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Does oil price uncertainty transmit to the Thai stock market?

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Abstract: This study investigates the impact of oil price volatility (uncertainty) on the Stock Exchange of Thailand. Monthly data from May 1987 to December 2013 are applied to the two-stage procedure. In the first step, a bivariate generalized autoregressive conditional heteroskedastic (GARCH) model is estimated to obtain the volatility series of stock market index and oil price. In the second step, the pairwise Granger causality tests are performed to determine the direction of volatility transmission between oil to stock markets. It this found that movement in real oil price does not adversely affect real stock market return, but stock price volatility does affect real stock return. In addition, there exists a positive one-directional volatility transmission running from oil to stock market. These findings give important implications for risk management and policy measures.

Keywords: Real stock price, real oil price, volatility transmission, emerging markets.
JEL classification: C22, G15, Q40

1. Introduction

Theoretically, real oil price shocks rather than nominal oil price shocks should affect decisions by economic agents in an economy. However, movements in real oil price are caused by both nominal oil price and the price level. If nominal oil price and the price level move together in the same direction, the effect of real and nominal oil prices on macroeconomic variables should be the same. Otherwise, real stock price should be the determinant of economic decision. The effect of oil price shocks on macroeconomic variables has been widely examined.

Recently, the focus is on the response of real stock prices to crude oil price. Jones and Gautam (1996) investigate the relationship between oil and stock markets. They find that the reaction of stock prices in the United States and Canada to oil price shocks depends on the impact of the shocks on real cash flows. However, oil price shocks cause larger changes in stock prices than subsequent changes in real cash flows in the United Kingdom and Japan. Their results are based on the standard cash flows/dividend valuation model. Using monthly data, Sadorsdy (1999) finds the evidence showing that oil price volatility affects real stock returns in the United States. Ciner (2001) investigates the relationship between oil prices and the stock market in the United States using daily data and find the evidence that oil shocks affect stock index returns. In addition, the linkage between oil and stock markets is stronger in the 1990s. Papapetrou (2001) uses a multivariate vector-autoregression to examine the dynamic relationship among oil prices, interest rates, real economic activity and employment in Greece. One of the main findings is that oil price significantly explains stock price movements. Basher and Sadorsky (2006) employ a multi-factor model to examine the impact of oil price changes on a large set of emerging stock market returns. The find strong evidence that oil price risk affects stock returns in those economies. Using monthly data, Park and Ratti (2008) examine the impact of oil price shocks on stock markets in the United States and 13 European countries. They find that an increase in real oil price shocks has a significant impact on real stock returns within the following month. The increased volatility of oil prices depresses real stock returns in many European countries, but not in the United States. For Norway, an oil-exporting country, there exists a positive response of real stock return to real oil price shocks. Furthermore, the asymmetric effect of oil price shocks on real stock returns is found in the United States and Norway. Cong et al. (2008) find that oil price shocks do not affect real stock returns of most Chinese stock market indexes, except for the indexes of manufacturing and oil companies. Apergis and Miller (2009) investigate the impact of oil price changes on stock market returns in the United States, Japan, Canada, and other five European countries under the vector autoregressive framework. They find that stock market returns do not respond in a large way to oil market shocks. Narayan and Narayan (2010) use daily data for the period 2000-2008 to investigate the impact of oil prices on Vietnam's stock prices. They find a positive and significant impact of oil prices on stock prices.

Some studies emphasize the mechanism of return and volatility transmission between oil and stock markets and their sector indices. Malik and Ewing (2009) use weekly data during 1992 to 2008 to examine volatility transmission between oil prices and equity sector returns. They employ bivariate GARCH models to estimate the mean and conditional variance simultaneously and find the existence of significant transmission of the United States sector index returns and volatility of oil prices. Arouri et al. (2011) employ a generalized vector autoregressive-generalized autoregressive conditional heteroskedastic (VAR-GARCH) approach to examine volatility transmission between oil and stock markets in Europe and the United States at sector level using weekly data. Their results show that there is a widespread direct spillover of volatility between oil and stock sector returns. Furthermore, the volatility cross effects run only from oil to stock sectors in Europe while bilateral spillover effects are observed in the United States. Masih et al. (2011) find a negative impact of oil price volatility on real stock return in South Korea. Jouini (2013) employs the VAR-GARCH procedure to investigate the link between world oil price and stock sectors in Saudi Arabia using weekly data during 2007 to 2011. The results show the existence of return and volatility transmission between oil price and stock sectors.

