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Asymmetric impacts of international energy shocks on macroeconomic activities

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ABSTRACT

While limited by its scarcity of natural resources, the impacts of energy price changes on Taiwan's economic activities have been an important issue for social public and government authorities. This study applies the multivariate threshold model to investigate the effects of various international energy price shocks on Taiwan's macroeconomic activity. By separating energy price changes into the so-called decrease and increase regimes, we can realize different impacts of energy price changes and their shocks on economic output. The results confirm that there is an asymmetric threshold effect for the energy-output nexus. The optimal threshold levels are exactly where the oil price change is at 2.48%, the natural gas price change is at 0.66%, and the coal price change is at 0.25%. The impulse response analysis suggests that oil price and natural gas shocks have a delayed negative impact on macroeconomic activities.

1. Introduction

Energy is essential to all economic activities, pushing developed and developing economies to pursue long-term stable energy prices and energy supply. These targets are very beneficial to economic development. However, greater energy consumption may increase the possibilities of global warming and climate change. According to the International Energy Outlook of Energy Information Administration (EIA) (2010), the global consumption of marketed energy from all fuel sources will persistently rise over the projection period of 2007–2035. Fig. 1 shows fossil fuels are expected to continue supplying much of the energy used worldwide. Although conventional fuels remain the largest source of energy, the global share of marketed liquids and natural gas consumption will correspondingly fall from 35% in 2007 to 30% in 2035 and from 22% in 2007 to 21% in 2035. On the contrary, the global share of marketed coal, nuclear, and renewable consumption will rise in the same periods. In particular, the global share of renewable consumption will rise from 9% in 2007 to 13% in 2035. It can be seen that clean energy still cannot replace the conventional type of energy use. In the reference case of International Energy Outlook of EIA, the use of liquids grows modestly or declines in all end-use sectors (except for the transportation sector), where in the absence of significant technological advances liquids will continue to provide much of the energy consumed.

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 economic output. The most acute supply shocks hitting the world economies since World War II have been the sharp increase of oil and other energy products' prices. Since the 1970s, oil prices in the world market have experienced fluctuations, including rather sharp increases during the first and second oil crises. During the two periods of 1973–1974 and 1978–1979, when the Organization of Petroleum Exporting Countries (OPEC) first imposed an oil embargo and the Iranian revolution disrupted oil supplies, respectively, the prices of a barrel of oil increased from $3.4 to $30.

Fig. 2 depicts the time series of international energy prices from 1983 to 2009, showing energy prices rapidly rising from $16 to $26 after the Gulf War in 1990. Due to a decline in 1999 following the Asian financial crisis, energy prices fell from $20.28 to $11.13. Since 2000, oil prices have been on an upward trend with repeated fluctuations. In particular, oil price volatility in the crude oil market rose spectacularly during 2004–2008. By March 13, 2008, the West Texas Intermediate (WTI) spot crude oil price had spiked to a historical high of $110.21 per barrel. EIA (2009) estimated that the January 2010 WTI futures contract under volatility at that time would be $61 per barrel at the lower limit and $104 per barrel at the upper limit under a 95% confidence

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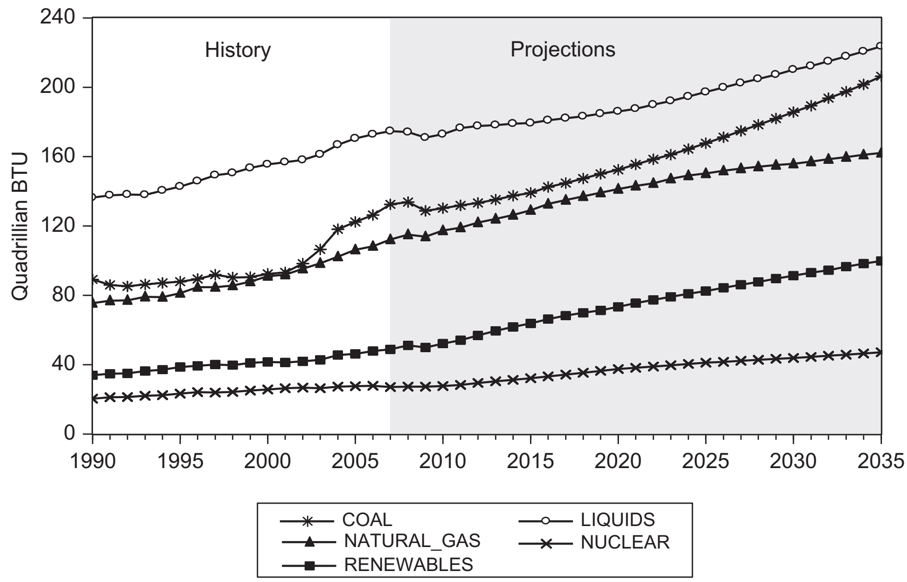

Fig. 1. Global marketed energy use by fuel type, 1990–2035.
Source: Energy Information Administration (2010).

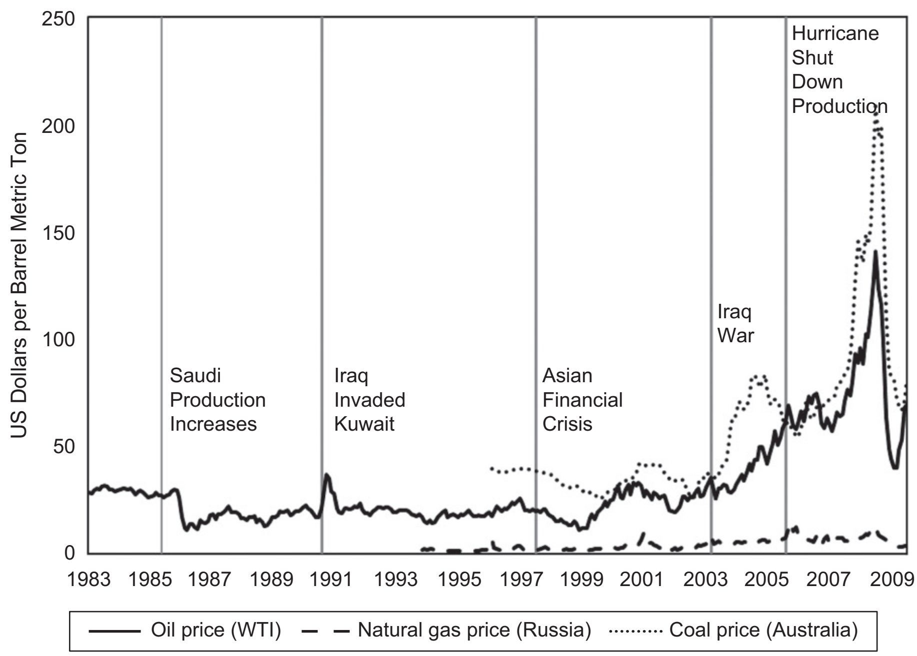

Fig. 2. Global marketed energy prices, 1983–2009.

interval. As a whole, oil prices are more volatile than prices of natural gas and coal. Although the volatility and historical event turning points of international energy prices are rather different, their long-term trends are quite similar.

