Co-movement Between Domestic Energy Price Index and WTI Oil Price Index, 1971-2008

Domestic energy price-setting is relatively affected by projected world oil prices in the past several years. Jiménez-Rodríguez and Sánchez (2005) report that oil price increases have a direct impact on economy activity for oil-importing countries. Indeed, rising oil prices are interpreted as an indicator of an increase in scarcity and that means oil will be less available on the domestic market. This phenomenon is expected to keep the domestic energy price at high levels over the near term.

World oil shocks not only directly affect domestic energy prices, but also imply the importance of domestic renewable industry development. To expedite domestic energy diversity as well as improve environment quality, a number of Taiwan's factories have developed a renewable industry since 1998. Through Taiwan's innovative pattern of learning-by-doing which borrows much production knowledge from its semiconductor production, the renewable industry such as photovoltaic is currently in the value inflow stage (Hu and Yeh, forthcoming). Compared to other countries, Taiwan ranks as the fourth largest solar cell producing country in the world. The empirical analysis of this dissertation highlights the status of its importance.

In sharp contrast to the volume of studies examining the link between oil price shocks and macroeconomic variables, there is currently not much existing literature on quantitative analyses of coal-price or gas-price shocks. There are also few analyses on the relationship between oil price shocks and financial markets such as the stock market. Market participants want a framework that identifies how energy price changes affect the stock market and labor market.

1.2 Research Motivation and Purpose

As energy prices play a critical role in influencing economic growth and economic activities, this phenomenon excites the research interest of this dissertation to address a linkage analysis of international energy prices and macroeconomic variables in Taiwan with linear and non-linear frameworks. Our research is motivated by the following reasons.

First, most studies (e.g., Burbidge and Harrison, 1984; Gisser and Goodwin, 1986; Mork, 1989; Hooker, 1996; Hamilton, 1996; Bernanke et al., 1997; Hamilton, 2003; Hamilton and Herrera, 2004) show that oil price shocks have a significantly negative impact on industrial production. However, little is known about the relationship between other energy prices and economy activities. For this reason, researchers may refocus their attention on the issue of natural gas price and coal price and their impact on economic activities.

Second, some of the related research (e.g., Mork, 1989; Mork et al., 1994;

Sadorsky, 1999; Papapetrou, 2001; Hu and Lin, 2008) already consider the asymmetrical relation in terms of the impact of an oil price change or its volatility on industrial production and stock returns. However, these studies arbitrarily use zero as a cutoff point and distinguish oil price changes into up (increase) and down (decrease). This shows that the traditional approaches using predetermined value(s) as a demarcation point are rather unreasonable. They neglect the asymmetrical relation to accurately gauge varying degrees of impacts of energy price change (or volatility) on macroeconomy. To solve the neglected phenomenon, we implement rigorous econometric methods to refine the true relation.

Third, early studies about the macroeconomic consequences of energy price shocks focus on developed economies. Recent studies examine other research samples such as European countries (e.g., Mork et al, 1994; Papapetrou, 2001; Cuñado and Pérez de Gracia, 2003; Jiménez-Rodríguez, 2008; Bjørnland, 2009) and Asian countries (e.g., Chang and Wong, 2003; Cuñado and Pérez de Gracia, 2005; Huang et al., 2005). However, few studies investigate the relationship between energy price and macroeconomy for Taiwan. In contrast to these studies, this dissertation assesses the dynamic effect of energy price shocks on the macroeconomy in Taiwan.

Based on the aforementioned argument, the purposes of this dissertation contain two parts: The first purpose is to examine the effects of energy price shocks (including crude oil, natural gas and coal) on Taiwan's industrial production from a linear perspective. Energy prices do not affect industrial production in isolation, but through the perceived effect on the macroeconomy. Therefore, we further analyze the dynamic relationship between energy price shocks and major macroeconomic variables (including stock price, interest rate, unemployment rate, exports and imports) by applying a vector error correction (VECM) model. Next, the variance decomposition (VDC) and the impulse response functions (IRF) are employed to capture the effects of energy price shocks on the macroeconomy. The results find how each variable responds to shocks by other variables of the system and explore the response of a variable to a shock immediately or with various lags.

The second purpose focuses on the impacts of an energy price change and the shock on the macroeconomy from an asymmetric perspective. According to Sadorsky (1999), the energy price adjustment may not immediately impact macroeconomic variables. An economic threshold for an energy price impact is the amount of price increase beyond which an economic impact on industrial production and stock prices is palpable. Huang et al. (2005) propose that a change in oil price explains the macroeconomic variables better than the shock caused by the oil price if an oil price change exceeds the threshold levels. Therefore, we apply the multivariate threshold error correction model by Tsay (1998) to analyze the relevant data. By separating energy price changes into decrease (down) and increase (up), the energy price changes as the threshold variable can analyze different impacts of energy price changes on industrial production. In particular, we assess the impact of energy price fluctuations on the Taiwan economy. The impulse response and the variance decomposition analysis now follow.

1.3 Organization of the Dissertation

This dissertation is organized in the following manner as Figure 1.4 shows: Chapter 1 states the motivation and purposes for this study. Chapter 2 reviews the related literature. Chapter 3 gives a brief introduction of research methods. Chapter 4 presents the empirical results of energy price shocks with the linear (one-regime) VECM model and the multivariate threshold error correction (two-regime) model and discusses the result. Chapter 5 concludes with a brief review of the principal findings and a discussion of directions for further study.

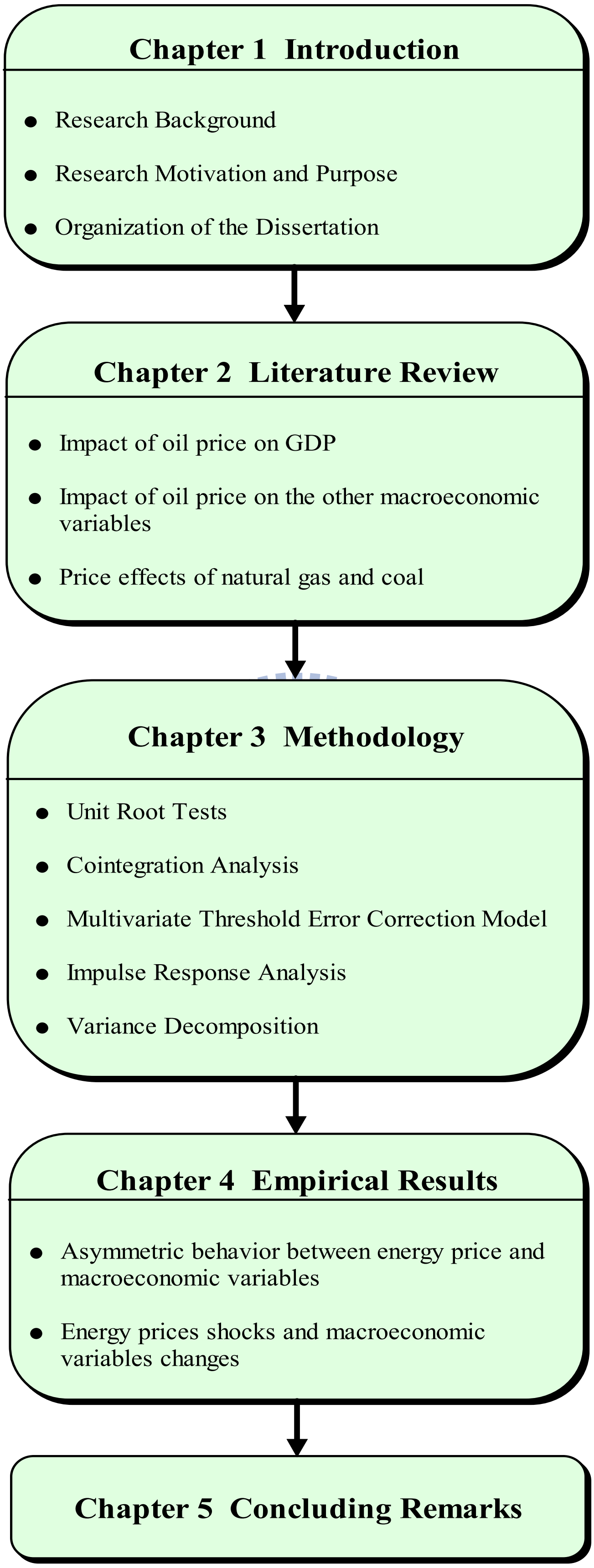

Figure 1.4 Research Flow Chart

Chapter 2 Literature Review

Since the 1970s many studies have examined the relationship between energy prices and the macroeconomy especially for oil price shocks. However, there is an inconsistent conclusion in the literature with different estimation procedures and data. According to the different energy prices used by researchers, previous studies can be divided into three streams of research: the impact of oil price on GDP, the impact of oil price on other macroeconomic variables, and the natural gas and coal price effect. A survey of the literature on the effects of energy price shocks on macroeconomy now follows.

2.1 Impact of Oil Price on GDP

There are extensive studies that explore the relationship between oil prices and economic activity. In a pioneer work, Hamilton (1983) using Granger causality examines the impact of oil price shocks on the United States economy, indicating that oil price increases partly account for every United States recession. A given oil price increase seems to have had a smaller macroeconomic effect after 1973 than an increase of the same magnitude would have had before 1973. Since then, many researchers extend and reinforce Hamilton's basic findings using different estimation procedures on new data (e.g., Burbidge and Harrison, 1984; Gisser and Goodwin, 1986; Mork, 1989; Hooker, 1996; Hamilton, 1996; Bernanke et al., 1997; Hamilton, 2003; Hamilton and Herrera, 2004). These studies conclude that there is a significant negative correlation between increases in oil prices and the subsequent recessions in the United States, but that oil price changes have different impacts on economies over time.

Following declines in oil prices during the global energy crisis of the 1980s, the impact from an energy price change and its shock on economic activities disappeared. Some researchers argue that the instability observed in this relationship and the past linear specification have led to the misrepresentation of the measure. Gradually, attention has shifted to asymmetric oil price shocks on economic activities (Mork, 1989; Mork et al., 1994; Lee and Ratti, 1995; Lee et al., 1995; Hamilton 1996; Ferderer, 1996).

By separating oil price changes into negative and positive, Mork (1989) finds that there is an asymmetrical relationship between oil price and real output. When the oil price is increasing, the increase in the cost of production and the decrease in the cost of resource allocation often offset each other. Alternatively, a decrease in oil price will decrease the cost of production. These two forces have a correspondingly significant impact on GDP. Mory (1993) follows Mork's (1989) measures and presents that positive oil price shocks Granger-cause the macroeconomic variables. Mork et al. (1994) again confirm that an oil price shock induced inflation reduces real balances for seven industrialized countries.

Besides examining the direct effects of oil price changes, some researchers try to use the variable of their volatility to investigate their shock on certain macroeconomic variables. Lee et al. (1995) examine the impact of an oil price change on aggregate economic activities by using a generalized autoregressive conditional heteroskedasticity (GARCH) model. They find that an oil shock in a price stable environment is more likely to have greater effects on GDP growth than those occurring in a price volatile environment. In the same way, Hamilton (1996) points out that the key question is whether the oil price increase is big enough to reverse any decreases observed in the immediate previous quarters. Both Lee et al. (1995) and Hamilton (1996) conclude that there is a negative relationship between increases in oil prices and real output in the

U.S. economy. In the same vein, Hamilton (2003) reports evidence of non-linearity with three earlier pieces of literature (Mork, 1989; Lee et al., 1995; Hamilton, 1996), indicating that oil price increases are much more important than oil price decreases and the formulation of Lee et al. (1995) has the best work.

Jiménez-Rodríguez and Sánchez (2005) use the multivariate VAR model to examine the effects of oil price shocks on real GDP growth in eight OECD countries. They find that oil price increase has a larger impact on GDP growth than oil price declines. A brief summary of the relationship between oil price and GDP is shown in Jones et al. (2004). First, most studies offer that the recessionary movements of GDP are largely attributable to oil price shocks. Second, asymmetric specifications of oil price shocks are found. Third, detailed empirical studies have proposed that a considerable reallocation of labor occurs after oil price shocks.

2.2 Impact of Oil Price on Other Macroeconomic Variables

In addition to exploring the relationship between oil price shocks and GDP, some economists have emphasized the relationship between oil price shocks and other macroeconomic variables. The related issues can be divided into three parts.

The first part is related to the macroeconomic level. Several models (e.g., Rasche and Tatom, 1981; Bruno and Sachs, 1982, Hamilton, 1983) and diverse episodes for oil price shocks (e.g., Davis, 1986; Carruth et al., 1998; Ferderer, 1996) present that an oil shock is one of the important influences on the macroeconomy. The directions for the causal relationship between oil price and macroeconomy can be concluded in four parts. First, oil price changes significantly impact economic activity (e.g., Papapetrou, 2001; Ewing et al., 2006; Jiménez-Rodríguez, 2008; Farzanegan and Markwardt, 2009). Second, there is an asymmetric correlation between oil price and the macroeconomy (e.g., Loungani, 1986; Mork, 1989; Lee et al., 1995; Hamilton, 2003; Cuñado and Pérez de Gracia, 2003; Cuñado and Pérez de Gracia, 2005; Jiménez-Rodríguez, 2009). Third, some researchers show effects of oil price shocks at a disaggregate level. For example, Davis and Haltiwanger (2001) analyze the effects of oil shocks on plant level employment. Edelstein and Kilian (2007) examine the effects of oil shocks on U.S. non-residential fixed investment expenditures. Finally, because of the government's tight monetary policy, economic activity does not originate from an oil price change (e.g., Bernanke et al., 1997; Balke et al., 2002; Hamilton and Herrera, 2004).

Hooker (1996) argues that oil price shocks promote directly to recession remains in some dispute, in part due to the correlation between oil prices and economic activity seems to be much weaker in data obtained since 1985. As can be seen from the aforementioned studies, there are some main channels for oil price shocks to influence economic activities, including consumer price index (e.g., Cuñado and Pérez de Gracia, 2005; Jiménez-Rodríguez, 2009; Bjørnland, 2009), stock price (e.g., Park and Ratti, 2008; Apergis and Miller, 2009), exchange rate (e.g., Farzanegan and Markwardt, 2009; Jbir and Zouari-Ghorbel, 2009), and unemployment rate (e.g., Bjørnland, 2009; Jiménez-Rodríguez, 2009). In addition, both Ferderer (1996) and Hooker (1996) suggest interest rates as a channel for oil price shocks to influence economic activity. Impulse response analysis shows that an oil price shock works primarily through the interest rate. There is also a strongly asymmetric response of the short-term interest rate to positive and negative oil price shocks and a modestly asymmetric response from the long-term rate. Park and Ratti (2008) prove that an increase in real oil price is associated with a significant increase in the short-term interest rate in the U.S. and eight out of thirteen European countries with one or two months. For a comprehensive survey of empirical results on the macroeconomic consequences of oil price shocks, see Jones et al. (2004).

The second part is related to stock markets. An increase in oil price causes expected earnings to decline, and this will bring about an immediate decrease in stock prices if the stock market is efficient. If the stock market is not efficient, then there may be lags in adjustment to oil price changes. There are several representative studies about the impact of oil price on stock prices (or stock returns). Those mainly with research data include the United States, United Kingdom, Japan, and Canada. Kaneko and Lee (1995) use a VAR model to estimate the relationship between energy price change and aggregate economic activities (including industrial production growth, inflation, stock prices, and exchange rate) in the U.S. and Japan, and they find that Japanese stock prices are affected by oil price shocks. Jones and Kaul (1996) further investigate the reaction of stock prices to oil price shocks and what may justify these movements. By using a cash-flow/dividend valuation model (i.e., Campbell, 1991), they find that oil prices can predict stock returns and output on their own.

Sadorsky (1999) considers the relationship between oil price shocks and stock returns using a four-variable VAR model. He discovers that oil price movements can explain more of the forecast error variance of stock returns than can interest rates. Beyond that, he shows an asymmetric effect on stock returns from oil price shocks. Increases in the price of oil have a significant effect on reducing stock prices, but not vice versa. There seems to be an asymmetric relation between oil price change (or its volatility) and economic activities (i.e., output, stock returns, and interest rates). This argument is once again re-confirmed by Ciner's (2001) and Hamilton's (2003) studies.