In an empirical model, some researchers include oil price variable as one of various determinants of stock market index. However, cointegration tests in a bivariate framework often fail to find a long-run equilibrium relationship between crude oil prices and stock prices in emerging stock markets. This might be because of omitted variables in the regression. One estimation method that can capture the link between crude oil and stock markets is the model of volatility spillovers. The present study attempts to find the linkages between world crude oil and domestic stock markets. The monthly data covering the period from May 1987 to December 2013 are used. The main findings are: (i) movement in real oil price does not adversely affect real stock market return, (ii) stock price volatility does affect real stock return, and (iii) there exists a positive one-directional volatility transmission running from oil to stock market. The rest of this paper is as the following. Section 2 describes the data and econometric methodology. Section 3 present empirical results, and the last section gives concluding remarks.

2. Data and econometric methodology

2.1 Data

Monthly data of stock market index, consumer price index, the dollar exchange rate, and crude oil price are used in this study. The stock market index series is obtained from the Stock Exchange of Thailand website while consumer price index and the dollar exchange rate series are obtained from the Bank of Thailand. The Brent crude oil price series expressed in dollar per barrel is obtained from Energy Information Administration. The data set covers the period from May 1987 to December 2013[1] with 320 observations.[2] Real stock price index is calculated by deflating nominal index by consumer price index. Real oil price is calculated by multiplying crude oil price by the dollar exchange rate and deflating by consumer price index. Real stock market return (r^{SP}) and real oil price change (r^{OP}) are the percentage rates of change of real stock market index and real crude oil price. The plots of two time series data are shown in Figure 1 (a and b). Both of them fluctuate regularly with the spike in the early 1990s for real oil price series resulting from 1991 Gulf War. These figures (1a and 1b) could exhibit multiple structural breaks. However, the series are stationary as reported in Table 1.

The unit root tests using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for real stock market return(r^{SP}) and change in real oil price (r^{OP}).