As energy prices play a critical role in influencing economic growth and economic activities, we want to analyze the linkage of international energy prices and macroeconomic variables in Taiwan with linear and asymmetric frameworks. This study is motivated by two reasons. First, several studies have indicated that oil price shocks have a significantly negative impact on industrial production (e.g., Mork, 1989; Hooker, 1996; Hamilton, 1996; Bernanke et al., 1997; Hamilton, 2003; Hamilton and Herrera, 2004), yet little is known about the relationship between other energy prices and economic activities. Second, some studies already consider the asymmetric relation in terms of the impact of an oil price change or its volatility on industrial production and stock returns (e.g., Mork, 1989; Mork et al., 1994; Sadorsky, 1999; Papapetrou, 2001). However, these studies use zero as a cutoff point for distinguishing oil price changes into up (increase) and down (decrease) segments.

The aforementioned studies may encounter some problems. First, using a predetermined value as a trigger point lacks any statistical verification. Second, they neglect the asymmetric association to accurately gage varying degrees of the impacts of energy price changes on the macroeconomy. Third, the two-regime model based on the value of a variable (greater than zero or less than zero) is somewhat arbitrary. Is it true that a very small increase in energy prices changes would have a significant negative effect on economic activities? Although oil price changes certainly affect economic activities, they will also affect the production sector when the oil price increase exceeds a certain economical threshold level. Finally, each energy price change may have different threshold values. Therefore, a two-regime model based on the value of zero is arbitrary. To cautiously respond to these arguments, we need more rigorous econometric models.

On the country level, oil is of particular importance to many Asian economies as most are net importers of this energy product. Because Taiwan is in fact an island country with limited indigenous energy resources and its energy import rate reached over 99.32% at the end of 2009, it has been identified as one of six Asian economies (including Japan, Philippines, Singapore, South Korea, and Thailand) that are easily subjected to world oil price fluctuation (Aoyama and Berard, 1998). For government authorities, understanding the different impacts of energy price changes on economic output would allow applicable policies to react to these shocks.

This study applies the multivariate threshold error correction model (MVTECM) by Tsay (1998) to analyze the impacts of different international energy price changes on Taiwan's macroeconomic activities. The energy price changes are treated as the threshold variable to test whether there is an asymmetric association in the multivariate VAR model. While it has been confirmed that the VAR model has an asymmetric threshold effect in the energy price–macroeconomy relationship, it is necessary to separate the regime based on the specified threshold values of each energy price change. We further analyze different impacts of an energy price shock on industrial production under different regimes.

The rest of this paper is as follows: Section 2 gives an overview of the related literature on oil price shocks and macroeconomic activity. Section 3 illustrates data sources and the methodology. Section 4 covers the empirical analysis. Finally, Section 5 addresses some concluding remarks and policy implications.

2. Literature review

The most severe supply shocks hitting the world economies since World War II have been the sharp increases in the price of oil and other energy products. Oil price shocks receive important consideration for their presumed role on macroeconomic variables. They have been identified as affecting the natural rate of unemployment (e.g., Carruth et al., 1998; Davis and Haltiwanger, 2001), depressing irreversible investment by their effects on uncertainty (Ferderer, 1996), and reducing the role of technology shocks in the real business cycle (Davis, 1986).

From a theoretical point of view, there are different reasons why an oil shock could affect macroeconomic variables, with some of them considering a non-linear specification of the oil price–macroeconomy relationship. For example, an oil shock can lead to lower aggregate demand since the price rise reallocates income between net oil import and net oil export countries. An oil price increase will reduce aggregate supply since higher energy prices prompt firms to purchase less energy. The productivity of any given amount of capital and labor declines and potential economic output falls accordingly. If labor supply is withdrawn voluntarily as a result, then potential output will be lower than it would otherwise be, thus compounding the direct impact of lower productivity. Moreover, it may have an asymmetric effect on economic activity if it affects the sectoral reallocations of resources or depresses irreversible investment through the effects on uncertainty (Ferderer, 1996).

From an empirical point of view, many studies find that oil price shocks affect output and inflation (e.g., Hamilton, 1983, 1996; Hooker, 1996; Mork, 1989, Mork et al., 1994). These energy price shocks have been an important source of economic fluctuation over the past three decades (Kim and Loungani, 1992).

Several studies address the question of whether there is a relationship between oil price shocks and macroeconomic key variables. In a pioneer work, Hamilton (1983) uses Granger causality to examine 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.

Following Hamilton (1983), the literature for net oil importing countries yields two fundamental questions. First, is the relationship between oil prices and economic output stable over time? Burbidge and Harrison (1984), Hooker (1996), Rotemberg and Woodford (1996), and Schmidt and Zimmermann (2007) show that for several industrial countries, oil price shocks have a significant negative impact on industrial production. However, they all conclude that oil price changes have different impacts on economies over time. It seems evident that the effects of oil price movements have weakened. Blanchard and Gali (2007) investigate the current response of inflation and output in a group of industrialized economies. They conclude that the main reasons behind the weak response of economies in recent years are smaller energy intensity, a more flexible labor market, and improvements in monetary policies.

The second question is: does an asymmetric relationship exist between oil price changes and economic activity? By separating oil price changes into negative and positive groups, Mork (1989) finds that there is an asymmetric relationship between oil prices and real output. When oil prices are increasing, the increase in production cost and the decrease in resource allocation cost often offset each other. Alternatively, an oil price slump 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 macroeconomic variables. Mork et al. (1994) again confirm that an oil price shock-induced inflation reduces real balances. Sadorsky (1999) considers the relationship between oil price shocks and stock returns using a four-variable VAR model, indicating that oil price movements can explain more of the forecast error variance of stock returns than can interest rates. Beyond that, he also shows an asymmetric effect on stock returns from oil price shocks. Increases in oil prices have a significant effect on reducing stock prices, but not vice versa. There hence seems to be an asymmetric relation between oil price change (or its volatility) and economic activities.

An oil price decrease depresses demand for some sectors, while unemployed labor does not immediately shift elsewhere (Hamilton, 2003). However, oil price changes impact unemployment when such changes persist for a long time along with adjustments in employment (Keane and Prasad, 1996). Davis (1986) offers separate time trends before and after 1974 in his unemployment equations. The evidence indicates that the estimated time trend coefficients are small and often statistically insignificant with most of the upward trends in unemployment over these samples. Carruth et al. (1998) present an asymmetric relationship among unemployment, real interest rates, and oil prices, noting 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 through the structural VAR models to measure oil prices by a weighted average of real oil prices. The result finds that an oil price shock can explain 25% of the cyclical variability in employment growth from 1972 to 1988. Lardic and Mignon (2008) also show that a long-lasting oil price increase can change production structures and have an impact on unemployment.

3. Data

The research sample herein contains time series datasets for three energy prices and six macroeconomic variables. The price of

Table 1
Definitions of variables.

Variables	Definitions of variables	Sources
oil	Logarithmic transformation of the monthly real West Texas Intermediate crude oil spot price index in US dollars (in 2006 prices)	IFS (2008)
gas	Logarithmic transformation of the monthly real Russian Federation natural gas spot price index in US dollars (in 2006 prices)	IFS (2008)
coal	Logarithmic transformation of the monthly real Australia coal spot price index in US dollars (in 2006 prices)	IFS (2008)
y	Logarithmic transformation of the monthly real industrial production index in NT dollars (in 2006 prices)	TEJ
sp	Logarithmic transformation of monthly real stock prices in NT dollars (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 of NT dollars (in 2006 prices)	AREMOS

oil (oil) is proxied by the West Texas Intermediate (WTI) crude oil spot price index in the commodity prices section. The price of natural gas (gas) is proxied by the Russian Federation natural gas spot price index. The price of coal (coal) is proxied by the Australia coal spot price index. Following Sadorsky (1999), our macroeconomic variables include the industrial production index (y), 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. The real interest rate is expressed by the nominal interest rate minus the growth rate of the consumer price index (at 2006 constant prices). To test the impacts of energy price changes on the labor market, the unemployment rate is treated as a desirable proxy. All monthly variables incur a seasonal adjustment before the VAR analysis.