Some studies (e.g., Lo and MacKinlay, 1990; Kaul and Seyhum, 1990; Sadorsky, 2003; Park and Ratti, 2008) use the volatility of oil price changes to test its relationship with stock returns. They propose that an increased volatility of oil prices significantly depresses real stock returns. In addition, El-Sharif et al. (2005) provide further background to previous findings on the link between oil prices and measures of stock market performance. Later studies (e.g., Cong et al., 2008; Park and Ratti, 2008; Apergis and Miller, 2009; Bjørnland, 2009) document the diverse relationship between oil price movements and stock prices. Both Huang et al. (1996) and Cong et al. (2008) find no evidence of the impact of an oil price change on stock returns. However, Park and Ratti (2008) show that the effect of oil price shocks on stock returns is contemporaneous in the U.S. and thirteen European countries. Bjørnland (2009) indicates that following a 10% increase in oil prices, Norway's stock returns increase by 2.5%. Apergis and Miller (2009) also find that different oil market structural shocks play a significant role in explaining the adjustments in stock returns.

The third part involves the labor market. Several studies address the question of whether there is a correlation between oil price and the labor market. A clear negative relationship between oil prices and employment is reported by Rasche and Tatom (1981), Hamilton (1983), Keane and Prasad (1996), Uri (1996), Raymond and Rich (1997), among others. Keane and Prasad (1996) further indicate that oil price increases reduce employment in the short run, but tend to increase total employment in the long run. The labor market responses may be quicker than previously thought in the shorter run. These results imply a possible substitution between energy and labor in the aggregate production function. Due to the substitute and complimentary abilities among different sectors of the labor market, there is a positive relationship between oil price increases and employment in the long run. Nevertheless, both Loungani (1986) and Kandil and Mirzaie (2003) argue for no evidence that changes in oil prices influence employment growth.

An oil price decrease depresses demand for some sectors, and unemployed labor is not immediately shifted elsewhere (Hamilton, 2003). However, oil price changes impact unemployment when the changes in oil prices persist for a long time as adjustments in employment (Keane and Prasad, 1996). Davis (1986) offers separate time trends before and after 1974 in his unemployment equations. He finds that the estimated time trend coefficients are small and often statistically insignificant with most of the upward trend in unemployment over these samples. Carruth et al. (1998) present an asymmetrical relationship among unemployment, real interest rates, and oil prices, meaning that oil price increases cause employment growth to decline more than oil price decreases cause employment growth to increase. Davis and Haltiwanger (2001) focus on how oil price movements influence the unemployment rate over time. They use the structural VAR models to measure oil price by a weighted average of real oil prices. The results find an oil price shock can explain 25% of the cyclical variability in employment growth from 1972 to 1988. The long-run relationship result is similar to Keane and Prasad (1996). Lardic and Mignon (2008) summarize six transmission channels of increasing oil prices (i.e., reduction of potential output, increased money demand, inflation including second round effects, negative terms of trade effects for oil importing countries, negative demand side impacts, and structural changes). They also show that a long-lasting oil price increase can thus change the production structures and have an impact on unemployment.

2.3 Price Effects of Natural Gas and Coal

Most studies show the effect of oil price shocks, but rarely consider the effect of natural gas or coal price shocks. Coal and natural gas are the two main alternative sources of energy. There are three effects of changing natural gas price controls: on regional economic activity (e.g., Leone, 1982), on inflation (e.g., Ott and Tatom, 1982), and on the distribution of income between households and suppliers (e.g., Stockfisch, 1982). These results find that the presumed effects of natural gas decontrol (higher price, higher inflation, and falling real incomes) are not expected to be significant. Hickman et al. (1987) examine the correlation between natural gas price and industrial production. They indicate that a 10% increase in natural gas price affects the same effect on real GDP growth. A permanent $1 increase in natural gas prices will reduce real GDP growth by 0.1 percentage points per year (the Economics and Statistics Administration, 2005).

Jin et al. (2009) examine the effects of energy prices and energy conservation on economic growth for the postwar U.S. economy. They use a five-variable VAR model that consists of real GDP, real capital, real energy prices, labor, and the Divisia energy consumption index. The Divisia index is constructed using expenditures on three major energy resources (i.e., oil, coal, and natural gas). They find that energy prices have significant negative effects on real economic growth and oil price shocks are greater than other resources. These results are consistent with earlier findings in Hamilton (1983) and Burbidge and Harrison (1984). Lutz and Meyer (2009) observe that a stabilizing effect via international trade and domestic structural change on the GDP of oil importing countries with a permanent oil price increase occurs. At least for Germany, it is not negatively influenced by higher oil and natural gas prices, even though a strong structural divergence can be observed.

Researchers have begun to analyze the causality relationship between coal consumption and economic growth in recent years. Yang (2000) shows a causality relationship between coal consumption and economic growth in Taiwan. Yoo (2006) finds that bidirectional causality running from GDP to coal consumption exists in South Korea. Both Li et al. (2008) and Li et al. (2009) cover that there is unidirectional causality between coal consumption and GDP in China and Japan. However, there are few studies specifically addressing coal price with economic growth. Table 2.1 briefly summarizes the aforementioned and existing literature about the effects of energy price changes on macroeconomic activities.

Table 2.1 An Overview of Previous Studies of the Impacts of Energy Price Shocks on Industrial Production and Macroeconomics Activities, 1999-2009.

Study	Country	Periods	Variables	Methodology	Main findings
Apergis and Miller (2009)	• Australia • Canada • France • Germany • Italy • Japan • UK • U.S.	1981-2007 Monthly	• Oil price • Stock price • CPI • Global economic activity	• Unit root • VAR • Co-integration • VDC	• Oil price small effect on stock market returns.
Bjørnland (2009)	Norway	1993-2005 Monthly	• Oil price • Stock price • Interest rate • Unemployment rate • CPI • Exchange rate	• VDC • IRF	• Oil price shocks' effect on stock returns.
Farzanegan and Markwardt (2009)	Iran	1975-2006 Quarterly	• Oil price • Real industrial GDP per capita • Inflation • Real public consumption expenditures • Real imports • Exchange rate	• Unit root • VAR • VDC • IRF	• Asymmetric effects of oil price shocks. • A positive oil price shocks' effect on industrial output growth.
Jbir and Zouari-Ghorbel (2009)	Tunisia	1993-2007 Quarterly	• Oil price • Industrial production index • Government spending • Consumer price index • exchange rate	• Unit root • VAR • Granger causality tests • IRF • VDC	• There is no direct impact of oil price shock on economic activity.
Jiménez-Rodríg-uez (2009)	U.S.	1947-2005 Quarterly	• Oil price • Real GDP • Unemployment rate • Long-run interest rate • Federal funds rate • Wage • Consumer price index	• VAR • Granger causality tests	• An asymmetric relationship between real GDP growth and changes in the price of crude oil.

Notes: VDC denotes the variance decomposition; IRF denotes the impulse response functions.

Table 2.1 An Overview of Previous Studies of the Impacts of Energy Price Shocks on Industrial Production and Macroeconomics Activities, 1999-2009 (Continued)

Study	Country	Periods	Variables	Methodology	Main findings
Jin et al. (2009)	Germany	1949-2001 Yearly	• Energy price • Real GDP • Real capital • Labor input • Energy consumption	• VAR • VDC • IRF • Sensitivity analysis	• Energy price shocks are observed to have significant negative effects on real economic growth.
Cong et al. (2008)	China	1996-2007 Monthly	• Oil price • Industrial production • Short-term interest rates • Consumer price index	• Unit root • VAR	• No impact on the real stock returns. • Increase in oil volatility may increase speculations in the mining index.
Jiménez-Rodríg -uez (2008)	• U.S. • UK • France • Germany • Italy • Spain	1975-1998 Monthly	• Oil price • Industrial output • Eight individual manufacturing industries	• VAR • IRF	• An oil price shock by industrial output is diverse across the four European countries. • Evidence on cross-industry heterogeneity of oil shock effects within the EMU countries is found.
Lardic and Mignon (2008)	• G7 • U.S. • European countries	1970-2004 Quarterly	• Oil price • GDP	• Unit root • Co-integration	• There is evidence for asymmetric cointegration between oil prices and GDP.
Park and Ratti (2008)	• U.S. • 13 European countries	1986-2005 Monthly	• Oil price • Industrial production • Short-term interest rates • Real stock returns	• Unit root • Co-integration • VAR • IRF	• A significant impact on real stock returns. • An increase in real oil price is associated with a significant increase in the short-term interest rate.
Ewing et al. (2006)	U.S.	1986-2004 Monthly	• Oil price • Heating oil • Gasoline	• Unit root • Co-integration • Momentum threshold autoregressive model (M-TAR)	• The futures and spot prices for each petroleum type are co-integrated.

Notes: VDC denotes the variance decomposition; IRF denotes the impulse response functions.

Table 2.1 An Overview of Previous Studies of the Impacts of Energy Price Shocks on Industrial Production and Macroeconomics Activities, 1999-2009 (Continued)

Study	Country	Periods	Variables	Methodology	Main findings
Cuñado and Pérez de Gracia (2005)	• Japan • South Korea • Singapore • Malaysia • Philippines • Thailand	1975-2002 Quarterly	• Oil price • CPI • Economic activity	• Unit root • Co-integration • Granger causality • Non-linear transformation	• There is evidence of asymmetries in the oil prices and macroeconomy relationship for some of the Asian countries.
El-Sharif et al. (2005)	UK	1989-2001 Daily	• Oil price • Exchange rate • Interest rate • Stock return	• Unit root • Pearson correlation matrix • Regression	• Oil and gas stock returns are impacted by several risk factors. • Oil and gas sectors reflect the direct impact of oil price variability on the income streams of producers.
Huang et al. (2005)	• U.S. • Canada • Japan	1970-2002 Quarterly	• Oil price • Industrial production • Interest rate • Stock return	• Unit root • Co-integration • Multivariate threshold tests • VDC • IRF	• An oil price change or its volatility has a limited impact on the economies if the change is below the threshold levels.
Jiménez-Rodríg-uez and Sánchez (2005)	• Japan • OECD	1972-2001 Quarterly	• Oil price • Real GDP • CPI • Exchange rate • Wage • Short-term interest rates • Long-term interest rates	• Granger causality • Multivariate VAR	• An asymmetric impact of oil prices on real GDP.
Chang and Wong (2003)	Singapore	1978-2000 Quarterly	• Oil price • GDP • COI • Unemployment rate	• Unit root • Co-integration • VECM • VDC • IRF	• The impact of an oil price shock on the Singapore economy is marginal.
Cuñado and Pérez de Gracia (2003)	15 European countries	1960-1999 Quarterly	• Oil price • Industrial Production • Inflation rate	• Unit root • Co-integration • Granger causality • Non-linear transformation	• Oil prices have permanent effects on inflation and asymmetric effects on production growth rates.

Notes: VDC denotes the variance decomposition; IRF denotes the impulse response functions.

Table 2.1 An Overview of Previous Studies of the Impacts of Energy Price Shocks on Industrial Production and Macroeconomics Activities, 1999-2009 (Continued)

Study	Country	Periods	Variables	Methodology	Main findings
Hamilton (2003)	U.S.	1949-2001 Quarterly	• Oil price • GDP	• Non-linear regression model	• Oil price increases are much more important than oil price decreases.
Sadorsky (2003)	U.S.	1984-2000 Monthly	• Oil price • Industrial production • Interest rate • Exchange rate • CPI	• Unit root • Ordinary least squares regression	• The conditional volatilities of oil prices, the term premium, and the consumer price index each have a significant impact on the conditional volatility of technology stock prices.
Balke et al. (2002)	U.S.	1965-1997 Monthly	• Oil price • GDP • CPI • Interest rate	• Unit root • Quasi-VAR • IRF	• Negative and positive oil price shocks have asymmetric effects on output and interest rates.
Davis and Haltiwanger (2001)	U.S.	1972-1988 Monthly	• Oil price • Job creation rate • Job destruction rate • Employment growth rate	• Panel VAR	• Oil shocks account for 20-25% of the variability in employment growth. • Employment growth responds asymmetrically to oil price ups and downs.
Papapetrou (2001)	Greece	1989-1999 Monthly	• Oil price • Stock return • Industrial production • Industrial employment growth rate	• Unit root • Co-integration • VDC • IRF	• Oil price changes affect economic activity and employment.
Sadorsky (1999)	U.S.	1947-1996 Monthly	• Oil price • Stock return • Interest rate	• Unit Root • Generalised autoregressive conditional heteroskedastic (GARCH) model	• Oil price movements explain a larger fraction of the forecast error variance in real stock returns than do interest rates. • Oil price volatility shocks have asymmetric effects on the economy.

Notes: VDC denotes the variance decomposition; IRF denotes the impulse response functions.

Chapter 3 Methodology

To more clearly express the econometric methodology, we outline the research process in Figure 3.1. The first step is to check the variables either stationarity or non-stationarity. The second step is to test the non-stationarity sequences are integrated of the same order and residual sequence is stationary. The traditional one-regime VAR model and the multivariate threshold error correction model will be introduced. Finally, impulse response function (IRF) and variance decomposition (VDC) track the dynamic relationship between macroeconomic variables within VAR models.

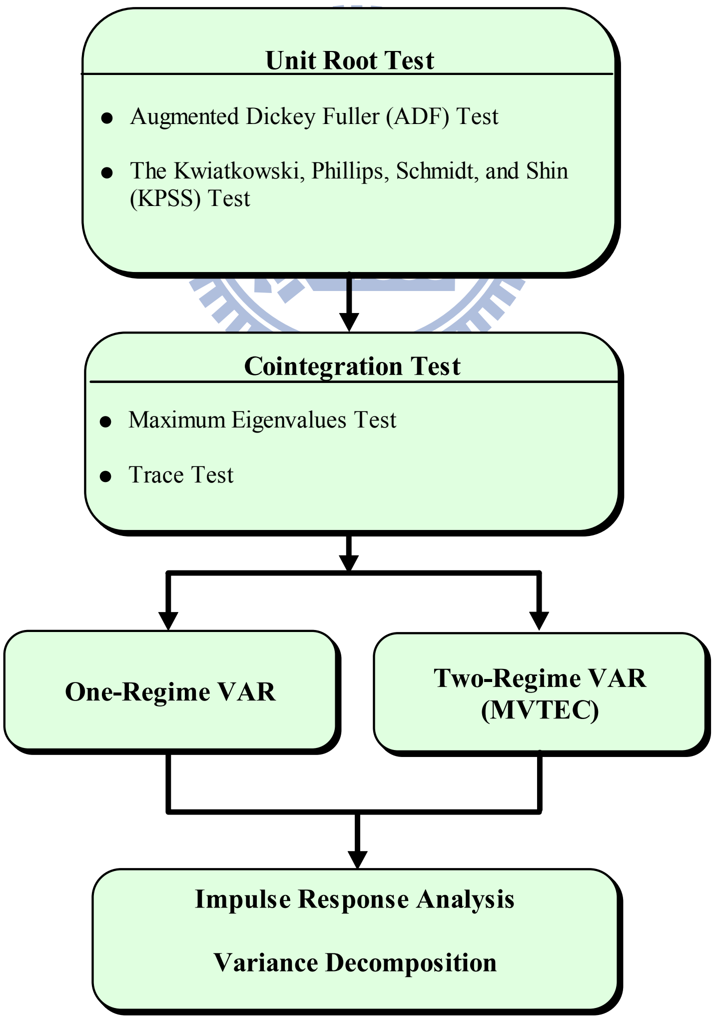

Figure 3.1 Methodology Flow Chart

3.1 Unit Root Tests

Some economic or financial time series variables have non-stationary characteristic if the data generating process of time series variables have random walk. Therefore, the first step is to check the variables either stationarity or non-stationarity.

A time series is a set of y_t observations, each one being recorded at a specific time t with stochastic process. A stationary series can be defined as one with a constant mean, constant variance and constant autocovariances for each given lag. The stationarity or otherwise of a series can strongly influence its behavior and properties. A change or an unexpected change in a variable to the system will gradually die away.

On the other hand, a non-stationary series necessarily has permanent components. The mean and variance of non-stationary series are time-dependent and the sample correlogram dies away slowly in finite samples. There is no long-run mean to which the series returns.

According to Granger and Newbold (1974), the use of non-stationary data leads to spurious regression. Its result may have higher coefficient of determinant and much significant t value. If standard regression techniques are applied to non-stationary data, the result could be a regression that 'looks' good under standard measures (significant coefficient estimates and a high R^2, but which is really valueless). There is a reason why the concept of non-stationarity is important and why it is essential that variables that are non-stationarity be treated differently from those that are stationarity. We adopt two applicable unit root methods for examining the existence of unit roots.