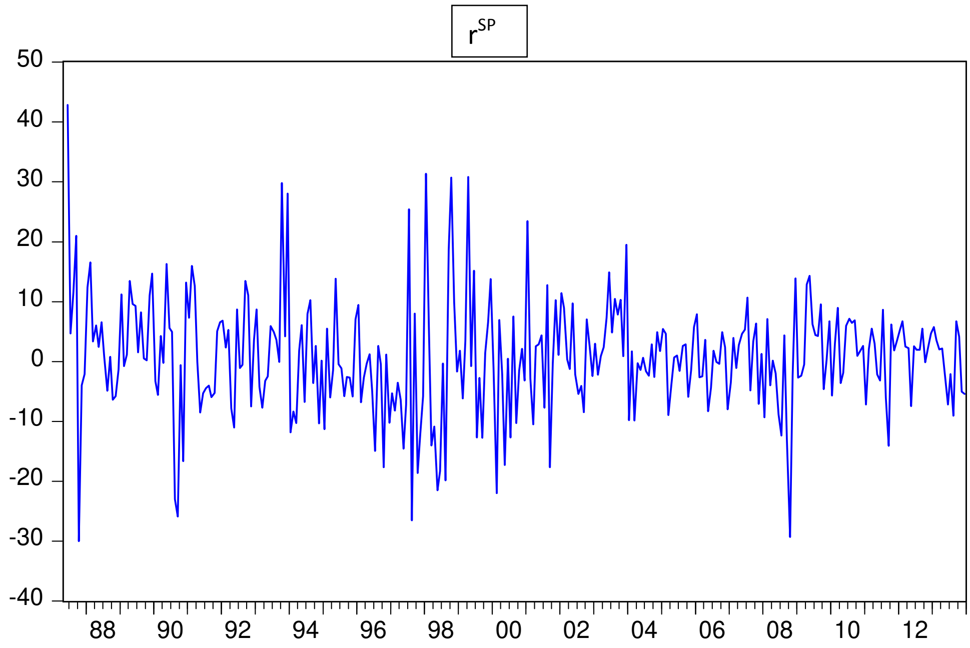
Table 1 Unit root test results

	ADF test with constant	ADF test with trend and constant	PP test with constant	PP test with trend and constant
r^{SP}	-16.822 [0] (0.000)***	-16.795 [0] (0.000)***	-16.825 [11] (0.000)***	-10.643 [11] (0.000)***
r^{OP}	-6.266 [12] (0.000)***	-6.270 [12] (0.000)***	-13.434 [16] (0.000)***	-13.430 [16] (0.000)***

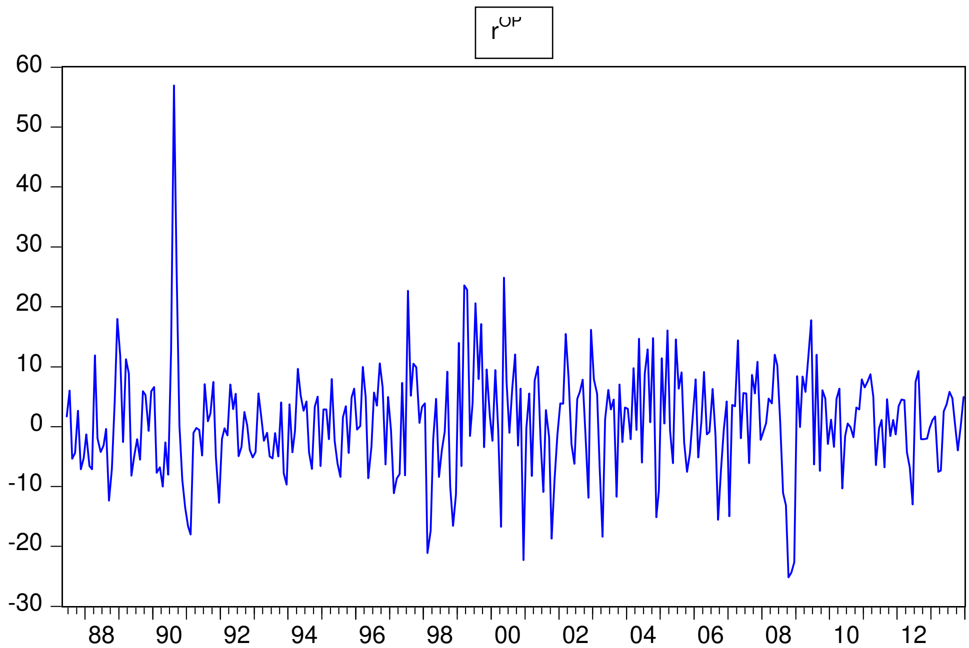
Note: r^{SP} stands for the percentage change in real stock market index (real stock market return), and r^{OP} stands for the percentage in real oil price. The number is bracket is the optimal lags chosen by Akaike information criterion (AIC) for ADF tests and is the optimal bandwidths chosen by Newey-West using Bartlett kernel for PP test. The number in parenthesis is the probability of accepting the null of unit root. *** indicates significance at the 1 percent level.

[1] The period is limited by the availability of crude oil price.

[2] In fact, the size and significance of parameters in the conditional variance depend on the data frequency being used. Monthly data set allows for a longer time span and can capture the long-run impact of volatility on other variables.



a. Real stock market return



b. Change in real oil price

Figure 1. Real stock market return and change in real oil price

The stationarity property of the two series enables one to perform the estimation of a bivariate GARCH model.

Summary statistics of real oil movement and real stock return series are reported in Table 2. The average monthly stock return is 0727 whereas the average monthly oil price rate of change is 0.728. The Jarque-Bera normality test rejects the null of a normal distribution of both series, indicating that least squares estimation is not suitable.

Table 2 Summary statistics

	r^{SP}	r^{OP}
Mean	0.727	0.728
Standard devidation	9.524	8.963
Skewness	0.273	0.654
Kurtosis	5.351	7.745
Jaque-Bera Statistic	77.152 (0.000)	321.973 (0.000)

Note: r^{SP} stands for the percentage change in real stock market index (real stock market return), and r^{OP} stands for the percentage in real oil price. The number in parenthesis is the probability of accepting the null of normality.