Since the VAR or VECM model is used to detect the asymmetric or non-linear relation, at least 200 datapoints are required for a delay of 12 periods as suggested by Hamilton and Herrera (2004). All data used in this study are monthly frequencies. The raw data are available with different time periods: oil is from July 1975 to May 2008, coal is from February 1979 to May 2008, and natural gas is from January 1985 to May 2008. 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). The 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 1 displays the descriptions of all variables.

Table 2
Results of unit root tests.[a]

	ADF		KPSS	
	Level	First differences	Level	First differences
Panel A. Oil price (1975:7–2008:5)				
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)				
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)				
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

[a] Values in the parenthesis in ADF and KPSS unit root tests are p-values provided by Mackinoon (1996) and Kwiatkowski et al. (1992), respectively.
** Indicates the parameters are significant at the 5% level.
*** Indicates the parameters are significant at the 1% level.

4. Empirical results

4.1. One-regime VAR analysis

Before formally conducting the VAR estimations, all variables need to be detected for stationarity. If all time series variables are non-stationary in levels but stationary in first-differences (i.e., integrated of order one, $I(1)$), then there could be a linear combination of these 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 deemed to be co-integrated. The stationary linear combination may be interpreted as a long-run equilibrium relationship between the variables; that is, the variables show co-movement over time.

The Augmented Dickey-Fuller (1979, ADF) and Kwiatkowski et al. (1992, KPSS) unit root tests are applied to check for the existence of the unit root. Table 2 indicates that all of the individual series in first differences are stationary at the 1% significance level. This result suggests that all variables are $I(1)$ time series. Based on the evidence of unit root tests, we then test the possibility of co-integration among the variables. We apply the maximum eigenvalue and trace statistic proposed by Johansen (1988) to test the existence of a co-integration relation for these $I(1)$ variables. The optimal lags of the VAR system for oil, coal, and natural gas specifications are determined by Bayesian Information Criterion (BIC) with 6, 3, and 4 lags, respectively. As shown in Table 3, the null hypothesis of zero co-integrating vectors is rejected by at least the 5% significance level, while the null hypothesis of at least one set of co-integrating relation cannot be rejected by both Trace and Max-eigenvalue tests. These results show strong evidence that at least one set of co-integration relation exists for three energy-type VAR specifications.

The investigation of the role of different energy prices and the dynamic properties measuring explanatory power is undertaken by performing both forecast error variance decomposition (VDC) and impulse response analysis (IRF). The VDC analysis can determine the proportion of the movements in time series that

Table 3
Results of the Johansen co-integration tests.

H_0	Eigenvalue	Trace	p-Value	Eigenvalue	Max-Eigen	p-Value
Energy price: oil price						
$r=0$	0.12	103.65***	0.00	0.12	51.55***	0.00
$r\le 1$	0.06	52.11	0.20	0.06	25.93	0.16
$r\le 2$	0.04	26.18	0.58	0.04	16.23	0.40
Energy price: coal price						
$r=0$	0.13	134.99**	0.01	0.13	46.23**	0.00
$r\le 1$	0.09	87.54	0.16	0.09	40.08	0.26
$r\le 2$	0.07	54.78	0.43	0.07	33.88	0.40
Energy price: natural gas price						
$r=0$	0.19	161.05***	0.00	0.19	57.31***	0.00
$r\le 1$	0.12	85.06	0.05	0.12	34.40	0.23
$r\le 2$	0.08	47.07	0.17	0.08	23.82	0.54

** Indicates the parameters are significant at the 5% level.
*** Indicates the parameters are significant at the 1% level.

Table 4
Variance decompositions of forecast error variance in the one-regime VAR model (12 periods forward).

	Shock sources[a]						
	ε^y	ε^{ep}	ε^{sp}	ε^r	ε^{un}	ε^{ex}	ε^{im}
Panel A. Energy price: oil price							
y	87.95	0.82	2.29	1.66	1.53	3.52	2.24
ep	1.36	91.54	2.48	0.90	0.93	1.46	1.34
sp	0.90	1.86	89.91	2.56	1.63	1.43	1.72
r	3.19	3.97	1.85	84.39	2.35	1.55	2.70
un	3.67	1.91	2.42	1.92	83.94	2.24	3.90
ex	11.38	2.14	0.75	0.77	2.57	80.48	1.91
im	12.98	2.20	2.26	0.79	1.27	28.55	51.96
Panel B. Energy price: coal price							
y	93.48	1.05	0.26	0.32	2.03	0.90	1.97
ep	0.38	95.16	1.49	0.13	0.22	0.17	2.45
sp	0.54	0.99	95.32	0.59	1.16	1.00	0.41
r	2.62	0.59	1.69	90.69	1.08	2.47	0.85
un	3.07	0.39	3.65	0.16	88.04	1.12	3.57
ex	13.35	2.01	1.16	0.98	2.48	75.19	4.82
im	15.48	1.41	0.89	1.25	1.73	21.39	57.86
Panel C. Energy price: natural gas price							
y	91.07	0.98	1.90	0.45	1.02	0.65	3.93
ep	1.56	89.70	0.93	2.42	0.90	1.11	3.38
sp	0.59	3.57	90.42	0.36	1.14	1.87	2.05
r	2.43	0.84	2.51	86.85	5.74	0.85	0.79
un	5.59	3.21	2.86	0.88	82.51	1.26	3.70
ex	16.69	3.98	0.56	2.62	2.01	62.19	11.94
im	20.83	4.04	0.85	1.48	1.97	25.68	45.16

[a] 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 price 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}).

are due to shocks in their own series as opposed to shocks in other variables. Table 4 elaborates on the proportions of impacts emanating from an energy price change in terms of VDC after 12 periods. Panel A shows that an oil price change explains 0.82% of output change, 1.86% of stock price change, 3.97% of interest rate change, 1.91% of unemployment rate change, 2.14% of export change, and 2.20% of import change. Export changes have the least explanatory power in output at 3.52% in the oil case and 0.90% in the coal case. This result conforms to the fact that Taiwan belongs to an export-oriented small open economy. We note that output change is only explained by 0.82% of oil price change, 1.05% of coal price change, and 0.98% of natural gas price change.

Although the size of impacts has been identified by computing the VDC, we cannot judge whether the causal impacts are, in fact, negative or positive, because the VDC does not show signs of the effects. The signs can be identified by computing impulse response functions. We perform IRF analysis to detect the impact of an energy price shock on Taiwan's macroeconomic activities. Fig. 3 presents that the responses of output growth, stock return, interest rate, unemployment rate, export change, and import change to energy prices over a horizon of 12 months to a positive shock in energy price change are equal to a one standard deviation (SD) innovation shock. 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, which is consistent with the findings of Hamilton (1983) and Mork (1989), who present decreases in industrial production after an oil price shock. An oil price shock also has a negative impact on stock prices, while it has a positive impact on interest rates and the unemployment rate. 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.