3.1.1 Augmented Dickey Fuller (ADF) Test

Dickey and Fuller (1979) consider a autoregressive process $AR(1)$ model $y_t = a_1 y_{t-1} + \varepsilon_t$, where the disturbances, ε_t, are assumed to be white noise, conditional on past y_t, and the first observation, y_1, is assumed to be fixed. By subtracting y_{t-1}

from both sides of the equation, we can rewrite the model as follows: $\Delta y_t = \gamma y_{t-1} + \varepsilon_t$, where $\gamma = a_1 - 1$. The unit root test is equivalent to testing $\gamma = 0$, that is, that there exists a unit root. The standard t-statistic for $\hat{\gamma}$ can be used to test $\gamma = 0$, but with the Dickey-Fuller critical values.

However, simple unit root test described above is valid only if the series is an $AR(1)$ process. If the series is correlated at higher order lags, the assumption of white noise disturbances is violated. Dickey and Fuller (1981) make a parametric correction for higher order correlation by assuming that the $\{y_t\}$ follows an $AR(p)$ process and extending model as follows:

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_{p-1} y_{t-p+1} + a_p y_{t-p} + \varepsilon_t \tag{1}$$

By adding and subtracting $a_p y_{t-p+1}$ from both sides of the equation then the differenced form is:

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_{p-2} y_{t-p+2} + (a_{p-1} + a_p) y_{t-p+1} - a_p \Delta y_{t-p+1} + \varepsilon_t \tag{2}$$

Next, add and subtract $(a_{p-1} + a_p) y_{t-p+2}$ to obtain:

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \ldots - (a_{p-1} + a_p) \Delta y_{t-p+2} - a_p \Delta y_{t-p+1} + \varepsilon_t \tag{3}$$

Continuing in this fashion, we get:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t, \tag{4}$$

where $\gamma = -\left(1 - \sum_{i=2}^{p} a_i\right)$ and $\beta_i = \sum_{j=i}^{p} a_j$

In Eq. (4), the coefficient of interest is γ. If $\gamma = 0$, the equation is entirely in first differences and so has a unit root. Three ADF test actually consider three different regression equations that can be used to test for the presence of a unit root:

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{5}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{6}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t . \tag{7}$$

The differences between the three regressions concerns the presence of the deterministic elements a_0 and $a_2 t$. Without an intercept and time trend belongs in Eq. (5); with only the intercept belongs in Eq. (6); and with both an intercept and trend belongs in Eq. (7). If the coefficients of a difference equation sum to one, at least one characteristic root is unity. If $\Sigma a_i = 1$ and $\gamma = 0$, the system has a unit root.

3.1.2 The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) Test

It is a well-established empirical fact that standard unit root tests fail to reject the null hypothesis of a unit root for most aggregate economic time series. In general, most of the standard unit root tests suffer from three problems. First, several approaches have severe size distortions when the moving average polynomial of the first differences series has a large negative autoregressive root (Schwert, 1989). Second, the testing statistics have low power when the root of the autoregressive polynomial is close to unity (DeJong et al., 1992; Kwiatkowski et al., 1992). Third, conducting the unit root tests often implies the selection of an autoregressive truncation lag, *k*, which is strongly related to the size distortions and the extent of power loss (Ng and Perron, 1995). Many studies (DeJong et al., 1989; Diebold and Rudebusch, 1991; DeJong and Whiteman, 1991; Phillips, 1991) suggest that, in trying to decide by classical methods whether economic data are stationary or integrated, it would be useful to perform tests of the null hypothesis of stationarity as well as tests of the null hypothesis of a unit root. The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test provides a straightforward test of the null hypothesis of stationarity against the alternative of a unit root.

Kwiatkowski et al. (1992) propose a test of the null hypothesis that an observable series is stationary around a deterministic trend. The series is expressed as the sum of deterministic trend, random walk, and stationary error, and the test is the LM test of the hypothesis that the random walk has zero variance. The KPSS statistic is based on the residuals from the OLS regression of y_t on the exogenous variables x_t:

$$y_t = x_t'\delta + \varepsilon_t$$

The Lagrange Multiplier (LM) statistic can be defined as:

$$LM = \sum_{t=1}^{T} S_t^2 / \hat{\sigma}_\varepsilon^2,$$

where S_t is a cumulative residual function (i.e., $S_t = \sum_{i=1}^{t} \hat{\varepsilon}_i, \quad i = 1, 2, \ldots, T$). We point out that the estimator of δ used in this calculation differs from the estimators for δ used by detrended GLS since it is based on a regression involving the original data and not on the quasi-differenced data. Finite sample size and power are considered in a Monte Carlo experiment.

Prior to performing the Johansen co-integration method, we need to determine the appropriate number of lag length of the VAR model. The Bayesian information criterion (BIC) (Schwarz, 1978) is employed. The test criteria to determine appropriate lag lengths and seasonality are the multivariate generalizations of the BIC. The BIC criterion is a purely statistical technique and allows data themselves to select optimal lags. Given any two estimated models, the model with the lower value of BIC is the one to be preferred. The selection of lag order of Δy_{t-i} can be used by the Bayesian information criterion (BIC):

$$BIC = -2 * \ln(L) + k * \ln(n) \tag{8}$$

where n is the number of observations, k is the number of free parameters to be estimated and L is the maximized value of the likelihood function for the estimated model. The BIC penalizes free parameters more strongly than does the Akaike information criterion (AIC) (Akaike, 1969).

3.2 Cointegration Analysis

The co-integration theory is defined that a linear combination of non-stationary variables is stationary (Engle and Granger, 1987). Although the Engle and Granger (1987) procedure is easily implemented, it does have two important defects. The first one is that such method has no systematic procedure for the separate estimation of the multiple cointegrating vectors. Another serious defect of the Engle and Granger (1987) procedure is that it relies on a two-step estimator. The coefficient a_1 is obtained by estimating a regression using the residuals from another regression. The error terms introduced by the researcher in first step is carried into second step. Fortunately, the Johansen co-integration method has been developed and can avoid two problems.

The Johansen co-integration method is provided by Johansen (1988) and Johansen and Juselius (1990). This procedure applying maximum likelihood estimators circumvent the low-power of using Granger two-step estimators and can estimate and test for the presence of multiple cointegrating vectors. Moreover, this test allows the researcher to test restricted versions of the cointegrating vectors and speed of adjustment parameters.

Let $\mathbf{y_t}$ denotes the $(n \times 1)$ vector $(y_{1t,} y_{2t,} \cdots, y_{nt})$. The maintained hypothesis is that y_t follows a VAR(P) in levels and all of the elements for y_t are I(1) process.

$$\mathbf{y_t} = A_1 \mathbf{y_{t\text{-}1}} + \mathrm{A}_2 \mathbf{y_{t\text{-}2}} + \ldots + \mathrm{A}_p \mathbf{y_{t\text{-}p}} + \varepsilon_t, \quad t = 1, 2, \ldots, T \tag{9}$$

where $\varepsilon_t \overset{i.i.d.}{\sim} N(0, \Omega)$.

Eq. (10) can be put in a more usable form by subtracting y_{t-1} from each side to obtain:

$$\Delta \mathbf{y_t} = (A_1 - I)\mathbf{y_{t\text{-}1}} + \mathrm{A}_2 \mathbf{y_{t\text{-}2}} + \ldots + \mathrm{A}_p \mathbf{y_{t\text{-}p}} + \varepsilon_t, \quad t = 1, 2, \ldots, T \tag{10}$$

Now add and subtract $(A_1 - I)\mathbf{y}_{\mathbf{t-2}}$ to obtain:

$$\Delta\mathbf{y}_{\mathbf{t}} = (A_1 - I)\mathbf{y}_{\mathbf{t-1}} + (A_2 + A_1 - I)\mathbf{y}_{\mathbf{t-2}} + \ldots + \mathrm{A}_p\mathbf{y}_{\mathbf{t-p}} + \varepsilon_t, \quad t = 1, 2, \ldots, T \tag{11}$$

Continuing in this fashion, we obtain:

$$\Delta\mathbf{y}_{\mathbf{t}} = \sum_{i=1}^{p-1} \pi\Delta\mathbf{y}_{\mathbf{t-i}} + \pi\Delta\mathbf{y}_{\mathbf{t-p}} + \varepsilon_t \tag{12}$$

where $\pi = -\left(I - \sum_{i=1}^{p} A_i\right)$

$$\pi_i = -\left(I - \sum_{j=1}^{i} A_j\right)$$

Suppose we obtained the matrix π and order the n characteristic roots such that $\lambda_1 > \lambda_2 > \ldots > \lambda_n$. If the variables in $\mathbf{y}_{\mathbf{t}}$ are not cointegrated, the rank of π is zero and all these characteristic roots will equal zero. Similarly, since $\ln(1) = 0$, each of the expressions $\ln(1 - \lambda_i)$ will equal zero if the variables are not cointegrated.

Suppose that each individual variable $\mathbf{y}_{\mathbf{it}}$ is $I(1)$ and linear combinations of $\mathbf{y}_{\mathbf{t}}$ are stationary. That implies π can be shown as

$$\pi = \alpha\beta'$$

where β is the matrix of cointegrating parameters, and α is the matrix of the speed of adjustment parameters. The number of cointegrating relations relies on the rank of π, and the rank of π is:

(1) $\mathrm{rank}(\pi) = n$, λ is full rank means that all components of y_t is a stationary process.

(2) $\mathrm{rank}(\pi) = 0$, λ is null matrix meaning that there is no cointegration relationships.

(3) $0 < \mathrm{rank}(\pi) = r < n$, the variables for y_t are cointegrated and the number of cointegrating vectors is r.

The test for the number of characteristic roots that are insignificantly different from unity can by conducted using the following two test statistics:

(1) Trace test:

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

$$H_0: \text{rank}(\pi) \le r,$$

$$H_1: \text{rank}(\pi) > r$$

where $\hat{\lambda}_i$ is the estimated values of the characteristic roots (also called eigenvalues) obtained from the estimated π matrix, r is the cointegrating vector, and T is the number of usable observations. The statistic tests the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r against a general alternative. If there is no cointegrating vector, it should be clear that λ_{trace} equals zero when all $\hat{\lambda}_i = 0$. The further the estimated characteristic roots are from zero, the more negative is $\ln(1-\hat{\lambda}_i)$ and the larger the λ_{trace} statistic.

(2) Maximum eigenvalues test:

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

H_0: there are r cointegrating vectors

H_1: there are $r+1$ cointegrating vectors

The statistic tests the null that the number of cointegrating vectors is r against the alternative of $r+1$ cointegrating vectors. If the estimated value of the characteristic root is close to zero, $\lambda_{\max}$ will be small. The critical values of the λ_{trace} and $\lambda_{\max}$ statistics follows a chi-square distribution in general.

3.3 Multivariate Threshold Error Correction (MVTEC) Model

The threshold autoregressive (TAR) model is first developed by Tong (1978). The TAR model assumes that different regimes can be determined based on the threshold variable. Hence, TAR models in which the process is piecewise linear in the threshold space. Tsay (1998) generalizes the univariate threshold principle of Tsay (1989) to a multivariate framework. He use predictive residuals to construct a test statistic for detecting threshold nonlinearity in a vector time series and propose a procedure for building a multivariate threshold model.

At the beginning, we consider the univariate TAR model which is also referred to as SETAR (self-exciting TAR). The SETAR(1) can be formed as:

$$\mathrm{y}_t = (\phi_{0,1} + \phi_{1,1}\mathrm{y}_{t-1})(1 - I[z_{t-1} > c]) + (\phi_{0,2} + \phi_{1,2}\mathrm{y}_{t-1})I[z_{t-1} > c] + \varepsilon_t \tag{13}$$

where ε_t is a white noise process, $z_{t-1} = y_{t-1}$, and c represents the threshold value. $I(\cdot)$ is an index function, which equals to one if the relation in the brackets holds, and equals to zero otherwise. Eq. (13) can be treated as a multivariate threshold VAR(1). Consider a k-dimensional time series $\mathrm{y}_t = (y_{1t}, \ldots, y_{kt})'$ and assume there is a cointegration relationship among these variables, then y_t follows a multivariate threshold error correction model (MVTEC) with threshold variable z_t and delay d and can be expressed as:

$$\begin{aligned}\mathbf{y_t} = {} & (\alpha_1 + \beta_1\theta_{t-1} + \sum_{i=1}^{p}\phi_{i,1}\mathbf{y_{t-i}})(1 - I[z_{t-d} > c]) + \\ & (\alpha_2 + \beta_2\theta_{t-1} + \sum_{i=1}^{p}\phi_{i,2}\mathbf{y_{t-i}})I[z_{t-d} > c] + \varepsilon_t \end{aligned} \tag{14}$$

where α_1 and α_2 are the constant vectors below and above the threshold value, respectively. p and d are the lag length of $\mathbf{y_t}$ and delay order of z_t, respectively. Both p and d are nonnegative integers. θ_{t-1} is an error correction term. The threshold variable is assumed to be stationary and have a continuous distribution. Model (14) has two regimes and is a piecewise linear model in the threshold space z_{t-d}.

Given observations $\{\mathbf{y_t}, \mathrm{z}_t\}$, where $t = 1, \ldots, n$, we have to detect the threshold nonlinearity of $\mathbf{y_t}$. Assuming p and d are known, the Eq. (14) can be re-written as:

$$\mathbf{y'_t} = \mathrm{X}'_t\Phi + \varepsilon'_t, \quad t = h+1, \ldots, n \tag{15}$$

where $h=\max(p,d)$, $X_t=(1,y'_{t-1},\ldots y'_{t-p},\theta_{t-1})'$ is a $(pk+1)$-dimensional regressor, and $\mathbf{\Phi}$ denotes the parameter matrix. If the null hypothesis holds, then the least squares estimates of (15) are useful. On the other hand, the estimates are biased under the alternative hypothesis. Eq. (15) remains informative under the alternative hypothesis when rearranging the ordering of the setup. For Eq. (15), the threshold variable z_{t-d} assumes values in $S=\{z_{h+1-d},\ldots z_{n-d}\}$. Consider the order statistics of S and denote the ith smallest element of S by $z_{(i)}$. Then the arranged regression based on the increasing order of the threshold variable z_{t-d} is

$$\mathbf{y}'_{\mathbf{t(i)+d}}=X'_{t(i)+d}\mathbf{\Phi}+\varepsilon'_{t(i)+d},\quad i=1,\ldots,n-h, \tag{16}$$

where $t(i)$ is the time index of $z_{(i)}$. Tsay (1998) use the recursive least squares method to estimate (16). If $\mathbf{y}_t$ is linear, then the recursive least squares estimator of the arranged regression (16) is consistent, so the predictive residuals approach white noise. Consequently, predictive residuals are uncorrelated with the regressor $X_{t(i)+d}$.

Let $\mathbf{\Phi}_m$ be the least squares estimate of $\mathbf{\Phi}$ of Eq. (16) with $i=1,\ldots,m$; i.e., the estimate of the arranged regression using data points associated with the m smallest values of z_{t-d}. Tsay (1998) suggests a range of m (between $3\sqrt{n}$ and $5\sqrt{n}$). Different values of m can be used to investigate the sensitivity of the modeling results with respect to the choice. It should be noted that the ordered autoregressions are sorted by the variable z_{t-d}, which is the regime indicator in the MVTEC model. Let

$$\hat{e}'_{t(m+1)+d}=\mathbf{y}_{\mathbf{t(m+1)+d}}-\hat{\mathbf{\Phi}}'_{\boldsymbol{\mu}}X'_{t(m+1)+d} \tag{17}$$

and

$$\hat{\eta}_{t(m+1)+d}=\hat{e}_{t(m+1)+d}/\left[1+X'_{t(m+1)+d}V_mX_{t(m+1)+d}\right]^{1/2}, \tag{18}$$

where $V_m = \left[\Sigma_{i=1}^{m} X_{t(i)+d} X'_{t(i)+d} \right]^{-1}$ is the predictive residual and the standardized predictive residual of regression (16). These quantities can be efficiently obtained by the recursive least squares algorithm. Next, consider the regression

$$\hat{\eta}_{t(l)+d} = X'_{t(l)+d} \Psi + w'_{t(l)+d}, \quad l = m_0 + 1, \ldots, n-h, \tag{19}$$

where m_0 denotes the starting point of the recursive least squares estimation. The problem of interest is then to test the hypothesis $H_0 : \Psi = 0$ versus the alternative $H_1 : \Psi \neq 0$ in regression (19). The $C(d)$ statistic is therefore defined as:

$$C(d) = (n - p - m - kp - 1) \times \left\{ \ln |S_o| - \ln |S_1| \right\}, \tag{20}$$

where the delay *d* implies the test depends on the threshold variable z_{t-d}, and

$$S_o = \frac{1}{n-h-m_0} \sum_{l=m_0+1}^{n-h} \hat{\eta}_{t(l)+d} \hat{\eta}'_{t(l)+d}$$

and

$$S_1 = \frac{1}{n-h-m_0} \sum_{l=m_0+1}^{n-h} \hat{w}_{t(l)+d} \hat{w}'_{t(l)+d},$$

where $\hat{w}_t$ is the least squares residual of regression (19). Under null hypothesis the y_t is linear and some regularity conditions, $C(d)$ is asymptotically a chi-squared random variable with $k(pk+1)$ degree of freedom.