2.2 Econometric methodology

The two-step approach is employed to explain the relationship between oil price volatility and the Thai stock market. In the first step, a bivariate generalized autoregressive heteroskedastic model with constant conditional correlation (ccc-GARCH model proposed by Bollerslev (1990) is employed to generate stock and oil price volatilities. In the second step, these generated series along with real stock market return and the rate of change in oil price series employed in the standard Granger (1969) causality test. Pagan (1984) criticizes this procedure because it produces the generated series of volatility or uncertainty. When these generated series are used as regressors in Granger causality test, the model might be misspecified. However, the full information maximum likelihood method that simultaneously tests the impact of volatility in the mean equation can give the same results (see Oteng-Abayie and Doe, 2013). Furthermore, the main advantage of the two-step procedure is that it provides room for the ability to establish causality between variables. The system equations in a ccc-GARCH(1,1) model comprises the following five equations.

$$r_t^{SP} = a_{1,0} + \sum_{i=1}^{p} a_{1,i} r_{t-i}^{SP} + \sum_{i=1}^{p} b_{1,i} r_{t-i}^{OP} + e_{1,t} \quad (1)$$

$$h_t^{SP} = \mu_1 + \alpha_{1,1}\varepsilon_{t-1}^{SP} + \beta_{1,1} h_{t-1}^{SP} \quad (2)$$

$$r_t^{OP} = a_{2,0} + \sum_{i=1}^{p} a_{1,i} r_{t-i}^{OP} + e_{2,t} \quad (3)$$

$$h_t^{OP} = \mu_2 + \alpha_{2,1}\varepsilon_{t-1}^{OP} + \beta_{2,1} h_{t-1}^{OP} \quad (4)$$

$$h_t^{SP,OP} = \rho_{12}(h_t^{SP})^{1/2}(h_t^{OP})^{1/2} \quad (5)$$

where r^{SP} is the real stock market return, and r^{OP} is the movement in real oil price (the rate of change), h^{SP} is the conditional variance of real stock market return, h^{OP} is the conditional variance of real oil price change, and $h^{SP,OP}$ is the conditional covariance of the two variables. The constant conditional correlation is ρ_{12}. The system equations can be estimated simultaneously.

The pairwise Granger causality test is performed in the following equation.

$$y_t = a + \sum_{i=1}^{k} \alpha_i y_{t-i} + \sum_{i=1}^{k} \beta_i x_{1,t-i} + \sum_{i=1}^{k} \gamma_i x_{2,t-i} + \sum_{i=1}^{k} \phi_i x_{3,t-i} + u_t \qquad (6)$$

where y is a dependent variable, and x_1, x_2, and x_3 are independent variables. If any independent variable causes the dependent variable, there should be at least one significant coefficient of that lagged independent variable. This also indicate that the F-statistic in the standard causality test must show significance for each pair of variables. In the present study, the sequence of variables that will enter into a vector autoregression is $\{r^{SP}, r^{OP}, h^{SP}, h^{OP}\}$, $\{r^{OP}, r^{SP}, h^{SP}, h^{OP}\}$, $\{h^{SP}, r^{SP}, r^{OP}, h^{OP}\}$, and $\{h^{OP}, r^{SP}, r^{OP}, h^{SP}\}$. The optimal lag length is determined by AIC. It should be noted that all variables in the test must be stationary. An unrestricted vector autoregressive (VAR) model is used to detect the sign of lagged variables.

3. Empirical results

3.1 Results from the bivariate GARCH estimation

The bivariate GARCH estimation for the system equations (1) to (5) to obtain the volatilily series are reported in Table 3.