Similar patterns can also be found in the case of natural gas prices. It can be seen that a one-unit SD gas price shock has a lag effect on industrial production in periods 4 and 6. The unemployment rate only starts to decrease in period 1 and exhibits an upward inclination pattern in period 3. The maximum positive effects are reached in periods 4 and 7. As to the case of coal prices, industrial production initially reacts negatively and significantly to a coal price change. After 5–6 periods, the effect gradually dies out. A negative response from stock prices is observed in period 2, but the effect is quite small and not significant. As expected, the interest rate increases immediately following the coal price shock and then gradually dies out.

The one-regime VAR model may suffer the average-out problem from positive and negative changes. Each macroeconomic model has a different level of dependence on oil and as such could have significant responses when energy price changes are modest or more. Thus, we have to offer more detailed responses. Sadorsky (1999) arbitrarily categorizes the energy price change into positive and negative change regimes, but he does not provide a statistical test on the necessity of using different regimes and does not reflect different dependence levels on energy prices. To overcome this problem, we apply the multivariate threshold error correction model (MVTECM) developed by Tsay (1998) to refine more valuable information.

4.2. Two-regime VAR analysis

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

We initially consider the univariate TAR model, which also conforms to SETAR (self-exciting TAR). The SETAR(1) is formed as

$$y_t=(\phi_{0,1}+\phi_{1,1}y_{t-1}+\gamma_{2,1}D_t)(1-I[z_{t-1}>c])+(\phi_{0,2}+\phi_{1,2}y_{t-1}+\gamma_{2,2}D_t)I[z_{t-1}>c]+\varepsilon_t, \quad (1)$$

where D_t is a matrix of monthly dummies, ε_t is a white noise process, $z_{t-1}=y_{t-1}$, and c represents the threshold value. Here,

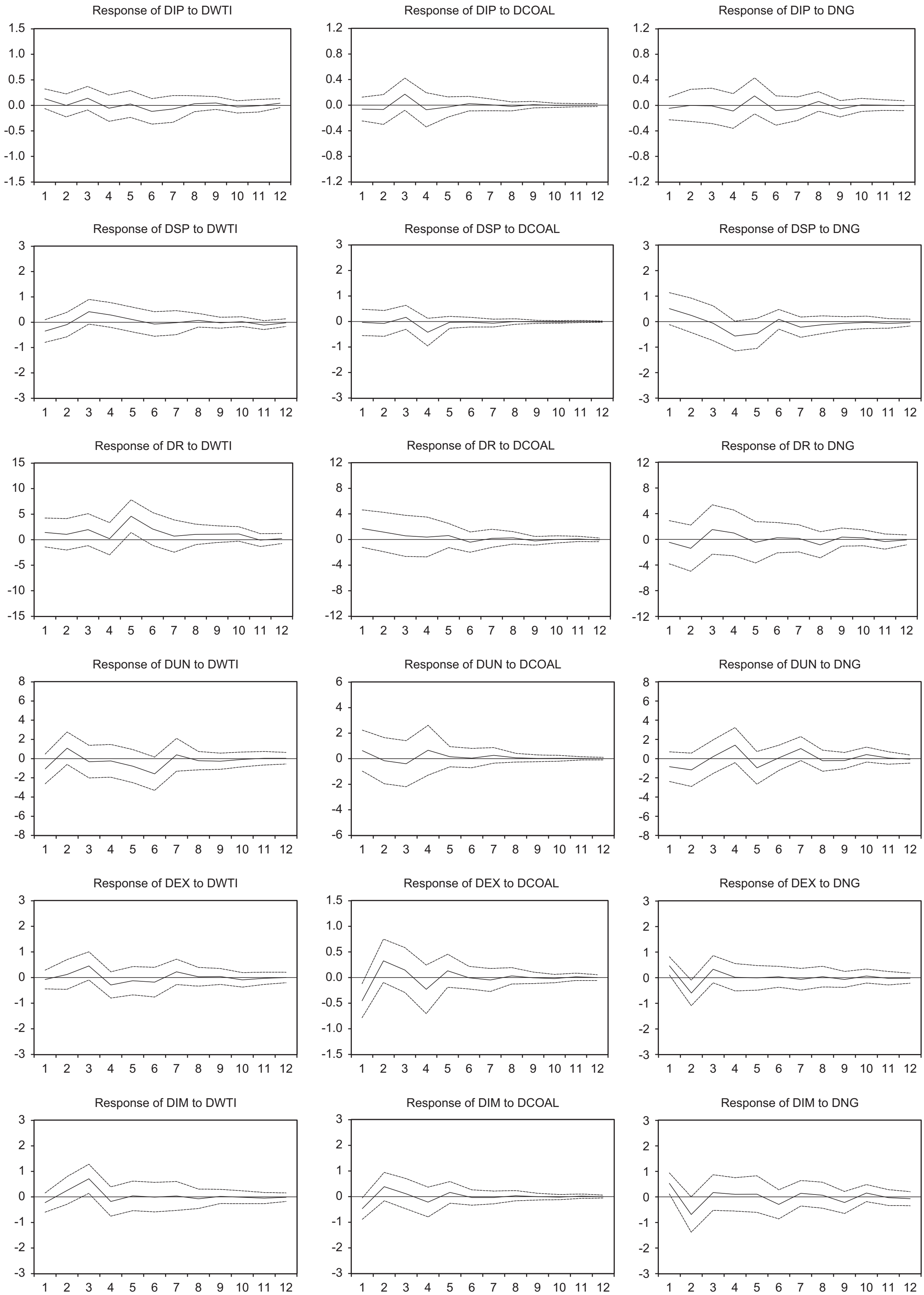

Fig. 3. Responses from one standard deviation shock of an energy price change in the one-regime VAR model (12 periods forward).

$I(\cdot)$ is an index function, which equals one if the relation in the brackets holds, and equals zero otherwise. Eq. (1) can be treated as a multivariate threshold VAR(1). We then consider a k-dimensional time series $y_t=(y_{1t},\ldots,y_{kt})'$ and assume there is a co-integration relationship among these variables, y_t follows a multivariate threshold error correction model (MVTEC) with threshold variable z_t, and delay d can be expressed as

$$y_t = \left(\alpha_1+\beta_1\theta_{t-1}+\gamma_1 d_t+\sum_{i=1}^{p}\phi_{i,1}y_{t\text{-}i}\right)(1-I[z_{t-d}>c]) + \left(\alpha_2+\beta_2\theta_{t-1}+\gamma_2 d_t+\sum_{i=1}^{p}\phi_{i,2}y_{t\text{-}i}\right)I[z_{t-d}>c]+\varepsilon_t, \quad (2)$$

where α_1 and α_2 are the constant vectors below and above the threshold value, respectively, and p and d are the lag length of y_t and the delay order of z_t, respectively. Both p and d are non-negative integers, and θ_{t-1} is an error correction term. The threshold variable is assumed to be stationary and has a continuous distribution. Model (2) has two regimes and can be regarded as a piecewise linear model in the threshold space z_{t-d}.

Given observations $\{y_t,z_t\}$, where $t=1,\ldots,n$, we have to detect the threshold non-linearity of y_t. Assuming p and d are known, and then Eq. (2) can be re-written as

$$y_t' = X_t'\Phi+\varepsilon_t', \quad t=h+1,\ldots,n, \quad (3)$$

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 Φ denotes the parameter matrix. If the null hypothesis holds, then the least squares estimates of (3) are useful. On the other hand, the estimates are biased under the alternative hypothesis.