3.4 Impulse Response Analysis

Impulse response function (IRF) tracks the dynamic relationship between macroeconomic variables within VAR models. It is an essential tool in empirical causal analysis and policy effectiveness analysis. In applied work it is often of interest to know the response of one variable to an impulse in another variable in a system that involves a number of other variables as well, or how long these effects require to take place. By imposing specific restrictions on the parameters of the VAR model the shocks can be attributed an economic meaning.

Consider the first-order structural VAR model with 7-variables:

$$\begin{bmatrix} 1 & b_{12} & b_{13} & \cdots & b_{17} \\ b_{21} & 1 & b_{23} & \cdots & b_{27} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{71} & b_{72} & b_{73} & \cdots & 1 \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{7t} \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \\ \vdots \\ b_{70} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \cdots & \gamma_{17} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \cdots & \gamma_{27} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_{71} & \gamma_{72} & \gamma_{73} & \cdots & \gamma_{77} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ \vdots \\ y_{7t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{7t} \end{bmatrix}$$

We can write the system in the compact form:

$$\mathbf{B}\mathbf{y}_{\mathbf{t}} = \mathbf{\Gamma}_{\mathbf{0}} + \mathbf{\Gamma}_{\mathbf{1}}\mathbf{y}_{\mathbf{t-1}} + \boldsymbol{\varepsilon}_{\mathbf{t}}$$

where

$$\mathbf{B} = \begin{bmatrix} 1 & b_{12} & b_{13} & \cdots & b_{17} \\ b_{21} & 1 & b_{23} & \cdots & b_{27} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{71} & b_{72} & b_{73} & \cdots & 1 \end{bmatrix}, \quad \mathbf{y}_{\mathbf{t}} = \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{7t} \end{bmatrix}, \quad \mathbf{\Gamma}_{\mathbf{0}} = \begin{bmatrix} b_{10} \\ b_{20} \\ \vdots \\ b_{70} \end{bmatrix}, \quad \mathbf{\Gamma}_{\mathbf{1}} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \cdots & \gamma_{17} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \cdots & \gamma_{27} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_{71} & \gamma_{72} & \gamma_{73} & \cdots & \gamma_{77} \end{bmatrix}.$$

Premultiplication by B^{-1} can obtain the vector autoregressive (VAR) model in standard form:

$$\mathbf{y}_{\mathbf{t}} = \mathbf{B}^{-1}\mathbf{\Gamma}_{\mathbf{0}} + \mathbf{B}^{-1}\mathbf{\Gamma}_{\mathbf{1}}\mathbf{y}_{\mathbf{t-1}} + \mathbf{B}^{-1}\boldsymbol{\varepsilon}_{\mathbf{t}} = \mathrm{A}_0 + \mathrm{A}_1\mathbf{y}_{\mathbf{t-1}} + e_t \tag{21}$$

where $\mathrm{A}_0 = \mathbf{B}^{-1}\mathbf{\Gamma}_{\mathbf{0}}$, $\mathrm{A}_1 = \mathbf{B}^{-1}\mathbf{\Gamma}_{\mathbf{1}}$ and $\mathbf{e}_{\mathbf{t}} = \mathbf{B}^{-1}\boldsymbol{\varepsilon}_{\mathbf{t}}$. For notional purposes, we can define a_{io} as element i of the vector A_0, a_{ij} as the element in row i and column j of the matrix A_1, and e_{it} as the element i of the vector e_t. Using this new notation, we can rewrite (21) in the equivalent form:

$$\begin{aligned} y_{1t} &= a_{10} + a_{11}y_{1t-1} + a_{12}y_{2t-1} + \ldots + a_{17}y_{7t-1} + e_{1t} \\ y_{2t} &= a_{20} + a_{21}y_{1t-1} + a_{22}y_{2t-1} + \ldots + a_{27}y_{7t-1} + e_{2t} \\ &\vdots \qquad\qquad\qquad \vdots \\ y_{7t} &= a_{70} + a_{71}y_{1t-1} + a_{12}y_{2t-1} + \ldots + a_{17}y_{7t-1} + e_{7t} \end{aligned} \tag{22}$$

or

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{7t} \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \\ \vdots \\ a_{70} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{17} \\ a_{21} & a_{22} & \cdots & a_{27} \\ \vdots & \vdots & \ddots & \vdots \\ a_{71} & a_{72} & \cdots & a_{77} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \\ \vdots \\ y_{7t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{7t} \end{bmatrix} \tag{23}$$

In model (21), the stability condition is that A_0 be less than unity in absolute value. Using the backward method to iterate model (21), we can obtain:

$$
\begin{aligned}
\mathbf{y_t} &= A_0 + A_1(A_0 + A_1\mathbf{y_{t\text{-}2}} + \boldsymbol{\varepsilon}_{\mathbf{t\text{-}1}}) + \boldsymbol{\varepsilon}_{\mathbf{t}} \\
&= (I + A_1)A_0 + A_1^2\mathbf{y_{t\text{-}2}} + A_1\boldsymbol{\varepsilon}_{\mathbf{t\text{-}1}} + \boldsymbol{\varepsilon}_{\mathbf{t}}
\end{aligned}
$$

where $I = 7 \times 7$ identity matrix.

Assuming the stability condition is met, so that we can write the particular solution for y_t as:

$$\mathbf{y_t} = \mu + \sum_{i=0}^{\infty} A_1^i \mathbf{e_{t\text{-}i}}\,. \tag{24}$$

It is important to note that the error terms (i.e., e_{1t}, $e_{2t}, \ldots,$ e_{7t}) are components of the seven shocks $e_{1t}, e_{2t}, \ldots, e_{7t}$. Since $\mathbf{e_t} = \mathbf{B}^{-1}\boldsymbol{\varepsilon}_{\mathbf{t}}$, we can compute $\{e_{1t}\}, \{e_{2t}\}, \ldots,$ $\{e_{7t}\}$ as:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{7t} \end{bmatrix} = \det(b) \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{17} \\ c_{21} & c_{22} & \cdots & c_{27} \\ \vdots & \vdots & \ddots & \vdots \\ c_{71} & c_{72} & \cdots & c_{77} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{7t} \end{bmatrix} \tag{25}$$

where $\det(b) = 1 + b_{12}b_{23}b_{34}b_{45}b_{56}b_{67}b_{71} + b_{13}b_{24}b_{35}b_{46}b_{57}b_{61}b_{72} + b_{14}b_{25}b_{36}b_{47}b_{51}b_{62}b_{73} + b_{15}b_{26}b_{37}b_{41}b_{52}b_{63}b_{74} + b_{16}b_{27}b_{31}b_{42}b_{53}b_{64}b_{75} + b_{17}b_{21}b_{32}b_{43}b_{54}b_{65}b_{76} - b_{12}b_{21}b_{37}b_{46}b_{64}b_{73} - b_{13}b_{31}b_{47}b_{56}b_{65}b_{74} - b_{14}b_{23}b_{32}b_{41}b_{57}b_{75} - b_{15}b_{24}b_{42}b_{51}b_{67}b_{76} - b_{16}b_{25}b_{34}b_{43}b_{52}b_{61} - b_{17}b_{26}b_{35}b_{53}b_{62}b_{71} - b_{27}b_{36}b_{45}b_{54}b_{63}b_{72}$, $c_{11} = 1 + b_{23}b_{34}b_{45}b_{56}b_{67}b_{72} + b_{24}b_{35}b_{46}b_{57}b_{62}b_{73} + b_{25}b_{36}b_{47}b_{52}b_{63}b_{74} + b_{26}b_{37}b_{42}b_{53}b_{64}b_{75} + b_{27}b_{32}b_{43}b_{54}b_{65}b_{76} - b_{23}b_{32}b_{47}b_{56}b_{65}b_{74} - b_{24}b_{42}b_{57}b_{75} - b_{25}b_{34}b_{43}b_{52}b_{67}b_{76} - b_{26}b_{35}b_{53}b_{62} - b_{27}b_{36}b_{45}b_{54}b_{63}b_{72} - b_{37}b_{46}b_{64}b_{73}$, $c_{17} = b_{21}b_{32}b_{43}b_{34}b_{65}b_{76} + b_{71} + b_{23}b_{34}b_{45}b_{56}b_{61}b_{72} + b_{24}b_{35}b_{46}b_{51}b_{62}b_{73} + b_{25}b_{36}b_{41}b_{52}b_{63}b_{74} + b_{26}b_{31}b_{42}b_{53}b_{64}b_{75} - b_{21}b_{36}b_{45}b_{54}b_{63}b_{72} - b_{31}b_{46}b_{64}b_{73} - b_{23}b_{32}b_{41}b_{56}b_{65}b_{74} - b_{24}b_{42}b_{51}b_{75} - b_{25}b_{34}b_{43}b_{52}b_{61}b_{76} - b_{26}b_{35}b_{53}b_{62}b_{71}$, $c_{71} = b_{12}b_{23}b_{34}b_{45}b_{56}b_{67} + b_{13}b_{24}b_{35}b_{46}b_{57}b_{62} + b_{14}b_{25}b_{36}b_{47}b_{52}b_{63} + b_{15}b_{26}b_{37}b_{42}b_{53}b_{64} + b_{16}b_{27}b_{32}b_{43}b_{54}b_{65} + b_{17} - b_{12}b_{27}b_{36}b_{45}b_{54}b_{63} -$

$b_{13}b_{37}b_{46}b_{64} - b_{14}b_{23}b_{32}b_{47}b_{56}b_{65} - b_{15}b_{24}b_{42}b_{57} - b_{16}b_{25}b_{34}b_{43}b_{52}b_{67} - b_{17}b_{26}b_{35}b_{53}b_{62}$, $c_{77} = b_{12}b_{23}b_{34}b_{45}b_{56}b_{61} + b_{13}b_{24}b_{35}b_{46}b_{51}b_{62} + b_{14}b_{25}b_{36}b_{41}b_{52}b_{63} + b_{15}b_{26}b_{31}b_{42}b_{53}b_{64} + b_{16}b_{21}b_{32}b_{43}b_{54}b_{65} + b_{26}b_{35}b_{53}b_{62} - b_{12}b_{21}b_{36}b_{45}b_{54}b_{63} - b_{13}b_{31}b_{46}b_{64} - b_{14}b_{23}b_{32}b_{41}b_{56}b_{65} - b_{15}b_{24}b_{42}b_{51} - b_{16}b_{25}b_{34}b_{43}b_{52}b_{61} - 1$.

Using model (24), model (23) can be re-written as:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{7t} \end{bmatrix} = \begin{bmatrix} \bar{y}_1 \\ \bar{y}_2 \\ \vdots \\ \bar{y}_7 \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{17} \\ a_{21} & a_{22} & \cdots & a_{27} \\ \vdots & \vdots & \ddots & \vdots \\ a_{71} & a_{72} & \cdots & a_{77} \end{bmatrix}^i \begin{bmatrix} e_{1t-i} \\ e_{2t-i} \\ \vdots \\ e_{7t-i} \end{bmatrix} \tag{26}$$

Equation (26) expresses $(y_{1t}, y_{2t}, \ldots, y_{7t})$ in terms of the $\{e_{1t}\}$, $\{e_{2t}\}$, …, $\{e_{7t}\}$ sequences. However, it is insightful to rewrite (26) in terms of the $\{\varepsilon_{1t}\}, \{\varepsilon_{2t}\}, \ldots, \{\varepsilon_{7t}\}$ sequences. Equations (25) and (26) can be combined to form:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{7t} \end{bmatrix} = \begin{bmatrix} \bar{y}_{1t} \\ \bar{y}_{2t} \\ \vdots \\ \bar{y}_{7t} \end{bmatrix} + \det(b) \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{17} \\ a_{21} & a_{22} & \cdots & a_{27} \\ \vdots & \vdots & \ddots & \vdots \\ a_{71} & a_{72} & \cdots & a_{77} \end{bmatrix}^i \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{17} \\ c_{21} & c_{22} & \cdots & c_{27} \\ \vdots & \vdots & \ddots & \vdots \\ c_{71} & c_{72} & \cdots & c_{77} \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{7t} \end{bmatrix}$$

Since the notation gets unwieldy, we can simplify by defining the 7×7 matrix ϕ_i with elements $\phi_{jk}(i)$:

$$\phi_i = \left[A_1^i / \det(b) \right] \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{17} \\ c_{21} & c_{22} & \cdots & c_{27} \\ \vdots & & \ddots & \vdots \\ c_{71} & c_{72} & \cdots & c_{77} \end{bmatrix}$$

Hence, the moving average representation of (26) can be written in terms of the $\{\varepsilon_{y_1 t}\}$, $\{\varepsilon_{y_2 t}\}, \ldots,$ $\{\varepsilon_{y_7 t}\}$ sequences:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{7t} \end{bmatrix} = \begin{bmatrix} \bar{y}_1 \\ \bar{y}_2 \\ \vdots \\ \bar{y}_7 \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) & \dots & \phi_{17}(i) \\ \phi_{21}(i) & \phi_{22}(i) & \dots & \phi_{27}(i) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{71}(i) & \phi_{72}(i) & \dots & \phi_{77}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{y_1 t-i} \\ \varepsilon_{y_2 t-i} \\ \vdots \\ \varepsilon_{y_7 t-i} \end{bmatrix}$$

or more compactly,

$$\mathbf{y_t} = \mu + \sum_{i=0}^{\infty} \phi_i \boldsymbol{\varepsilon}_{\mathbf{t-i}} \,. \tag{27}$$

The coefficients of ϕ_i can be used to generate the effects of $\left[\varepsilon_{y_1 t}, \varepsilon_{y_2 t}, \dots, \varepsilon_{y_7 t}\right]$ shocks on the entire time paths of the $\{y_{1t}\}, \{y_{2t}\}, \dots, \{y_{7t}\}$ sequences. It should be clear that forty-nine elements $\phi_{jk}(0)$ are impact multiplier. For instance, the coefficient $\phi_{12}(0)$ is the instantaneous impact of a one-unit change in ε_{zt} on y_t. In the same way, the elements $\phi_{11}(1), \phi_{12}(1), \dots,$ $\phi_{17}(1)$ are the one period responses of unit changes in $\left[\varepsilon_{y_1 t-1}, \varepsilon_{y_2 t-1}, \dots, \varepsilon_{y_7 t-1}\right]$ on y_{1t}, respectively. Updating by one period indicates that $\phi_{11}(1)$, $\phi_{12}(1)$, ..., $\phi_{17}(1)$ also represent the effects of unit changes in $\left[\varepsilon_{y_1 t}, \varepsilon_{y_2 t}, \dots, \varepsilon_{y_7 t}\right]$ on y_{1t+1}.

The accumulated effects of unit impulses in $\left[\varepsilon_{y_1 t}, \varepsilon_{y_2 t}, \dots, \varepsilon_{y_7 t}\right]$ can be obtained by the appropriate addition of the coefficients of the impulse response functions. Note that after n periods, the effect of $\varepsilon_{y_2 t}$ on the value of y_{1t+n} is $\phi_{12}(n)$. Thus, the cumulated sum of the effects of $\varepsilon_{y_2 t}$ on the $\{y_{1t}\}$ sequence is:

$$\sum_{i=0}^{n} \phi_{12}(i)$$

Letting n approach infinity yields the long-run multiplier. Since the $\{y_{1t}\}$, $\{y_{2t}\}, \dots,$ $\{y_{7t}\}$ sequences are assumed to be stationary, it must be the case that for all j and k, $\sum_{i=0}^{\infty} \phi_{jk}^2(i)$ is finite. The sets of coefficients $\phi_{11}(i), \phi_{12}(i), \dots, \phi_{77}(i)$ are called the impulse response functions. We can plot the impulse response functions (i.e., plotting the coefficients of $\phi_{jk}(i)$ against i) is a practical manner to visually present the behavior of the $\{y_{1t}\}$, $\{y_{2t}\}$,…, $\{y_{7t}\}$ series in response to the various shocks.