Eq. (3) remains informative under the alternative hypothesis when rearranging the ordering of the setup. For Eq. (3), 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 $z_{(i)}$. The arranged regression based on the increasing order of the threshold variable z_{t-d} is then

$$y_{t(i)+d}' = X_{t(i)+d}'\Phi+\varepsilon_{t(i)+d}', \quad i=1,\ldots,n-h, \quad (4)$$

where $t(i)$ is the time index of $z_{(i)}$. Tsay (1998) uses the recursive least squares method to estimate (4). If y_t is linear, then the recursive least squares estimator of the arranged regression (4) is consistent, and so the predictive residuals approach white noise. Consequently, predictive residuals are uncorrelated with the regressor $X_{t(i)+d}$.

Let Φ_m be the least squares estimate of Φ in Eq. (4) with $i=1,\ldots,m$; i.e., the estimate of the arranged regression using datapoints 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. We let

$$\hat{e}_{t(m+1)+d}' = y_{t(m+1)+d}-\hat{\Phi}_{\mu}'X_{t(m+1)+d}' \quad (5)$$

and

$$\hat{\eta}_{t(m+1)+d} = \hat{e}_{t(m+1)+d}/[1+X_{t(m+1)+d}'V_m X_{t(m+1)+d}]^{1/2}, \quad (6)$$

where $V_m=[\Sigma_{i=1}^{m}X_{t(i)+d}X_{t(i)+d}']^{-1}$ is the predictive residual and the standardized predictive residual of regression (4). These quantities can be efficiently obtained by the recursive least squares algorithm.

We next consider the regression

$$\hat{\eta}_{t(l)+d} = X_{t(l)+d}'\Psi+w_{t(l)+d}', \quad l=m_0+1,\ldots,n-h, \quad (7)$$

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 (7). The $C(d)$ statistic is therefore defined as

$$C(d) = (n-p-m-kp-1)\times\{\ln|S_o|-\ln|S_1|\}, \quad (8)$$

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 (7). Under the null hypothesis that y_t is linear and some regularity conditions, $C(d)$ is asymptotically a chi-squared random variable with $k(pk+1)$ degrees of freedom.

The delay order (d) of the threshold variable reflects the speed of response based on the economic impact of a positive energy price change and its shock. The value of the threshold level reflects the tolerance of the impact. Table 5 displays the results of the $C(d)$ test in the framework of the VECM model. As shown in Table 5, we can reject the null hypothesis of the linear specification for all energy price types. The delay orders are both equal to two (i.e., $d=2$) for the case of coal price change and natural gas change while equal to one (i.e., $d=1$) for the case of oil price change. In other words, the results favor the MVTECM model. The optimal threshold levels therefore are found in terms of oil price at 2.48%, natural gas price at 0.66%, and coal price at 0.25%, respectively. The results of threshold effect testing are similar to the findings of Huang (2008), who obtains the optimal threshold level of oil price change (1.55%).

In order to delineate the response of economic activities in regime two (energy price change exceeds c^*) and regime one (energy price change is less than or equal to c^*), we employ the VDC or the IRF analysis for each regime. When the linear VAR model is divided into two regimes, the number of observations in regime one is obviously higher than in regime two. Specifically, the percentage of the sample size in regime two is 17% in the case of oil prices, 36% in the case of coal prices, and 18% in the case of natural gas prices. This evidence can be attributed to the anomaly fluctuations in energy price change that are captured.

Tables 6–8 indicate the proportions of impacts emanating from an oil price change in terms of VDC. When an energy price change is below the threshold value c^* (or regime one), it explains a significant portion of industrial production change by (i) a 6.29% oil price change and a 3.43% gas price change, and the lowest explanatory innovation are both in the interest rate change, and (ii) a 0.88% coal price change (the highest is 1.51% explained stock price change). When an energy price change exceeds the threshold level, energy price innovations significantly explain much more variance on industrial production than in the regime one. This is strikingly different from the results of the one-regime VAR model, which exhibits significant responses from stock market and macroeconomic variables when the oil price change is modest or more.

Table 5
Results of threshold effect tests.

Threshold variable	Delay (d)	$C(d)$ p_value	Threshold value (c^*) (%)[a]	Regime one ($Z_{t-d}\le$ c)	Regime two ($Z_{t-d}\ge$ c)
Oil	1	398.58 (0.01)	2.48	326	68
Coal	2	277.55 (0.00)	0.25	225	126
Natural gas	2	428.24 (0.00)	0.66	231	49

[a] c^* is the optimal threshold value determined by the location of the minimum log det$|\Sigma|$, and Σ is the variance–covariance matrix for the corresponding multivariate VECM models.

Table 6
Variance decomposition results using oil price changes as the 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 ($Z_{t-d} \leq c^{*}$)							
y	83.04	6.29	2.77	1.36	1.56	1.73	3.25
ep	2.43	91.06	2.52	0.61	1.40	0.99	0.99
sp	0.48	0.95	92.68	1.01	2.43	0.99	1.47
r	2.96	1.09	3.98	80.80	5.02	4.20	1.95
un	10.97	1.10	2.80	1.40	77.72	0.56	5.45
ex	33.89	3.13	2.23	0.24	0.93	58.55	1.02
im	25.75	3.53	4.55	0.40	3.32	24.20	38.24
Panel B. Regime two ($Z_{t-d} > c^{*}$)							
y	42.53	9.28	4.01	18.45	9.10	10.13	6.49
ep	8.34	47.27	7.16	20.32	3.28	3.53	10.09
sp	6.95	15.49	38.24	13.94	4.40	9.26	11.72
r	6.89	23.41	7.53	45.31	3.93	3.31	9.62
un	5.31	6.95	7.08	8.56	63.91	3.84	4.34
ex	2.99	14.76	13.89	7.42	6.55	39.55	14.84
im	6.57	14.44	19.93	5.17	4.42	23.24	26.24

Table 7
Variance decomposition results using coal price changes as the 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 ($Z_{t-d} \leq c^{*}$)							
y	96.22	0.88	1.51	0.41	0.05	0.65	0.29
ep	2.83	89.49	0.20	1.30	1.44	3.85	0.90
sp	0.14	0.03	97.20	0.34	0.70	0.78	0.80
r	1.19	0.91	0.88	93.65	2.51	0.56	0.32
un	1.24	0.41	1.28	0.08	93.68	2.23	1.07
ex	15.63	5.15	1.10	0.20	0.93	76.33	0.67
im	19.76	3.03	0.73	1.23	1.73	23.96	49.56
Panel B. Regime two ($Z_{t-d} > c^{*}$)							
y	92.45	1.23	0.27	3.44	1.41	0.64	0.55
ep	1.01	93.70	2.20	0.66	0.43	1.55	0.44
sp	2.18	0.17	88.39	0.52	2.94	4.68	1.12
r	3.26	2.01	0.78	92.71	0.32	0.71	0.22
un	1.49	3.38	1.29	0.60	88.14	3.52	1.58
ex	17.21	6.86	11.62	3.39	1.29	58.31	1.33
im	10.55	2.78	3.98	1.37	1.09	29.98	50.25

Table 8
Variance decomposition results using natural gas price change as the 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 ($Z_{t-d} \leq c^{*}$)							
y	85.98	3.43	1.23	0.91	1.19	1.50	5.75
ep	0.12	92.64	1.16	2.06	1.26	1.19	1.57
sp	1.91	1.51	88.15	0.69	1.22	5.05	1.47
r	1.88	1.52	3.19	86.14	5.48	1.32	0.46
un	4.47	4.59	1.68	1.13	85.93	0.70	1.50
ex	12.33	4.46	1.21	4.62	1.48	68.18	7.72
im	15.21	3.77	2.55	4.41	1.94	29.59	42.54
Panel B. Regime two ($Z_{t-d} > c^{*}$)							
y	77.51	4.17	5.40	4.74	3.79	2.65	1.73
ep	17.33	43.73	6.20	12.51	9.51	5.90	4.83
sp	6.72	10.85	36.53	30.75	8.16	3.98	3.01
r	8.81	5.09	9.05	57.93	8.11	4.46	6.54
un	4.41	9.49	7.03	10.65	57.58	1.45	9.38
ex	32.77	6.70	11.64	10.75	4.62	28.46	5.06
im	38.63	4.30	10.49	15.25	6.56	9.43	15.34

In the oil case, the largest source of shocks for output involves changes in interest rate (18.45%) and in turn 10.13% for export, 9.28% for oil price, 4.01% for stock return, 6.49% for import, and 9.10% for unemployment rate, respectively. The explanatory power of an oil price change is greater than the interest rate in regime two. 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.

In the coal price case, the explanatory power is relatively low. In both regimes, the proportions of explanatory power of gas price change on industrial output are roughly the same (0.88% vs. 1.23%). Natural gas price shocks are the principle source of industrial output's variation. Natural gas shocks contribute to output growth after one year at 4.17%, which is similar to 4.74% for interest rate shocks and 3.79% for unemployment rate shocks. The output and interest rate innovations are the main factors explaining the stock returns.

Figs. 4 and 5 show the two-regime impulse response functions from one-standard deviation shocks to industrial production (DIP), stock prices (DSP), real interest rates (DR), unemployment rates (DUN), exports (DEX), and imports (DIM). Fig. 4 presents the impulse responses of macroeconomic activities to energy price shocks in regime one. It can be seen that (i) an oil price shock has a positive impact on industrial production, yet the effect gradually dies out after 5–6 periods, (ii) coal price shocks have a delayed positive impact on industrial production and have a slight negative impact on stock prices that lasts for approximately 4 periods, and (iii) following a natural gas price shock, the unemployment rate increases by 2%. A natural gas price shock has a positive impact on interest rates and unemployment rate.

Fig. 5 indicates that coal and gas price shocks have an immediate negative impact on industrial production. An oil price shock has a slight positive impact on industrial production that lasts for approximately 8 periods. The graph presents that the responses of stock prices to shocks in coal prices and natural gas prices are positive up to the first period and eventually decline. Moreover, a coal price shock has a positive impact on the interest rate, but after 7–8 periods the effect gradually dies out. The responses of the unemployment rate to shocks in oil prices and coal prices are positive up to the first period and eventually decline.

4.3. Detecting the parameter stability

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) test for general parameter stability. They suggest applying the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMSQ) tests to assess the parameter constancy.

The CUSUM test essentially detects instability in the intercept alone (i.e., Kramer et al., 1988). Another test proposed from a similar motivation is CUSUMSQ, which 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 5% critical lines to find parameter instability if the cumulative sum goes outside the area between the two critical lines. Figs. 6 and 7, respectively, plot the CUSUM and CUSUMSQ statistics when energy price changes are less than or equal to threshold level (regime one). Both plots are confined within the 5% critical bounds, suggesting that residual variance is somewhat stable over time. Thus, the estimated MVTECM models are stable over time. It ascertains that applying two-regime error correction models does not suffer from any problem caused by a structural break.

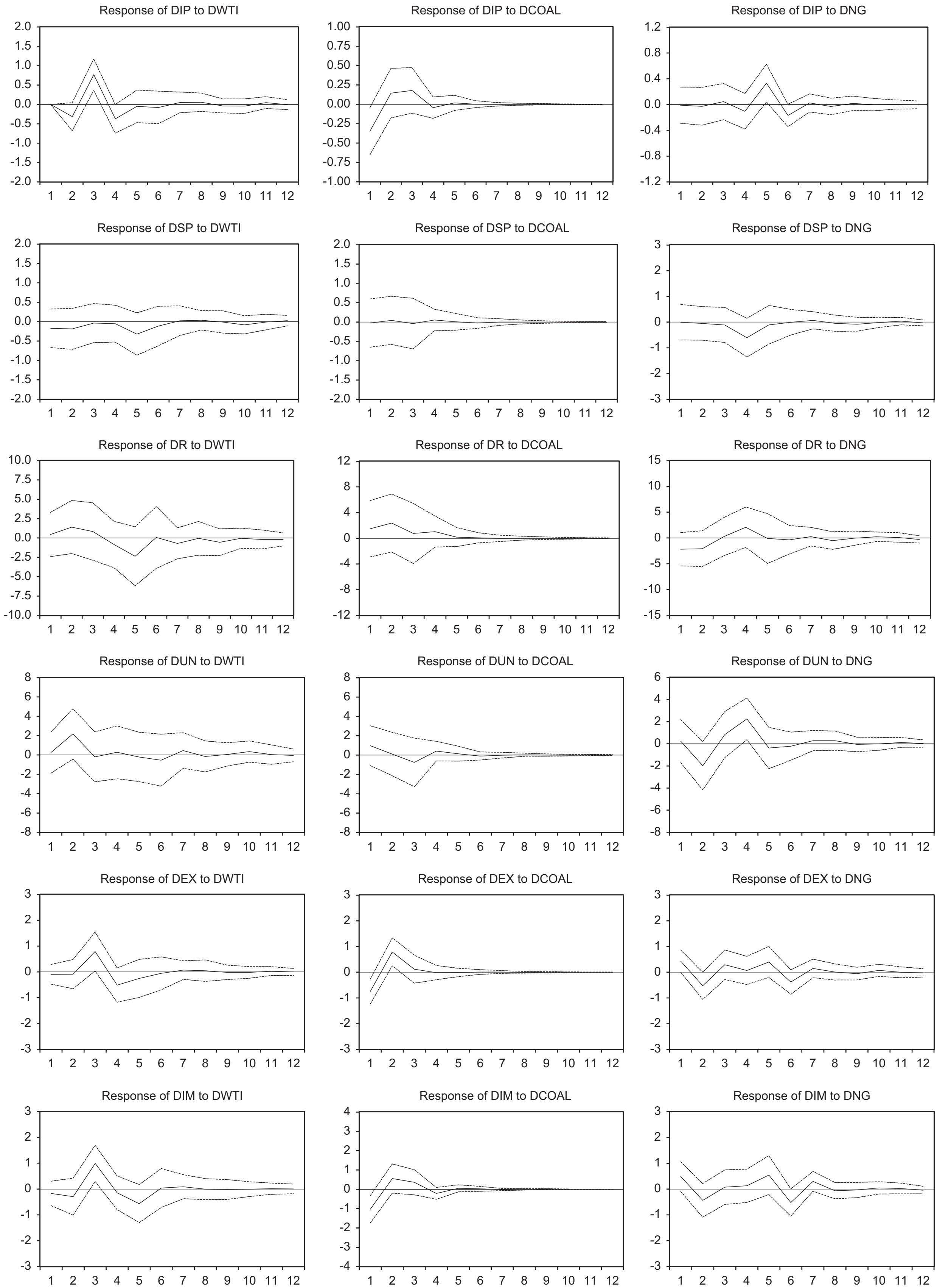

Fig. 4. Impulse responses from one standard deviation shock of an energy price change in the regime one VAR model (12 periods forward).