As explained in the previous section, knowledge of the various a_{ij} and variance/covariance matrix Σ is not sufficient to identify the primitive system. Hence, the econometricians have to impose an additional restriction on the two-variable VAR system in order to identify the impulse responses.

3.5 Variance Decomposition

If we use the equation (27) to conditionally forecast y_{t+1}, the one-step ahead forecast error is $\phi_0 \varepsilon_{t+1}$. In general,

$$\mathbf{y}_{\mathbf{t+n}} = \mu + \sum_{i=0}^{\infty} \phi_i \boldsymbol{\varepsilon}_{\mathbf{t+n-i}} ,$$

So that the n-period forecast error $\mathbf{y}_{\mathbf{t+n}} - E_t \mathbf{y}_{\mathbf{t+n}}$ is

$$\mathbf{y}_{\mathbf{t+n}} - E_t \mathbf{y}_{\mathbf{t+n}} = \sum_{i=0}^{n-1} \phi_i \boldsymbol{\varepsilon}_{\mathbf{t+n-i}}$$

Forecasting solely on the $\{x_{1t}\}$ sequence, the n-step ahead forecast error is:

$$\begin{aligned}
\mathbf{y}_{\mathbf{1t+n}} - E_t \mathbf{y}_{\mathbf{1t+n}} = {} & \phi_{11}(0)\boldsymbol{\varepsilon}_{\mathbf{y_1 t+n}} + \phi_{11}(1)\boldsymbol{\varepsilon}_{\mathbf{y_1 t+n-1}} + \cdots + \phi_{11}(n-1)\boldsymbol{\varepsilon}_{\mathbf{y_1 t+1}} \\
& + \phi_{12}(0)\boldsymbol{\varepsilon}_{\mathbf{y_2 t+n}} + \phi_{12}(1)\boldsymbol{\varepsilon}_{\mathbf{y_2 t+n-1}} + \cdots + \phi_{12}(n-1)\boldsymbol{\varepsilon}_{\mathbf{y_2 t+1}} \\
& + \phi_{13}(0)\boldsymbol{\varepsilon}_{\mathbf{y_3 t+n}} + \phi_{13}(1)\boldsymbol{\varepsilon}_{\mathbf{y_3 t+n-1}} + \cdots + \phi_{13}(n-1)\boldsymbol{\varepsilon}_{\mathbf{y_3 t+1}} \\
& + \cdots + \phi_{1n}(0)\boldsymbol{\varepsilon}_{\mathbf{y_n t+n}} + \phi_{1n}(1)\boldsymbol{\varepsilon}_{\mathbf{y_n t+n-1}} + \cdots + \phi_{1n}(n-1)\boldsymbol{\varepsilon}_{\mathbf{y_n t+1}}
\end{aligned}$$

Denote the variance of the n-step ahead forecast error variance of y_{1t+n} as $\sigma_{y_1}(n)^2$:

$$\begin{aligned}
\sigma_{y_1}(n)^2 = {} & \sigma_{y_1}^2 \left[\phi_{11}(0)^2 + \phi_{11}(1)^2 \cdots + \phi_{11}(n-1)^2 \right] + \sigma_{y_2}^2 \left[\phi_{12}(0)^2 + \phi_{12}(1)^2 \cdots + \phi_{12}(n-1)^2 \right] \\
& + \sigma_{y_3}^2 \left[\phi_{13}(0)^2 + \phi_{13}(1)^2 \cdots + \phi_{13}(n-1)^2 \right] + \cdots + \sigma_{y_n}^2 \left[\phi_{1n}(0)^2 + \phi_{1n}(1)^2 \cdots + \phi_{1n}(n-1)^2 \right]
\end{aligned}$$

Since all values of $\phi_{jk}(i)^2$ are necessarily nonnegative, the variance of the forecast error increases as the forecast horizon n increases. Note that it is possible to decompose the n-step ahead forecast error variance due to each one of the shocks. The proportions of $\sigma_{y_1}(n)^2$ due to shocks in the $\{\varepsilon_{y_1t}\}, \{\varepsilon_{y_2t}\}, \ldots, \{\varepsilon_{y_7t}\}$ sequences are:

$$\frac{\sigma_{y_1}^2\left[\phi_{11}(0)^2+\phi_{11}(1)^2+\cdots+\phi_{11}(n-1)^2\right]}{\sigma_{y_1}(n)^2} \tag{28}$$

$$\frac{\sigma_{y_2}^2\left[\phi_{12}(0)^2+\phi_{12}(1)^2+\cdots+\phi_{12}(n-1)^2\right]}{\sigma_{y_1}(n)^2} \tag{29}$$

$\vdots$

$$\frac{\sigma_{y_7}^2\left[\phi_{1n}(0)^2+\phi_{1n}(1)^2+\cdots+\phi_{1n}(n-1)^2\right]}{\sigma_{y_1}(n)^2} \tag{30}$$

Equations (28), (29) and (30) are the forecast error variance decomposition (VDC), showing the proportion of the movements in a sequence due to its own shocks versus shocks to the other variable. If $\{\varepsilon_{y_2t}\}, \{\varepsilon_{y_3t}\}, \ldots, \{\varepsilon_{y_7t}\}$ shocks explain none of the forecast error variance of $\{y_{1t}\}$ at all forecast horizons, we can say that the $\{y_{1t}\}$ sequence is exogenous. In applied research, it is typical for a variable to explain almost all its forecast error variance at short horizons and smaller proportions at longer horizons.

However, impulse response analysis and variance decompositions can be useful tools to examine the relationships among economic variables. If the correlations among the various innovations are small, the identification problem is not likely to be particularly important. The alternative orderings should yield similar impulse response and variance decompositions.

Chapter 4 Empirical Results

4.1 Data Description

A total of nine time series datasets, including three energy prices and six macroeconomic variables, are applied in this study. The oil price (oil) data are collected from the West Texas Intermediate (WTI) crude oil spot price index in the commodity prices section. The gas price (gas) data are collected from the Russian Federation natural gas spot price index. The coal price (coal) data are collected from the Australia coal spot price index. Following Sadorsky (1999), we employ the six macroeconomic variables: industrial production index (ip), stock prices (sp), interest rate (r), unemployment rate (un), exports (ex) and imports (im). The industrial production index represents the level of output produced within an economy in a given year. In order to test for the impact in the labor market, the unemployment rate is chosen as a desirable proxy.

All data used in this study are monthly frequencies. Since the VAR or VECM model is used to estimate the non-linear relation, at least 200 data points are needed for a delay of 12 periods as suggested by Hamilton and Herrera (2004). The length of the available data is different and covers the period from 1975:M7-2008:M5 (oil price), 1979:M2-2008:M5 (coal price), and 1985:M1-2008:M5 (natural gas price). The energy price data are obtained from International Financial Statistics (IFS) CD-ROM. The macroeconomic variables are obtained from Taiwan Economic Journal (TEJ) and Advanced Retrieval Econometric Modeling System (AREMOS). All variables are deflated by the base year 2006 consumer price index (CPI) and a natural logarithm (except for interest rate and unemployment rate) is taken before conducting the analysis. Table 4.1 summarizes a description of all variables.

Table 4.1 Definitions of Variables

Variables	Definitions of variables	Source
oil	Logarithmic transformation of monthly real West Texas Intermediate crude oil spot price index in US dollar (in 2006 prices)	IFS (2008)
gas	Logarithmic transformation of monthly real Russian Federation natural gas spot price index in US dollar (in 2006 prices)	IFS (2008)
coal	Logarithmic transformation of monthly real Australia coal spot price index in US dollar (in 2006 prices)	IFS (2008)
ip	Logarithmic transformation of monthly real industrial production index in NT dollar (in 2006 prices)	TEJ
sp	Logarithmic transformation of monthly real stock prices in NT dollar (in 2006 prices)	TEJ
r	Monthly real interest rate	TEJ
un	Monthly unemployment rate	TEJ
ex	Logarithmic transformation of monthly real exports in NT dollars (in 2006 prices)	AREMOS
im	Logarithmic transformation of monthly real imports in millions NT dollar (in 2006 prices)	AREMOS

4.2 One-regime VAR analysis

4.2.1 Results of Tests for Unit Roots and Cointegration

To facilitate the comparison with early studies, we first apply the linear VAR model. Before the VAR or MVTEC model is formally employed in the statistical analysis, all the variables need to be tested for stationarity. If not, we must examine the existence of a cointegration relation. We use the Augmented Dickey-Fuller (1979, ADF) and Kwiatkowski et al. (1992, KPSS) unit root tests to check for the existence of unit root. An examination of Table 4.2 indicates our results are consistent, irrespective of using either the ADF unit root or KPSS unit root test. The statistic indicates that all of the individual series in first differences are stationary at the 1% significance level. This outcome suggests that all variables are integrated of order one or $I(1)$. Thus, we use the differenced variables in the following analysis.

Table 4.2 Results of Unit Root Tests

	ADF		KPSS	
Panel A. Oil price (1975:7-2008:5)				
	Level	First differences	Level	First differences
oil	-0.989	-15.422***	0.402***	0.106
y	-0.357	-4.790***	2.408***	0.010
sp	-1.286	-18.248***	1.755***	0.080
r	-1.236	-16.639***	1.567***	0.048
un	-1.790	-4.334***	1.484***	0.126
ex	-2.157	-4.773***	0.292***	0.102
im	-0.524	-6.080***	2.359***	0.148
Panel B. Coal price (1979:2-2008:5)				
	ADF		KPSS	
	Level	First differences	Level	First differences
coal	-0.331	-14.577***	0.768***	0.455
y	-0.329	-4.507***	2.254***	0.014
sp	-1.375	-17.211***	1.431***	0.096
r	-0.990	-15.531***	1.548***	0.095
un	-2.209	-4.486***	1.417***	0.070
ex	-0.152	-4.709***	2.224***	0.055
im	0.048	-14.774***	2.261**	0.028
Panel C. Natural gas price (1985:1-2008:5)				
	ADF		KPSS	
	Level	First differences	Level	First differences
gas	-0.918	-6.374***	0.594**	0.446
y	-0.325	-4.273***	1.957***	0.020
sp	-2.798	-15.456***	0.489**	0.187
r	-1.291	-12.323***	1.255***	0.082
un	-1.606	-3.635***	1.358***	0.088
ex	0.048	-4.462***	1.929***	0.146
im	-1.013	-23.082***	1.920***	0.109

Note: '***' and '**' denote significance at 1% and 5%, respectively. Values in the parenthesis in ADF and KPSS unit root tests are *p*-values provided by Mackinoon (1996) and Kwiatkowski et al. (1992), respectively.

Based on the evidence for the presence of a unit root in all the data series, the next stage tests the possibility of cointegration among the variables. Two or more individual series may be non-stationary, but a linear combination of these individual series may be stationary. If such a stationary linear combination exists, then the non-stationary time series are said to be co-integrated. The stationary linear combination is called a co-integrating equation and may be interpreted as a long-run equilibrium relationship between the variables that is the variables have co-movement over time. If there is only one long-run relationship among the variables, then those variables share a single route of convergence towards the equilibrium path. If there is more than one long-run relationship, then there exist multiple forces pushing towards convergence paths among the variables.

We apply the maximum eigenvalue and trace statistic proposed by Johansen (1988) to test the existence of a cointegration relation for these $I(1)$ variables. To determine the optimal lag length of the VAR model three versions of system are initially estimated: 2, 5, and 6-lag versions. A BIC is then employed to test that all three specifications are statistically equivalent. All tests reject the null hypothesis that all the versions of VAR are statistically equivalent. In particular, the following results suggest $l = 6$ for the oil price, $l = 2$ for the coal price, and $l = 5$ for the natural gas.

As shown in Table 4.3, there exist cointegration relations among variables. On the basis of the results the existence of a long-run relationship for all specifications finds statistical support in Taiwan over the period under examination.

Table 4.3 Results of the Johansen Cointegration Tests

Energy price: Oil price						
H_0	Eigenvalue	Trace	p-value	Eigenvalue	Max-Eigen	p-value
$r=0$	0.15	153.33***	0.00	0.15	61.72***	0.00
$r\leq 1$	0.08	91.61	0.24	0.08	31.75	0.37
$r\leq 2$	0.05	59.86	0.48	0.05	20.41	0.79
Energy price: Coal price						
H_0	Eigenvalue	Trace	p-value	Eigenvalue	Max-Eigen	p-value
$r=0$	0.17	133.06***	0.00	0.17	65.18***	0.00
$r\leq 1$	0.07	67.87	0.41	0.07	25.35	0.54
$r\leq 2$	0.05	42.52	0.59	0.05	18.12	0.69
Energy price: Natural gas price						
H_0	Eigenvalue	Trace	p-value	Eigenvalue	Max-Eigen	p-value
$r=0$	0.15	124.22***	0.01	0.15	43.98**	0.04
$r\leq 1$	0.11	80.24	0.09	0.11	33.17	0.12
$r\leq 2$	0.10	47.07	0.38	0.10	28.30	0.09

Note: '***' and '**' denote significance at 1% and 5%, respectively.

4.2.2 Results of the Variance Decomposition

To investigate the dynamic properties of the VAR system, the study now estimates the variance decomposition analysis and the estimation of impulse response functions. The variance decomposition analysis can determine the proportion of the movements in time series that are due to shocks in their own series as opposed to shocks in other variables, including energy price. Table 4.4 presents the variance decomposition results based on the VECM model for energy price. To facilitate a comparison with prior models, we employ the BIC to determine the optimal lag. The optimal lag length is determined at 12 months, where the BIC value reaches its minimum. After that, the BIC is found to rise. Each percentage shows how much of the unanticipated changes in macroeconomic variables are explained by the energy price variable over a 12-month horizon.

Table 4.4 Variance Decompositions of Forecast Error Variance in One-regime VAR Model (12 Periods Forward)

	Shock sources						
	ε^{y}	ε^{ep}	ε^{sp}	ε^{r}	ε^{un}	ε^{ex}	ε^{im}
Panel A. Energy price: Oil price							
y	77.59	1.94	2.72	1.95	7.55	5.33	2.91
ep	1.99	90.32	2.22	0.96	1.00	1.97	1.54
sp	1.09	1.54	89.87	2.22	2.75	0.90	1.62
r	1.50	3.88	1.64	84.49	4.02	2.48	1.99
un	20.27	2.52	1.97	2.04	66.60	3.29	3.31
ex	28.61	2.63	1.90	0.51	2.26	60.10	4.00
im	26.95	2.09	2.96	0.86	1.51	23.16	42.46
Panel B. Energy price: Coal price							
y	93.95	0.52	0.14	0.08	0.27	4.97	0.09
ep	0.57	93.97	1.60	0.04	1.67	0.27	1.88
sp	0.26	0.22	95.98	0.91	1.61	0.75	0.27
r	2.33	0.96	0.86	92.80	1.48	0.35	1.22
un	14.45	0.40	0.96	0.53	81.18	0.76	1.73
ex	47.60	1.57	1.05	0.28	0.64	47.72	1.15
im	40.29	1.45	0.45	0.59	1.27	13.05	42.90
Panel C. Energy price: Natural gas price							
y	81.02	0.86	2.43	2.22	2.99	8.07	2.41
ep	1.43	89.22	1.41	2.35	0.83	0.96	3.80
sp	0.80	3.53	86.41	1.58	2.79	2.56	2.38
r	1.66	1.18	1.12	86.88	4.86	2.48	1.83
un	19.98	2.66	3.58	1.22	62.77	4.48	5.31
ex	46.46	2.54	1.89	1.35	0.85	39.33	7.59
im	42.29	3.02	2.23	1.31	0.52	14.99	35.63

Note: Values in the parenthesis are standard errors estimated through 500 Monte Carlo replications. Variance decomposition explaining the variation in variables is due to industrial production shocks (ε^{y}), energy prices shocks (ε^{ep}), stock price shocks (ε^{sp}), interest rate shocks (ε^{r}), unemployment rate shocks (ε^{un}), export shocks (ε^{ex}), and import shocks (ε^{im}).