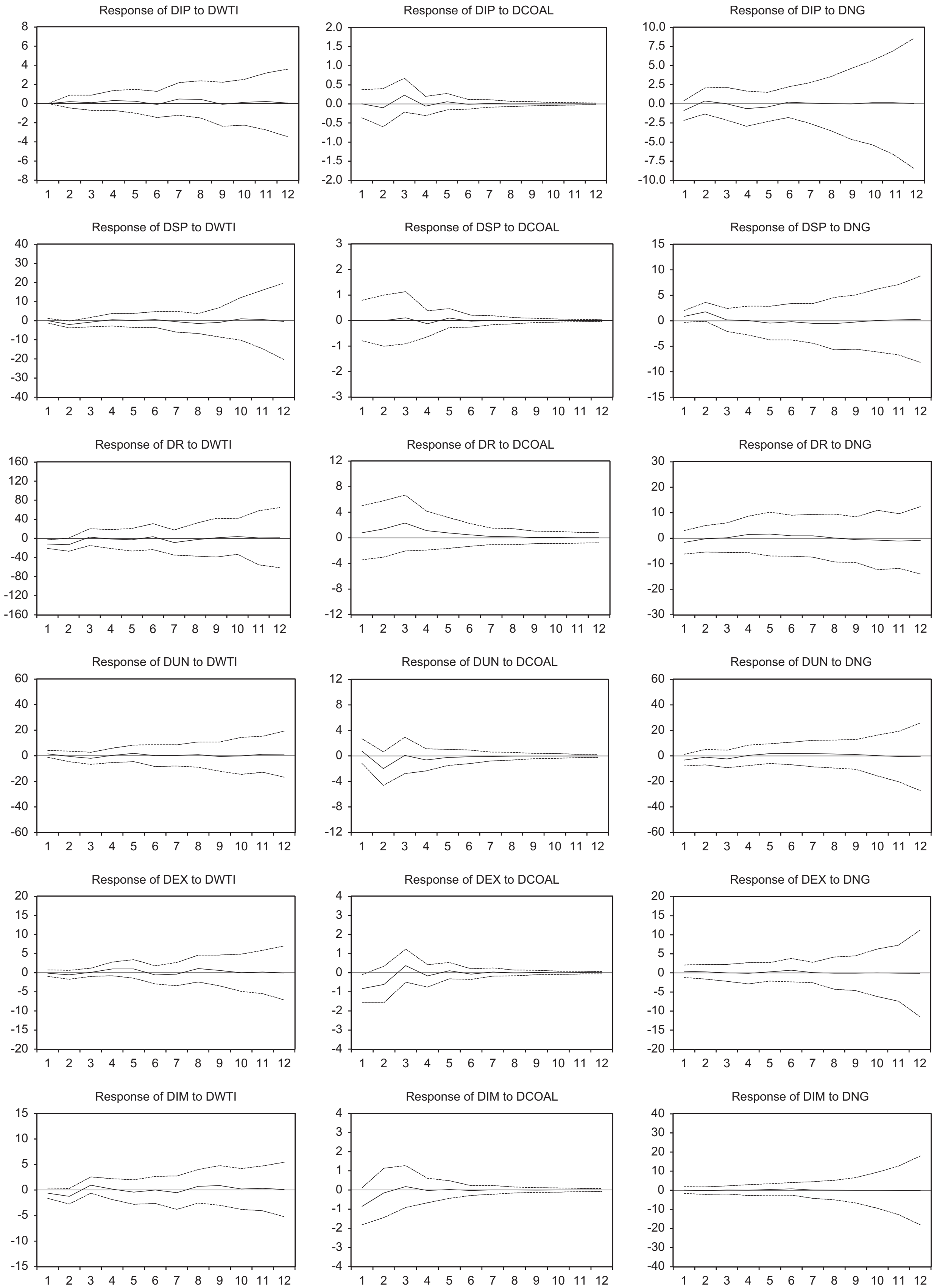

Fig. 5. Impulse responses from one standard deviation shock of an energy price change in the regime two VAR model (12 periods forward).

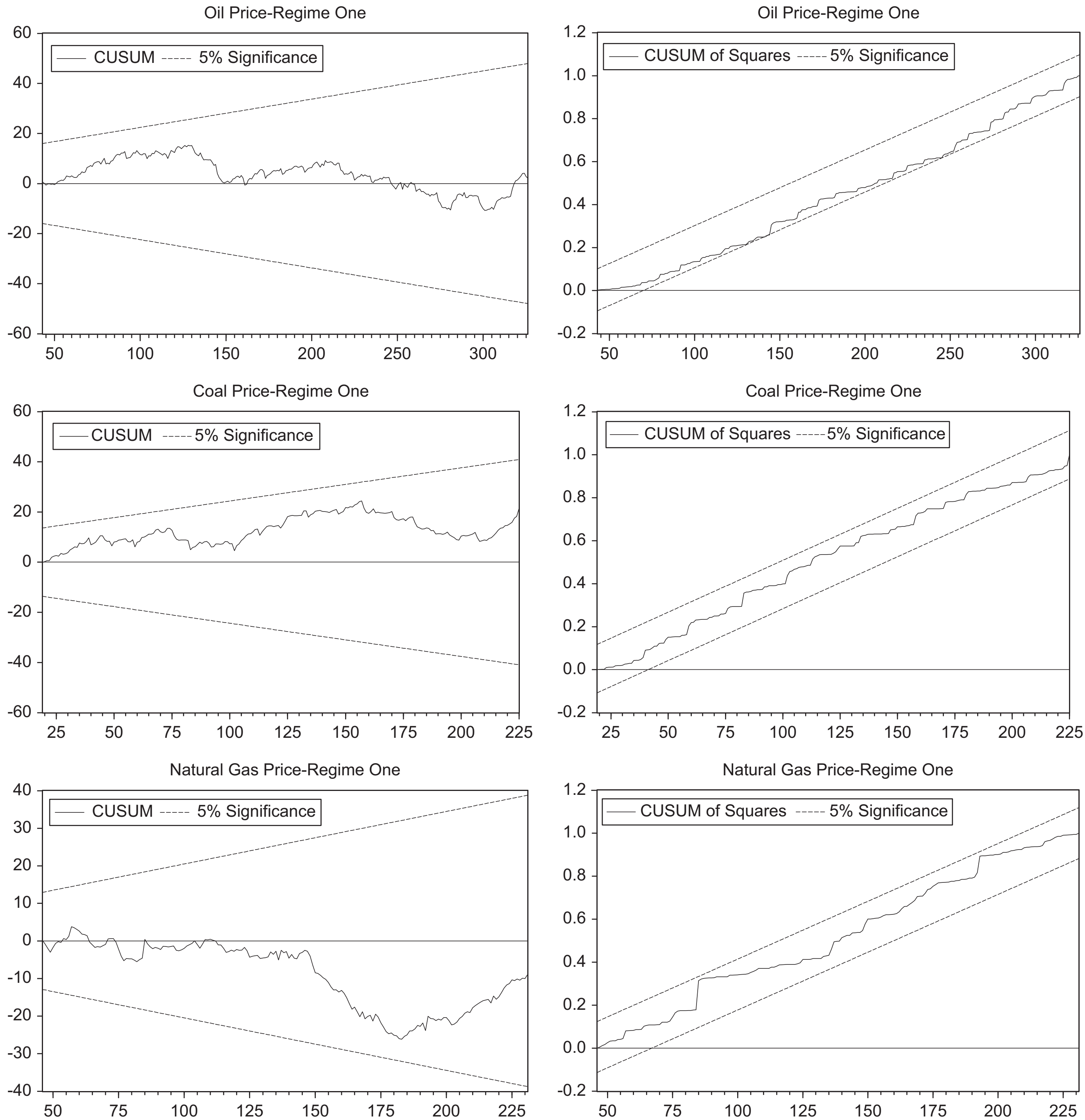

Fig. 6. Plots of the CUSUM and CUSUM of square tests in regime one.