The industrial production variable's own shocks account for 77.59% to 93.95% of the forecast variance. After a year (12 months), oil prices, stock prices, interest rate, unemployment rate, exports and imports account for 1.94%, 2.72%, 1.95%, 7.55%, 5.33% and 2.91% of the industrial production forecast error variance, respectively. Coal price changes explain 0.52% of the industrial production and natural gas price changes explain 0.86% of the industrial production. Compared to the other energy prices (i.e., coal price and natural gas price), oil price changes in Taiwan have the largest explanatory effect for industrial production.

For the energy price variable, almost all of the variance decomposition come from the movement itself. After a year almost 90.32% of the oil price variability is explained by its own innovations, while 1.99%, 2.22%, 0.96%, 1.00%, 1.97% and 1.54% are attributed to industrial production changes, stock price changes, interest rate changes, unemployment rate changes, export changes, and import changes. It means that changes in industrial production and stock prices are found to affect oil price significantly. Moreover, imports are found to affect both coal and natural gas prices significantly.

After one year (12 months), 89.87% of the stock price variability is attributed to changes in itself, 1.54% to oil price changes, 2.22% to interest rate changes, and 2.75% to unemployment rate changes. Moreover, coal price changes explain a 0.22% change in stock prices, slightly lower than 0.91% explained by the interest rate. Both the explanatory power of oil price and coal price changes are no greater than that of the interest rate being attributed to the use of the one-regime model. However, natural gas price shocks are important driving forces behind stock price variability, explaining almost 3.53% of the variation in stock prices in the short term (about a year).

The interest rate variable's own shocks account for most of the forecast error variance. The oil price change explains about 3.88% of the interest rate change (greater than 1.64% explained by stock price change). Compared to other energy prices, a natural gas price change has stronger explanatory power on the interest rate.

For the unemployment variable, the unemployment variations are still mainly due to its own changes of about 62.77% - 81.18%, while approximately 2.52% is attributed to oil price changes, 0.40% to coal price changes, and 2.66% to natural gas price changes. In other words, a natural gas price change has stronger explanatory power on unemployment. As expected, an industrial production change is another explanatory effect for the unemployment rate except for own shocks.

For the exports and imports variables, an industrial production change has significant explanatory power. The energy price changes have rather limited explanatory power on exports and imports. Although the size of impacts has been identified by computing VDCs, we cannot make a judgment for whether the causal impacts are, in fact, negative or positive, because the VDCs do not show the signs of the effects. The signs can be identified by computing impulse response functions (IRFs).

4.2.3 Results of the Impulse Response Analysis

The impulse response functions illustrate the qualitative response of the variables in the system to shocks in energy prices. Figure 4.1 presents the impulse response functions of each oil price change (DWTI), coal price change (DCOAL), and natural gas price change (DNG) from one-standard deviation shocks to industrial production (DIP), stock price (DSP), real interest rates (DR), unemployment rates (DUN), exports (DEX) and imports (DIM) in the one-regime VAR model.

An oil price shock has a negative impact on industrial production. It responds negatively in period 2, and its responses exhibit more volatility. An oil price shock has a delayed negative impact on industrial production.

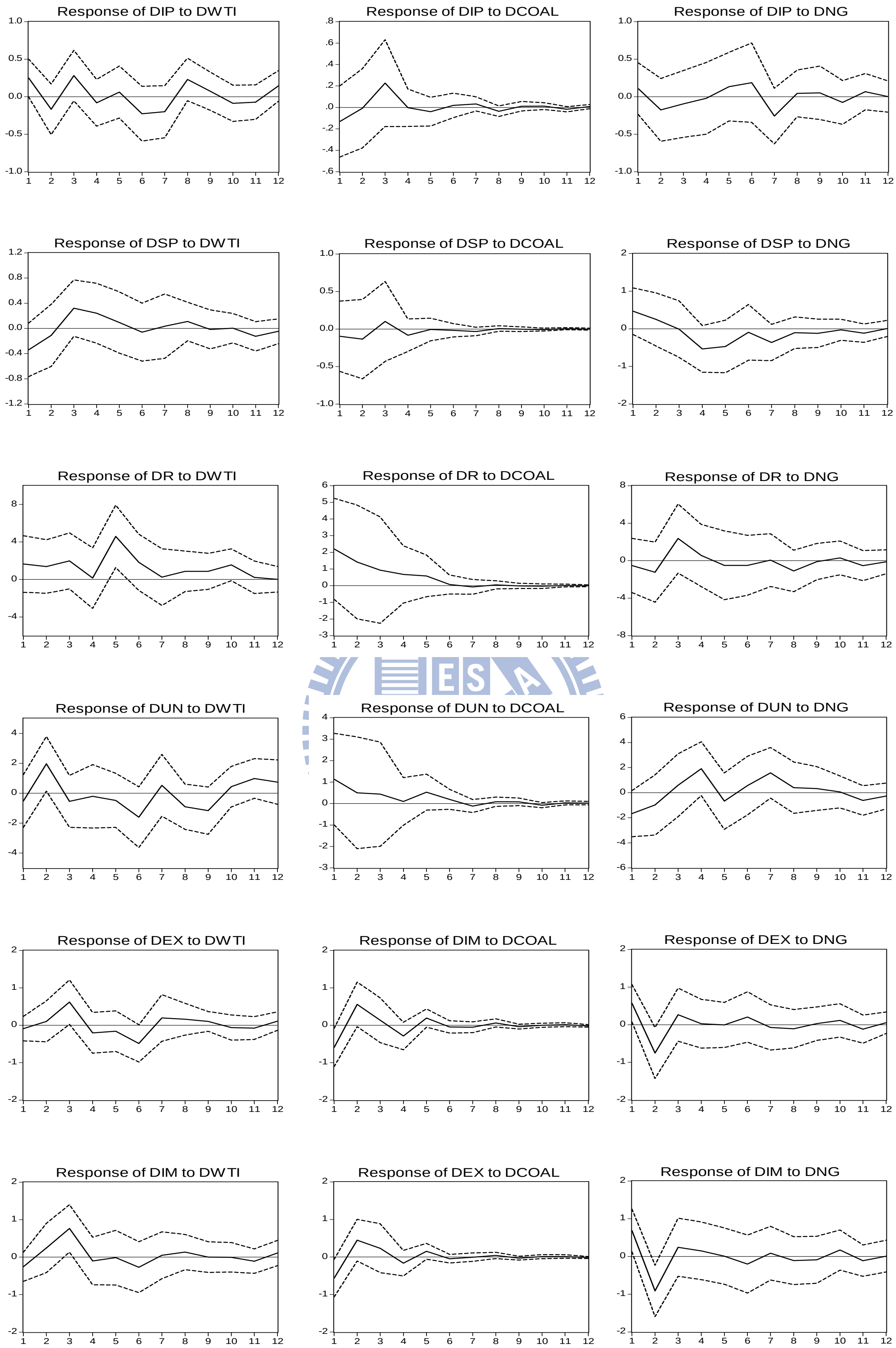

Figure 4.1 Impulse Responses from One Standard Deviation Shock of Energy Price Change in the Linear VAR Model (12 Periods Forward)

Such a finding is consistent with those of Hamilton (1983) and Mork (1989), who find decreases in industrial production after an oil price shock. Following an oil price shock, stock prices decrease immediately by 0.3%, showing that an oil price shock has a negative impact on stock prices. An oil price shock has a positive impact on interest rates. This result can be expected as increases in oil prices create inflationary effects in the economy which consequently bring an upward pressure on interest rates. The phenomenon sustains itself for approximately 12 periods. The maximum effect is reached after 4-5 periods, when the interest rate has increased by 4%. An oil price shock has a positive impact on the unemployment rate which increases by 2% in period 2.

As the middle of Figure 4.1 shows, we can observe the following impulse responses for a coal price shock. The industrial production reacts a negatively and significantly to a coal price change in the first period. After 4-5 periods, the effect gradually dies out. A negative response from stock prices is observed in period 2, but the effect is small and not significantly different from zero. As expected, the interest rate increases immediately following the oil price shock and then gradually dies out. A coal price shock always keeps a positive impact on the unemployment rate that lasts for approximately 6 periods. Following a coal price shock, both exports and imports decrease immediately by 0.5% in period 1 and then increase by 0.5% in period 2.

Finally, the impact of the natural gas price shock on macroeconomic variables is shown in the right of Figure 4.1. Similar to an oil price shock, there is a lag effect on industrial production. The industrial production decreased in periods 2 and 7 from a natural price shock. A natural gas price shock has a delayed negative impact on stock prices. With a delayed stock price response in Taiwan, stock prices at first rise and then decrease, this lasts for approximately 5-6 periods. The unemployment rate only starts to decrease in period 1 and it exhibits an upward inclination pattern in period 3.

The maximum positive effects are reached in periods 4 and 7.

There may be some problems emanating from positive and negative changes in the one-regime model. For instance, there are no significant responses identified for stock prices to a one-standard deviation coal price shock. Each macroeconomic variable should exhibit significant responses when energy price changes are modest or more. That is to say, we need to offer more detailed responses. Sadorsky (1999) arbitrarily categorizes the energy price change into positive and negative changes. He does not provide a statistical test on the necessity of using different regimes and does not reflect different dependence levels on energy price. To overcome the problem, we use the multivariate threshold error correction (MVTEC) model developed by Tsay (1998).

4.3 Two-regime VAR analysis

4.3.1 Estimating the Threshold Levels and the Delay of Threshold Variables

Before employing the MVTEC model, it is necessary to test the existence of the non-linear relationship in terms of the threshold variables (i.e., oil price, coal price, and natural gas price) during these two periods. The *C(d)* statistic based on the arranged regression (Tsay, 1998) can be used to test the linear relation. Table 4.5 displays the tests results.

Table 4.5 Results of Threshold Effect Tests

Threshold variable	Delay (*d*)	C(*d*) *p*-value	Threshold value (c^*)	Regime one	Regime two
Oil	1	354.36 (0.04)	2.48%	326	68
Coal	1	180.52 (0.00)	0.22%	223	128
Natural Gas	1	397.87 (0.00)	0.87%	239	41

Note: Regime one refers to $Z_{t-d} \leq c$ and Regime two $Z_{t-d} \geq c$. c^* is the optimal threshold value determined by the location of the minimum log det|∑|, and ∑ is the variance–covariance matrix for the corresponding multivariate VECM models.

Based on Table 4.5, we can reject the null hypothesis of the linear model using oil price as a threshold variable. It means that the result favors the MVTEC model. By the same token, we find a similar result when coal price or natural gas price is used as a threshold variable. There is a non-linear relationship between energy price and industrial production. The delay (d) of the threshold variable reflects the speed of response based on the economic impact of a positive energy price change and its shock. Results about the length of delay are similar to Huang's (2008) result: when a country has a higher energy import ratio, it will have a shorter delay in terms of its economic response from the positive impact of an energy price change. In this study the impact of energy price changes (i.e., oil price, coal price, and natural gas price) on production is rapid (one month).

The threshold value (c) reflects the critical level of the impact. In order to estimate the optimal threshold value c^*, we search procedure targets at the middle 60% to 80% of the arranged dataset. From the estimated results of threshold effect tests in Table 4.5, the optimal threshold levels c are as follows: the highest level is oil price at 2.48%, the next highest is natural gas price at 0.87%, and the lowest level is coal price at 0.22%. When the oil price change (1 month before) exceeds 2.48%, its impact is significantly different from that if the price change is less than 2.48%. Similarly, when the coal price change (1 month before) exceeds 0.22%, its impact is significantly different from that if the price change is less than 0.22%. The impact on industrial production is different from when the natural gas price change (1 month before) exceeds 0.87%.

4.3.2 Results of the Variance Decomposition in the MVTEC Model

In order to depict the response of macroeconomic activities in regime one (energy price changes are less than or equal to c^*) and regime two (energy price changes exceed

c^*), we employ the VDC and the IRF analyses for each regime. Table 4.6 reports proportions of impacts emanating from an oil price change in terms of VDC. When an oil price change is below the threshold value c^*, an oil price change explains about 7.12% of industrial production change (greater than 1.98% explained by an interest rate change). Similarly, the proportions of the explanatory power of oil price and interest rate on unemployment change are roughly the same: 2.09% vs. 2.06%. On the other hand, when an oil price change exceeds the threshold value c^*, it explains much more on industrial production than does the interest rate (17.22% vs. 4.39%). However, oil price changes explain less significantly on stock prices (7.45% vs. 14.85%) and unemployment (6.87% vs. 14.11%) than the interest rate.

Table 4.6 Variance Decomposition Results Using Oil Price Changes as Threshold Variable (12 Periods Forward)

	Shock sources						
	ε^y	ε^{ep}	ε^{sp}	ε^r	ε^{un}	ε^{ex}	ε^{im}
Panel A. Regime one							
y	79.60	7.12	3.53	1.98	3.38	1.62	2.77
ep	2.16	89.71	2.62	0.65	2.05	1.23	1.59
sp	0.81	1.01	90.38	1.38	3.57	0.96	1.90
r	2.97	1.09	4.63	79.64	4.78	4.67	2.21
un	13.62	2.09	2.50	2.06	73.74	0.89	5.09
ex	34.81	2.98	2.08	0.39	1.00	57.53	1.22
im	28.36	4.12	3.68	0.68	3.63	22.72	36.79
Panel B. Regime two							
y	51.86	17.22	7.79	4.39	3.61	8.14	6.99
ep	4.85	30.93	4.63	17.89	4.88	18.28	18.53
sp	18.11	7.45	34.99	14.85	10.98	4.74	8.88
r	9.91	17.84	8.01	33.91	6.59	9.55	14.18
un	13.12	6.87	10.17	14.11	37.27	9.83	8.64
ex	34.28	15.60	12.75	6.50	10.09	16.67	4.13
im	36.28	21.16	13.75	6.68	5.51	7.70	8.93

Note: Regime one pertains to $Zt\text{-}d \leq c^*$ while regime two pertains to $Zt\text{-}d > c^*$.

Given these results, the oil price change in Taiwan significantly explains industrial production. In the one-regime model, an oil price change has rather limited explanatory power on industrial production in comparison to the real interest rate (1.94% vs. 1.95%). In the two-regime model, however, an oil price change significantly explains macroeconomic activities especially for Taiwan's industrial production. This phenomenon perhaps is due to the fact that the explanatory power of oil price changes is less than that of the interest rate being attributed to the use of the one-regime model.

Table 4.7 illustrates the impact of coal price changes on macroeconomic variables in terms of the VDC. When a coal price change is below the threshold value, it explains a significant portion of change in industrial production (4.11%), unemployment

Table 4.7 Variance Decomposition Results Using Coal Price Changes as Threshold Variable (12 Periods Forward)

	Shock sources						
	ε^{y}	ε^{ep}	ε^{sp}	ε^{r}	ε^{un}	ε^{ex}	ε^{im}
Panel A. Regime one							
y	87.78	4.11	3.53	0.26	0.69	2.30	1.32
ep	0.98	91.53	0.14	0.87	1.23	4.87	0.38
sp	0.37	0.53	93.26	0.96	2.22	1.61	1.05
r	2.85	0.93	0.65	91.45	3.18	0.42	0.52
un	11.45	3.19	0.53	0.40	81.65	2.30	0.50
ex	37.91	4.29	0.83	0.37	0.69	54.55	1.36
im	34.42	5.82	0.79	1.04	1.93	17.74	38.26
Panel B. Regime two							
y	82.71	4.20	1.46	3.44	1.03	3.85	3.32
ep	2.66	83.08	2.30	1.11	7.34	1.66	1.86
sp	4.28	3.88	77.08	2.23	4.49	2.90	5.15
r	3.55	4.60	5.78	75.03	3.27	3.93	3.84
un	6.50	2.75	4.44	4.01	76.10	4.64	1.56
ex	31.57	8.02	6.20	7.42	3.64	36.98	6.18
im	23.01	10.22	8.80	3.60	2.81	21.76	29.80

Note: Regime one pertains to $Zt\text{-}d \leq c^{*}$ while regime two pertains to $Zt\text{-}d > c^{*}$.

(3.19%), exports (4.29%), and imports (5.82%). When a coal price change exceeds the threshold value c^* (regime two), the coal price change explains about 3.88% of the stock price change (greater than 2.23% explained by the interest rate change). Within the linear model, a coal price change exerts less significant impact than an interest rate change (0.22% vs. 0.91%). This is strikingly different from the results of the two -regime model, which displays significant responses from stock markets when the coal price change is modest or more. Furthermore, a coal price change has higher explanatory power on unemployment in comparison to the one-regime model. It also explains a significant portion of export change (8.02%) and import change (10.22%).