5. Conclusions and policy implications

Following the 2003 Iraq War and from the increased oil demand from developing countries, Asian countries have been filled with tension and uncertainty after oil prices began to rise again in early 2004. As oil prices have increased, we refocus attention to the issue of energy price change and its impact on economic activities. Even though there are some related studies of the use of an asymmetric relation to examine the impact of an oil price change on an economy, research studies do not consider the speed of oil price adjustment before estimation and also neglect the impact from oil price shocks. To overcome the weakness of prior studies, we apply the multivariate threshold VAR model proposed by Tsay (1998), whereby the threshold value determined by the dataset delineates the sample instead of using the arbitrary zero as a cutoff point. We explore 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 results confirm that there exists a threshold non-linearity relationship between energy prices and macroeconomic variables. The optimal threshold levels are 2.48% in terms of oil price change,

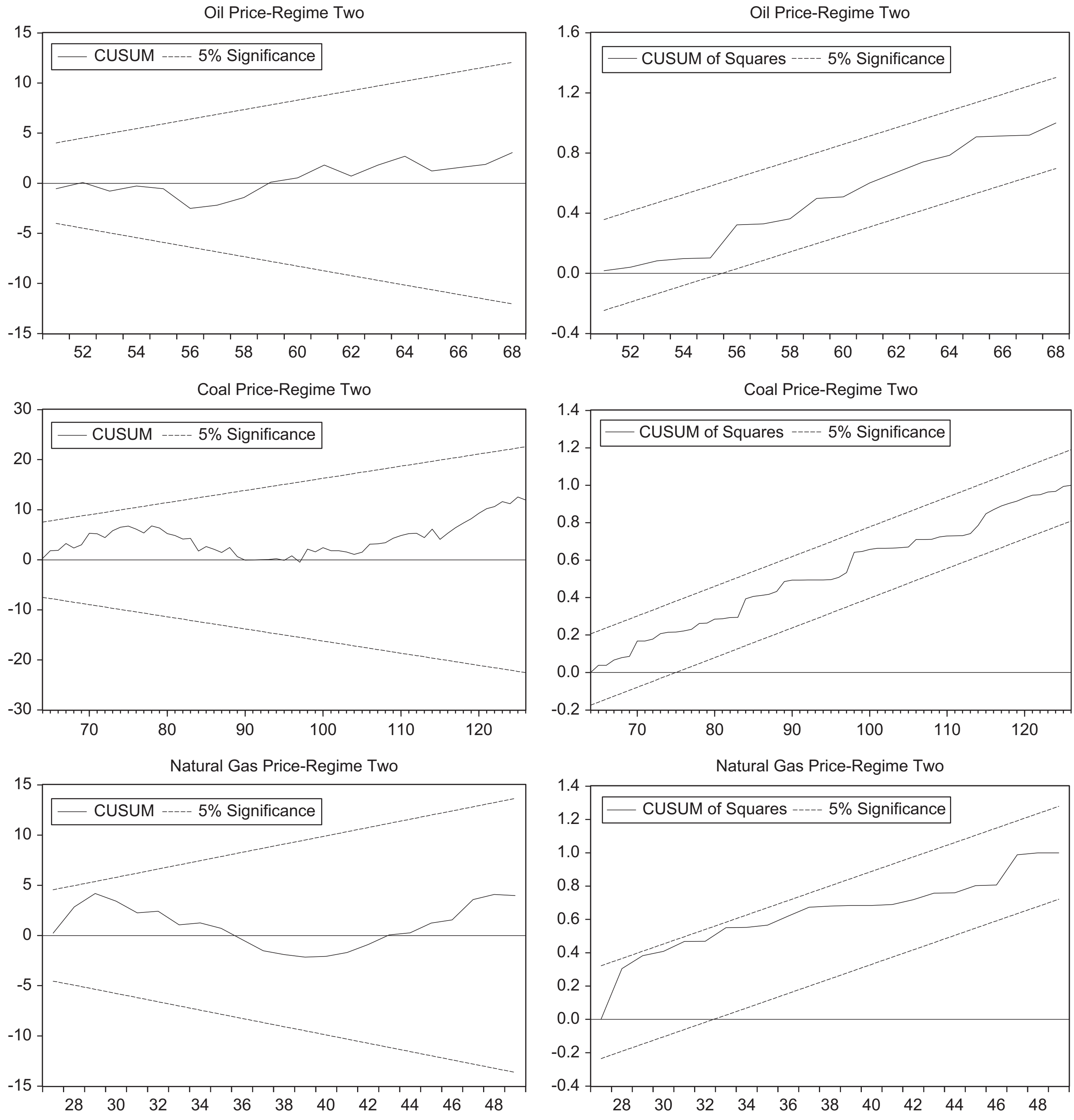

Fig. 7. Plots of the CUSUM and CUSUM of square tests in regime two.

0.66% in terms of natural gas price change, and 0.25% in terms of coal price change. Due to Taiwan's high economic development, the threshold of the critical level is greater as evidenced 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 technologies. 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 indicate, the delay from the threshold variable is only one month for an oil price change, while coal and natural gas price changes both incur two months. Compared to other energy price changes (i.e., coal price and natural gas price), oil price changes have the largest explanatory effect on Taiwan's industrial production. Moreover, such changes better explain industrial production than the real interest rate when oil price changes exceed the threshold value (regime two). For Taiwan's labor market, international energy price shocks have a positive effect on the unemployment rate in the short term, implying that an increase in energy prices will increase the cost of production which in turn results in a higher level of unemployment.

Policy implications derived from this study need to be clarified. In order to design an applicable energy price policy, we need to consider the asymmetric relationships between energy prices and the macroeconomy. In particular, we have to capture a degree of economic tolerance zone that protects the economy from the impact of an international price change and its shock. It is evident that oil prices have the largest threshold level of economic tolerance among the major international energy prices for Taiwan. By inspecting the pattern of energy consumption in the industrial sector, we can explain this phenomenon. In the energy balance sheet published by the Bureau of Energy, the overall proportion of coal consumption in the industrial sector is 0.88, while the overall ratio is 0.74 for imported liquid natural gas, and 0.53 for crude oil and petroleum products. Higher coal and natural gas prices will directly increase production and operating costs. Therefore, firms are more sensitive to the energy price fluctuations. They merely are able to prevent minor price increases from harming their economic benefits. Based on our evidence, when an international energy price change exceeds an estimated optimal threshold level, energy price shocks will have a significant effect on industrial production. To cope with the situation, government authorities should adopt tariff reductions, subsidies, and adjust domestic energy prices at different times. These measures may reduce any impacts directly from international energy price fluctuations.

Even though we have found possible factors to explain Taiwan's macroeconomic fluctuations and the speed of adjustment from the impact of energy price shocks, there are still some limitations to this research, including a host of possible exogenous factors that may affect macroeconomic variables and delay of the effect such as the degree of openness of the economy and fiscal and exchange rate policies (e.g., Bohi, 1991). These omitted variables may be included in future analyses for testing the robustness of the result. In addition, international energy price changes may impact open economies both directly and indirectly. Future research studies can identify these direct and indirect channels of oil price shocks on the labor market.

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