Table 4.8 presents the VDC results from natural gas price changes. As can be seen from the table (regime one in which a natural gas price change is below the threshold value c^*), a natural gas price change has significant explanatory power. It indicates that a natural gas price change (1) explains more on industrial production change than does an interest rate change (6.49% vs. 1.42%); (2) accounts more on stock price change than does an interest rate change (3.89% vs. 1.91%); (3) accounts more on unemployment in comparison to the interest rate (6.06% vs. 3.17%) and (4) explains more on exports (4.26%) and imports (6.20%) than other macroeconomic variables. In regime two, it indicates that a natural gas price change can explain more on unemployment than does an interest rate change (25.15% vs. 4.68%). Furthermore, a natural gas price change has significant explanatory power on exports (11.42% vs. 4.26%) and imports (18.16% vs. 6.20%) in comparison to regime one. In particular, the explanatory power of a natural gas price change is greater than the interest rate under two regimes. This result is consistent with findings by Park and Ratti (2008) in that the contributions from energy price shocks are greater than that of interest rates on the stock market.

The results of variance decomposition of energy price change are summarized: (1) an oil price change has significant explanatory power on industrial production in regime one. (2) When an oil price change exceeds the threshold value (regime two), an oil price change not only reports maximum proportions of industrial production, but the explanatory power rises in comparison to regime one. (3) A coal price change has significant explanatory power on industrial production in regime one. (4) A coal price change has higher explanatory power on stock price than the interest rate in regime one. (5) A natural gas price change has significant explanatory power on industrial production in regime one. (6) A natural gas price change has higher explanatory power on stock prices than the interest rate in regime one.

Table 4.8 Variance Decomposition Results Using Natural Gas Price Change as Threshold Variable (12 Periods Forward)

	Shock sources						
	ε^{y}	ε^{ep}	ε^{sp}	ε^{r}	ε^{un}	ε^{ex}	ε^{im}
Panel A. Regime one							
y	76.64	6.49	4.71	1.42	3.54	4.95	2.26
ep	2.58	84.70	0.92	1.76	2.15	2.16	5.73
sp	0.47	3.89	80.22	1.91	3.37	8.11	2.03
r	1.27	1.12	2.79	85.42	5.21	2.66	1.52
un	11.82	6.06	2.34	3.17	63.82	7.36	5.43
ex	42.72	4.26	2.74	1.67	1.89	43.08	3.64
im	35.74	6.20	1.90	5.15	1.78	21.40	27.83
Panel B. Regime two							
y	73.87	4.82	3.56	13.18	1.65	0.65	2.27
ep	10.96	52.03	9.11	8.82	3.14	9.50	6.44
sp	4.37	5.37	77.60	7.09	1.86	3.01	0.70
r	14.19	8.84	18.19	47.99	7.60	2.17	1.02
un	6.51	25.15	16.96	4.68	37.65	2.48	6.57
ex	23.81	11.42	25.43	3.49	2.35	31.38	2.12
im	30.26	18.16	24.66	5.25	1.07	10.60	9.99

Note: Regime one pertains to $Zt\text{-}d \leq c^{*}$ while regime two pertains to $Zt\text{-}d > c^{*}$.

4.3.3 Results of the Impulse Response Analysis in the MVTEC Model

In this section we study the impact of energy prices on macroeconomic activities by analyzing impulse response functions. Figures 4.2 to 4.4 present the impulse response functions of each energy price (DWTI, DCOAL, and DNG) from one-standard deviation shocks to industrial production (DIP), stock price (DSP), real interest rates (DR), unemployment rates (DUN), exports (DEX), and imports (DIM) in the two-regime models.

The left of Figure 4.2 presents the impulse responses of macroeconomic variables to an oil price shock in regime one. When an oil price change is below the threshold value c^* (regime one), it can be seen that an oil price shock has a positive impact on industrial production. The response of industrial production to oil price shocks is rising in periods 1 and 3. After 5 to 6 periods, the effect gradually dies out. Moreover, an oil price shock has a persistently negative impact on stock prices over 11 periods. The oil price shock has an immediate positive response in the interest rate, and then falls. This result can be expected as increases in oil price create inflationary effects in the economy which consequently bring an upward pressure on interest rates. The results for the unemployment rate are somewhat stronger. Except for the first one minor negative response, the graph shows persistent positive responses of unemployment to a shock in oil price. The maximum effect is reached in the second period when the unemployment rate increases by 2%.

The left of Figure 4.3 presents the impulse responses of macroeconomic variables to an oil price shock in regime two. When an oil price change exceeds the threshold value c^* (regime two), an oil price shock has an immediate positive impact on industrial production, and after a minor negative shock it tends to remain for a significant period of time. The IRF analysis shows that oil price shocks exhibit more volatility in the one-regime model than in the two-regime model.

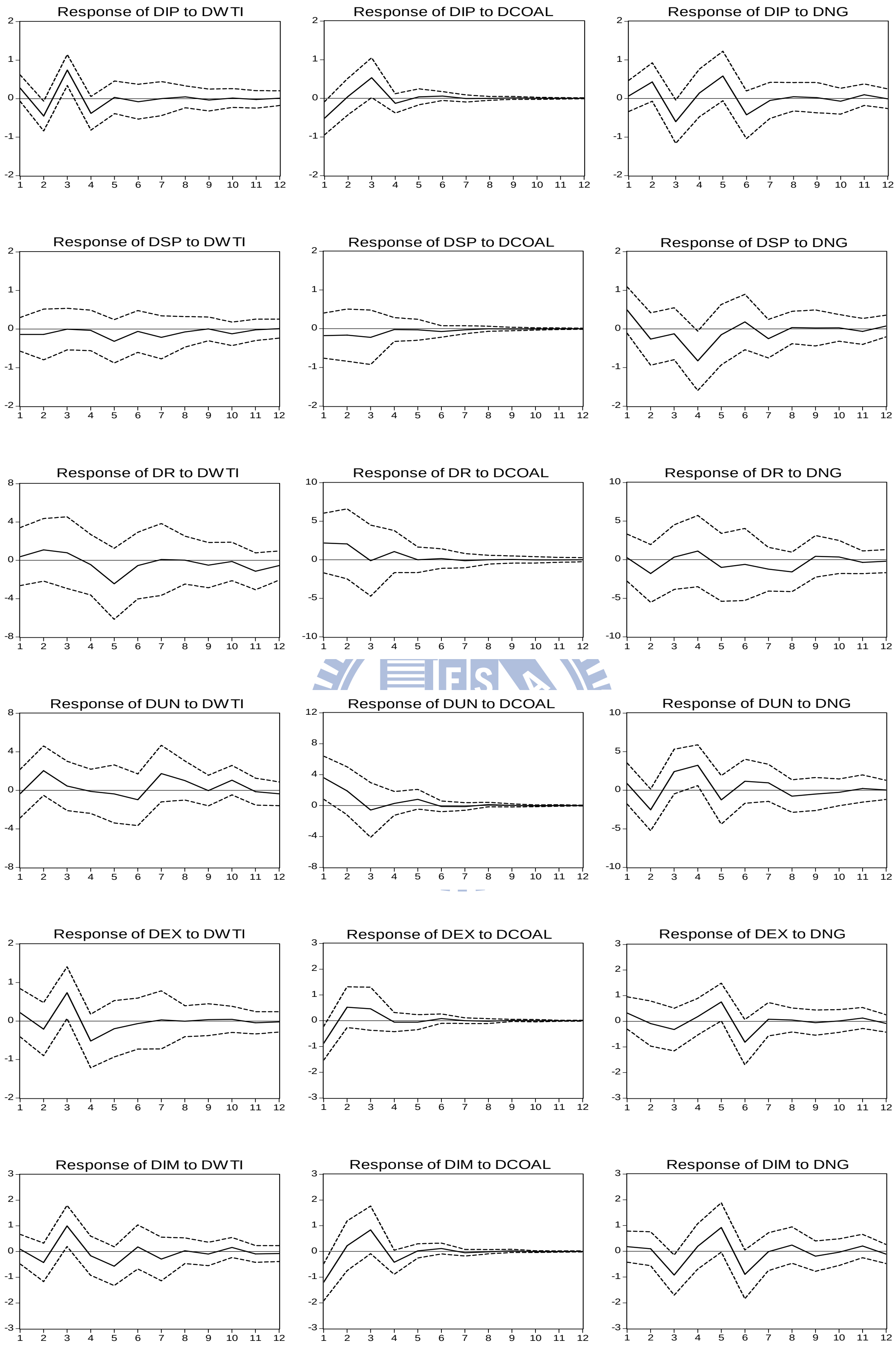

Figure 4.2 Impulse Responses from One Standard Deviation Shock of Energy Price Change in the Regime One VAR Model (12 Periods Forward)

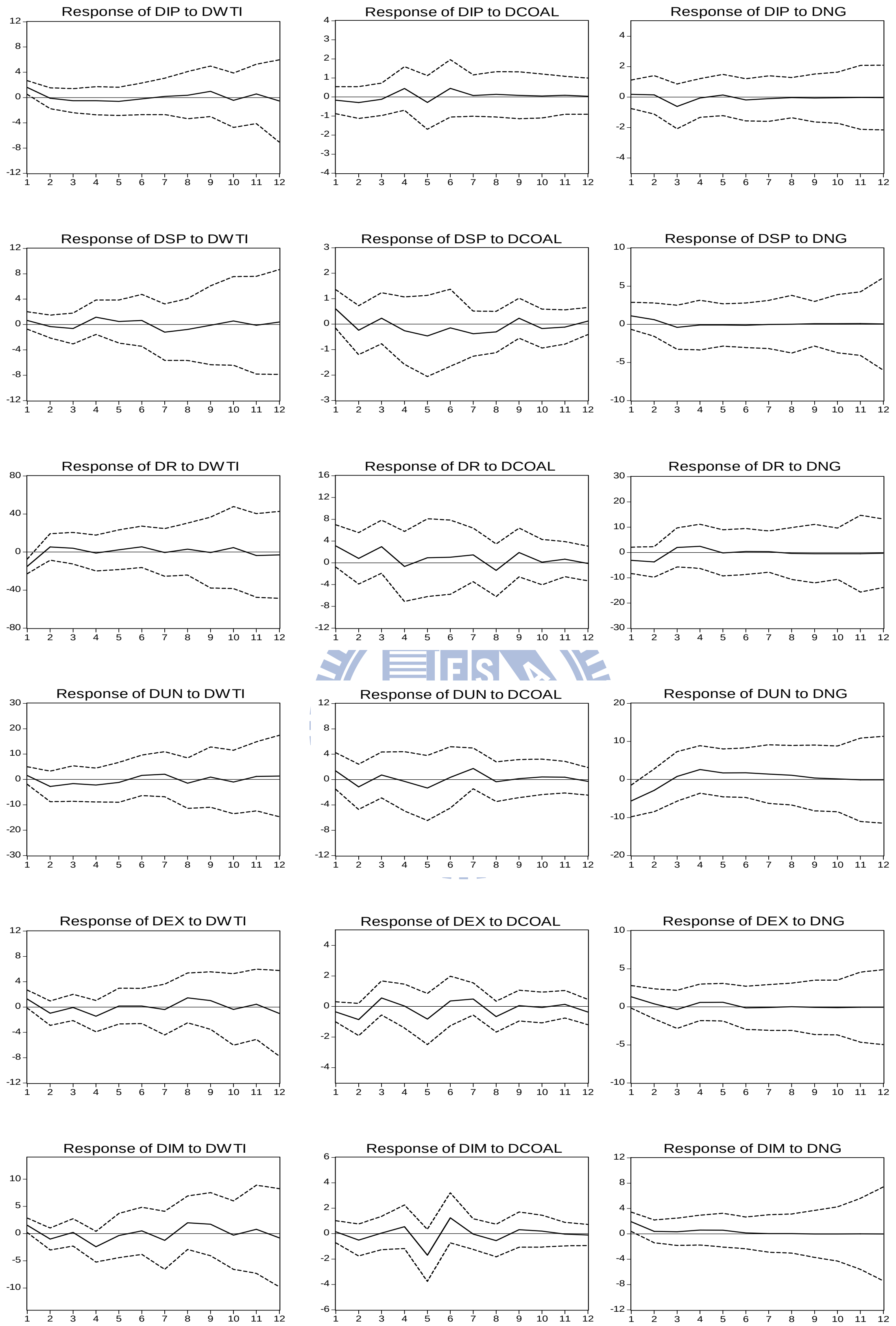

Figure 4.3 Impulse Responses from One Standard Deviation Shock of Energy Price Change in the Regime Two VAR Model (12 Periods Forward)

The response of stock prices to shocks in oil price is positive up to the first period and eventually declines. An oil price shock has an initial minor negative impact on interest rates and then the increase lasts for approximately 12 periods. The responses of the unemployment rate are only after an initial slight positive impact and then fall.

The middle of Figures 4.3 and 4.4 shows the responses of macroeconomic variables to a one-standard deviation coal price shock. When a coal price change is below the threshold value c^* (regime one), it can be observed that a positive coal price shock increases industrial production in period 3. However, the responses of industrial production increase for one period and then fall. After 3-4 periods, the effect gradually dies out. This result suggests that coal price shocks have a delayed positive impact on industrial production. A coal price shock has a slight negative impact on stock prices that lasts for approximately 4 periods. In particular, the unemployment rate initial rise lasts for approximately 2 periods and then decreases in period 3. The results show that following a 10% increase in coal price, the unemployment rate increases immediately by 3–4%. The maximum effect is reached in the first period, after which the effect gradually dies out. By the same token, a positive coal price shock increases exports and imports for the two periods and affects Taiwan economy positively.

When a coal price change exceeds the threshold value c^* (regime two), a coal price shock has a slight negative impact on industrial production that lasts for approximately 3 periods. In periods 4 and 6, the response of industrial production to shocks in coal price is increasing and then the effect dies out. As expected, a coal price shock has a negative impact on stock prices. The graph presents that the response of stock prices to shocks in coal price is positive up to the first period and it eventually declines. A coal price shock has a negative impact on the interest rate expected for periods 4 and 8. Similar to stock prices, there is a lag effect on the unemployment rate.

Figures 4.3-4 show the responses of six variables to a natural gas price shock. When a natural gas price change is below the threshold value c^* (regime one), a natural gas price shock has a significant positive impact on industrial production. The industrial production initial rise lasts for approximately 2 periods and increases in periods 4-5. The figure also shows that following a natural gas price shock, stock prices increase immediately by 0.5%. After that, stock prices decrease persistently for 2-4 periods. The maximum effect is reached in period 4, when stock prices have decreased by 1%. The responses exhibit more volatility and last for a long term. As expected, a natural gas price shock has a positive impact on the interest rate.

When a natural gas price change exceeds the threshold value c^* (regime two), a natural gas price shock has a small negative impact on the interest rate. After 3-4 periods, the effect gradually dies out. As expected, stock prices initially rise, probably affected by the rise in economic activity, and then die out in period 3.

The results of the impulse response of energy price changes are summarized: (1) In the two-regime model, energy price shocks have negative impact on industrial production. When energy price changes are below the threshold value c^*, the impulse responses of oil price shocks exhibit more volatility than coal and natural gas price shocks. In addition, the threshold values reflect periods of industrial production for each energy price: natural gas, oil, and coal. It also finds that an oil price shock has a delayed negative impact on industrial production with one lag in regime two. In particular, the impulse responses of energy price shocks in regime one are more than that of energy price shocks in regime two. (2) As evident from the IRFs, energy price shocks have a negative impact on stock prices in regime two. The threshold values reflect responses of stock prices for each energy price: natural gas, oil, and coal. Moreover, the longest response period for stock prices is in an oil price shock. When energy price changes exceed the threshold value c^*, energy price shocks have delayed negative impacts on the stock market. Within the framework of the one-regime model, a significant relationship between energy price change and stock prices is few and far between. The findings speak to the fact that the two-regime model seems to offer more detailed responses. (3) As expected, interest rates initially rise, probably affected by the rise in economic activity, and then fall. However, an oil price shock or a natural gas price shock has an immediate positive response from the interest rate in regime two. (4) In the two-regime model, energy price shocks have positive response on the unemployment rate. (5) As indicated from the above results, when an energy price change is below the threshold value c^*, it is capable of explaining a significant portion of macroeconomic activities.

4.3.4 Results of the Parameter Stability Tests

It is important to note that the research periods in our study cover a somewhat volatile time of unforeseen economic events in Taiwan. The problem is that the estimated parameters in regressions may change over time and, if left undetected, have the potential to bias the results. In order to avoid this bias, we use the Pesaran and Pesaran (1997) tests for general parameter stability. They suggest applying the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMSQ) tests proposed by Brown et al. (1975) to assess the parameter constancy.

The CUSUM test is essentially a test to detect instability in the intercept alone (i.e., Kramer et al, 1988). Another test proposed from a similar motivation is the CUSUM of squares test. This test can be viewed as a test for detecting instability in the variance of the regression error. The CUSUM and CUSUMSQ tests both plot the cumulative sum together with the 5% critical lines to find parameter instability if the cumulative sum goes outside the area between the two critical lines. Assuming there are k parameters in the model, the CUSUM test is based on the statistic:

$$W_t = \sum_{r=k+1}^{t} \omega_r / s \quad \text{for} \quad t = k+1, \ldots, T, \tag{31}$$

where ω_r is the recursive residual and s is the standard error of the regression fitted to all T sample points. The significance of any departure from the zero line is assessed by reference to a pair of 5% significance lines, and the distance between which increases with t. The CUSUM of squares test is:

$$W_t = \left(\sum_{r=k+1}^{t} \omega_r^2 \right) \Big/ \left(\sum_{r=k+1}^{T} \omega_r^2 \right) \tag{32}$$

The expected value of s_t under the hypothesis of parameter constancy is

$$E(s_t) = (t-k)/(T-k),$$

which goes from zero at t=k to unity at t=T. The significance of the departure from its expected value is assessed by reference to a pair of parallel straight lines around the expected value.

Figure 4.4 plots the CUSUM and CUSUMSQ statistics when energy price is the dependent variable and energy price changes are less than or equal to c^* (regime one). The results indicate no instability in the coefficients as the plots of the CUSUM and CUSUMSQ statistics are confined within the 5% critical bounds of parameter stability. On the other hand, when energy price changes exceed the threshold value c^* (regime two), the graphical representations of the tests are plotted in Figure 4.5. Both the CUSUM and the CUSUMSQ plots are confined within the 5% critical bounds, suggesting that the residual variance is somewhat stable over time. In other words, if there is a structural break, then they will tend to drift above the bounding lines at the 5% level of significance. As shown in Figure 4.4, both tests suggest that the null hypothesis of the absence of a structural break cannot be rejected at the 5% level of significance. Thus, the models are stable over time. It appears that applying two-regime error correction models does not suffer from any problem caused by a structural break. Similar conclusions can be found from Figure 4.5.

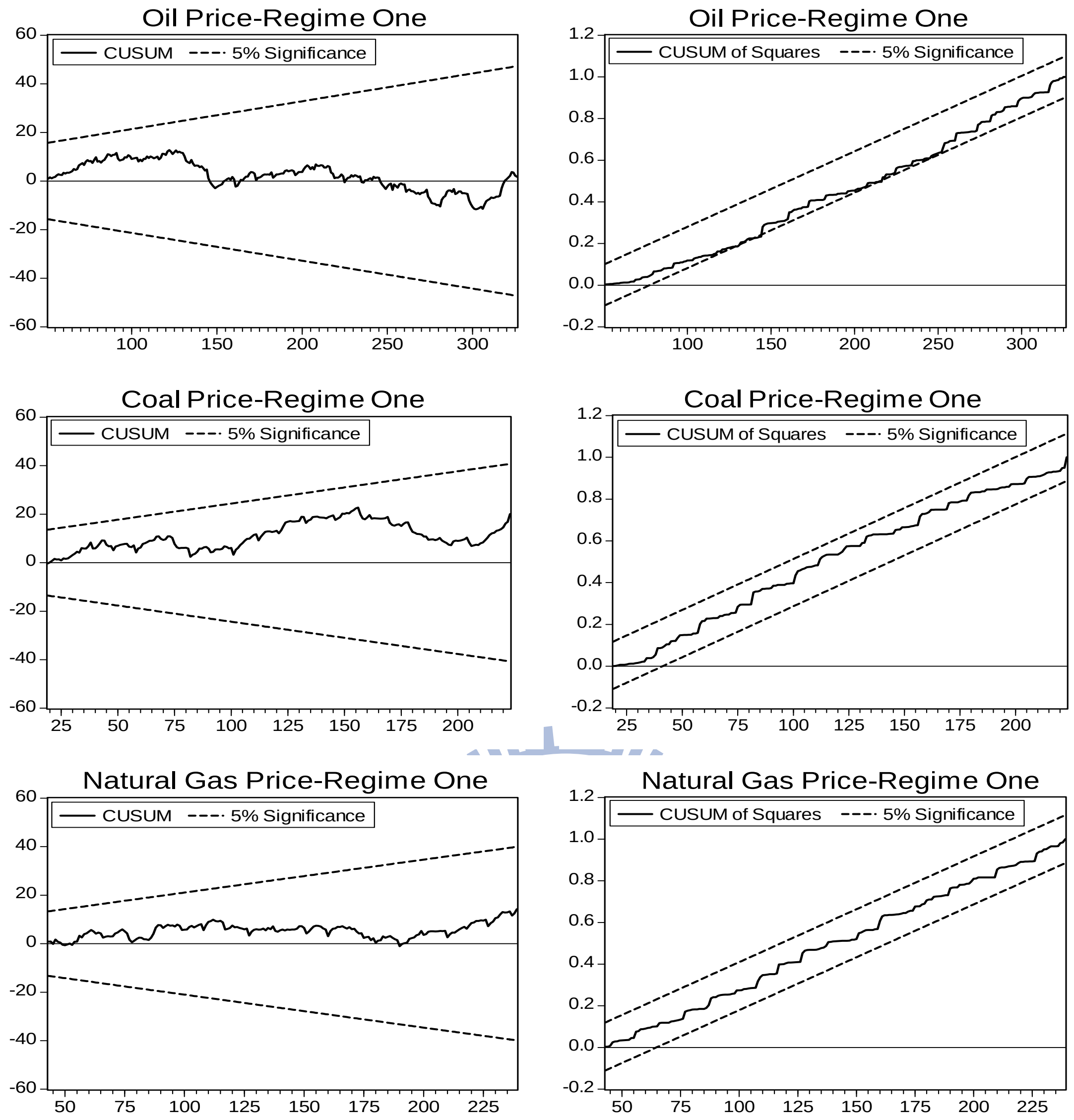

Figure 4.4 Plots of the CUSUM and CUSUM of Square Tests in Regime One

Note: Values in the vertical axis refer to the CUSUM statistic and in horizontal axis represent the time point in *t* of regime one.

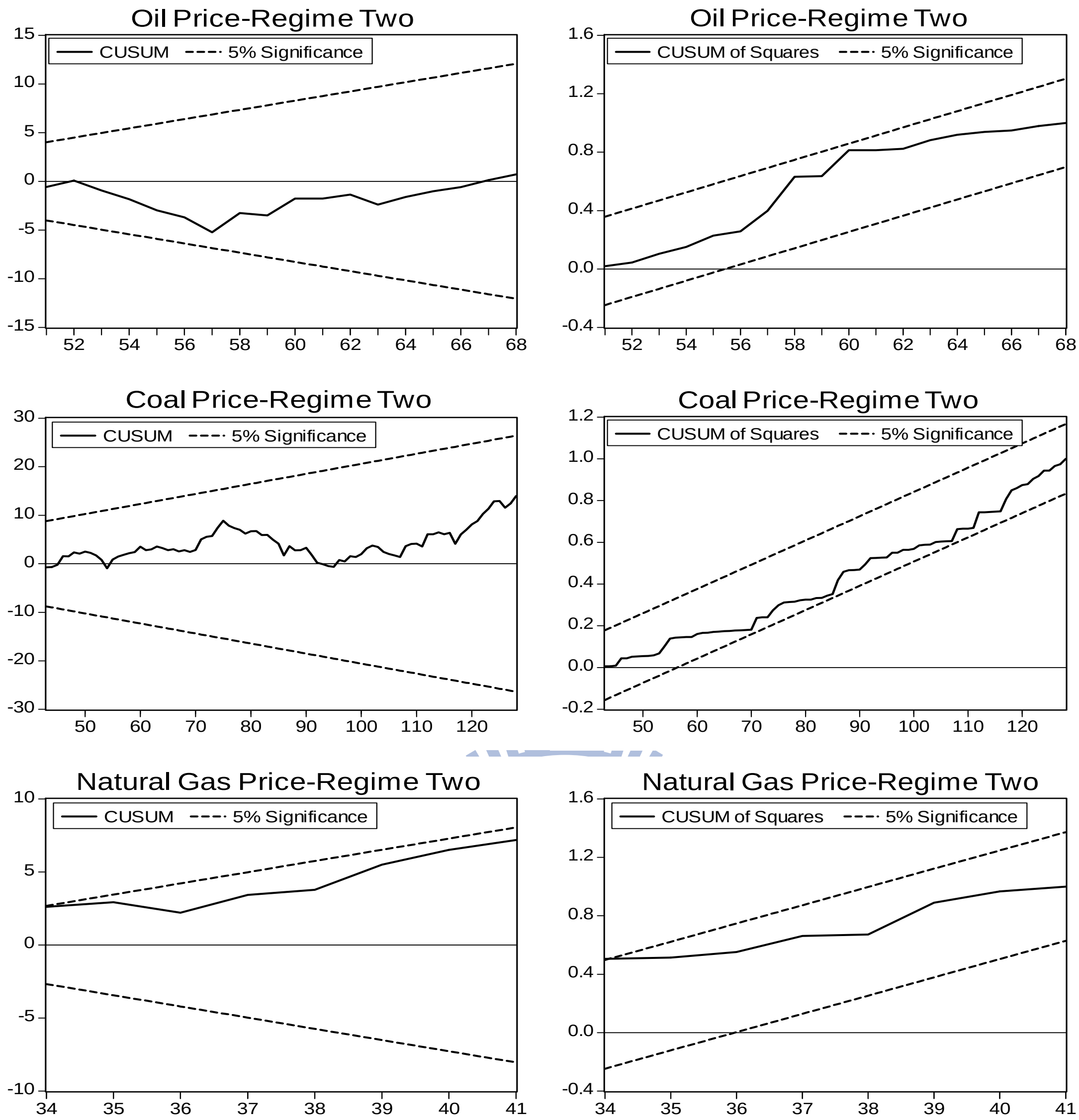

Figure 4.5 Plots of the CUSUM and CUSUM of Square Tests in Regime Two

Note: Values in the vertical axis refer to the CUSUM statistic and in horizontal axis represent the time point in *t* of regime two.

Chapter 5 Preliminary Conclusions and Policy Implications

Because of the 2006 Iraq War and the increased demand for oil from developing countries, uncertainty in Asia fueled by such tensions again and oil prices began to rise again in early 2004. As oil prices increase, we refocus attention on the issue of energy price changes and their impact on economic activities. Even though there are related studies on the use of an asymmetrical relation to examine the impact of an oil price change on the economy, they do not consider the speed of oil price adjustment before estimation and neglect the impact of oil price shocks. In addition, there is a shortage of research regarding the impact of coal price and natural gas price on macroeconomic activities in Taiwan.

To overcome the weakness of prior studies, we apply the MVTEC model proposed by Tsay (1998). The threshold value determined by the dataset delineates the sample instead of using the arbitrary zero as a cutoff point. We try to find the speed of response (delay periods *d*) and the degree of critical level (threshold value *c*) as a consequence of the impact of a positive energy price change and its shock. The next step is to find the factors affecting the speed and the critical level of the impact. Compared to the results of the non-linear model, we also use a linear model to estimate the effects of energy price shocks (including crude oil, natural gas, and coal) on Taiwan's macroeconomic activities. Furthermore, we employ the VDC and IRF to capture the effects of energy price shocks on the macroeconomy.

The main purpose of this paper explores the effects of international energy price shocks and macroeconomic activity in Taiwan. The preliminary findings are: (1) There is a threshold non-linearity relationship between energy price variables and macroeconomic variables. (2) The optimal threshold levels are 2.48% in terms of oil price change, 0.87% in terms of natural gas price change, and 0.22% in terms of coal price change. Due to Taiwan's higher economic development, the threshold of critical level is greater as evidence by the positive impact of an oil price change and its shock. The optimal threshold value seems to vary according to how an economy depends on imported energy and the attitude towards accepting energy-saving technology. (2) If a country has a higher energy import ratio and acquires a higher ratio of energy use in the industrial sector, then it will have a shorter delay in terms of its economic response from the positive impact of an energy price change. As our results show, the delays of the threshold variable are only one month and their responses are very quick. (3) Compared to the other energy prices (i.e., coal price and natural gas price), an oil price change has the largest explanatory effect on Taiwan's industrial production. Moreover, it better explains industrial production than the real interest rate when an oil price change exceeds the threshold value (regime two). (4) A coal price change significantly explains stock prices in the two-regime model compared to the one-regime model. A natural gas price change has higher explanatory power on stock prices than the interest rate when a natural gas price change is below the threshold value (regime one). In a similar vein, a natural gas price change has stronger explanatory power on the unemployment rate. (5) Energy price shocks have a negative impact on Taiwan's macroeconomic activities especially in industrial production and stock prices in regime two. Both oil price shocks and natural gas shocks have a delayed negative impact on industrial production with one lag when energy price changes exceed the threshold level. By the same token, energy price shocks have delayed negative impacts on the stock market. (6) To Taiwan's labor market, international energy price shocks have a positive effect on the unemployment rate in the short term. It means that an increase in energy prices will increase the cost of production which in turn results in higher levels of unemployment. (7) In summary, the findings speak to the fact that the two-regime model seems to offer more detailed and noticeable responses.

Based on the aforementioned findings, we observe that energy prices have significant impacts on Taiwan's macroeconomic activity. In order to reduce the impact of energy price shocks and promote sustainable development in Taiwan, we further address the trend of Taiwan's energy development and some energy strategies for domestic policy makers. The first one is to actively develop the domestic renewable (or green) industry. A niche for energy development in Taiwan is to explore renewable (or green) energy especially solar power energy. For example, Taiwan's government actively subsidizes the installation expense of photovoltaic (PV) systems and promotes the exhibition of PV products (e.g., solar cars, solar water heating systems, solar electric power systems, and so on) in recent years. With strong policy support, the installation will reach a growth rate of 30% in 2009. In addition, Taiwan ranks as the fourth largest solar cell producing country in the world and is in the stage of value inflow. This means that the domestic photovoltaic (PV) industry has a higher market to sales ratio. This evidence suggests that industrial decisions must be made to pursue a sustainable PV industry. Most producers can increase more labor and capital, in order to further reduce the domestic unemployment rate. Authorities should encourage other domestic industries to reinvest in the upstream and downstream of the PV industry.

The second one is to promote greater scale efficiency and to obtain competitive advantages for the domestic energy industry. An integrated supply chain can help manufacturers grasp market demand trends and boost market share especially for the PV industry. The highly vertically integrated supply chain helps domestic firms create a complete interaction between upstream and downstream and allows for more innovative opportunities. The sources of material control and customer retention are two key factors to keep energy industrial competitive advantages. Moreover, integrated innovation is rather noteworthy, suggesting that the condition for success is for both Taiwan and China to cooperate across the industry chain. Policy-makers should change the integration direction 'from sand to system' to 'from system to sand'.

The final one is to achieve energy technological breakthroughs. Taiwan's past innovative pattern is 'learning by doing' which borrows much production knowledge from its semiconductor production. For the domestic PV industry, it has been proven effective in gaining market power from material innovation, technical innovation, application innovation, and financial innovation. Taiwan's government has to support further concrete cooperation and technological interchange from domestic and foreign R&D centers.

Even though we have found possible factors of explaining Taiwan's macroeconomic variable fluctuations and the speed of adjustment from the impact of energy price shocks, there are still some limitations to this thesis. The potential limitations of this research are as follows:

(1) There is a host of possible exogenous factors that may affect the macroeconomic variables and the delay of the effect such as degree of openness of the economy, and fiscal and exchange rate policy (e.g., Bohi, 1991). These omitted variables may be included in future analyses to test the robustness of the result.

(2) Oil price shocks display a slight effect on Taiwan's labor market. In fact, international energy prices may affect open economies both directly and indirectly. Future research can identify the direct and indirect channels of oil price shocks on the labor market.

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