Table 3 Results from the estimates of a bivariate AR(p)-cccGARCH(1,1) model
Panel A: Real stock return equation
Conditional mean equation: $r^{SP}_t = 0.893 + 0.085\, r^{SP}_{t-1} - 0.065\, r^{OP}_{t-1}$ (1.747)* (1.403) (-1.273) Conditional variance equation: $h^{SP}_t = 4.433 + 0.128\, \varepsilon^{SP}_{t-1} + 0.186\, h^{SP}_{t-1}$ (2.125)**(3.702)*** (17.279)*** (t-statistic in parenthesis)
Panel B: Equation of oil price change
Conditional mean equation: $r^{OP}_t = 0.265 + 0.208\, r^{OP}_{t-1}$ (0.621) (3.105)*** Conditional variance equation: $h^{OP}_t = 7.583 + 0.128\, \varepsilon^{OP}_{t-1} + 0.186\, h^{OP}_{t-1}$ (0.099) (4.799)*** (9.282)*** (t-statistic in parenthesis)
Panel C: Conditional covariance equation
$h^{SP,OP}_t = -0.062(h^{SP}_t)^{1/2}(h^{OP}_t)^{1/2}$ (-1.033) (t-statistic in parenthesis)
Panel D: System diagnostic test using residual Portmanteau tests for autocorrelation
$Q(8) = 34.242$ (0.361) (p-value in parenthesis)

Note: r^{SP} stands for the percentage change in real stock market index (real stock market return), r^{OP} stands for the percentage in real oil price, h^{SP} stands for stock return volatility, and h^{OP} stands for oil price volatility. ***, **, and * denote significance at the 1, 5, and 10 percent, respectively.

The assumption of constant conditional correlation facilitates the simplicity of the system estimation. The mean equation for real stock market return is assumed to be dependent on the lag of real oil price change while the mean equation for real oil price change is assumed to be independent of the lag of real stock market return.[3] The lags are chosen so that the system equations are free of serial correlation. Panels A and B contain the results of the conditional means and variances for stock market return and oil price change, respectively. Referring to Panel A, stock market return is not affected by oil price change. In Panel B, Oil price change is affected by its one-period lag. The coefficients in the two conditional variance equations are non-negative. Both conditional variance equations give significant ARCH and GARCH terms (α and β). The sum of the coefficients of the ARCH and GARCH terms for real stock return is 0.998 whereas the sum of coefficients for real oil price change is 0.939. These results show that the GARCH variance series as measures of volatility or uncertainty is stationary. The constant conditional correlation in Panel C is -0.062, which is low and not statistically significant. The system diagnostic test using residual portmanteau test for autocorrelation accepts the null of no autocorrelation as indicated by Q(8) statistic. Therefore, the system equations are free of serial correlation. The volatility series are generated so as to examine their impacts on stock market return and volatility in the standard Granger causality test.

3.2 Granger causality results

The results of the pairwise Granger causality test are reported in Table 4.

Table 4 Pairwise Granger causality test results

Hypothesis	F-statistic	p-value
r^{OP} does not cause r^{SP}	0.913 (-)	0.435
h^{SP} does not cause r^{SP}	2.392*(-)	0.069
r^{SP} does not cause h^{SP}	0.988 (+)	0.399
h^{OP} does not cause r^{SP}	1.991 (+)	0.115
r^{OP} does not cause h^{SP}	4.126***(+)	0.007
h^{OP} does not cause h^{SP}	4.792***(+)	0.003

Note: r^{SP} stands for the percentage change in real stock market index (real stock market return), r^{OP} stands for the percentage in real oil price, h^{SP} stands for stock return volatility, and h^{OP} stands for oil price volatility. The optimal lags of 3 are determined by AIC. ***, **, and * denote significance at the 1, 5, and 10 percent, respectively. The sign + and – in parenthesis indicate positive and negative causality.

The results show some important findings. First, an increase in real oil price seems to cause real stock market return to fall, but this result is not statistically significant. Therefore, there

[3] The country is an oil-importing country. Therefore, its stock market cannot affect world oil price.

is no evidence that real oil price change can cause a decline in real stock market return. Second, stock price volatility negatively affects real stock market return, i.e., an increase in oil price volatility causes stock market return to increase, and vice versa. Third, stock market return does not affect stock price volatility. Fourth, real oil price volatility does not affect real stock market return, but it affects real stock price volatility. An increase in oil price volatility causes an increase in stock price volatility and vice versa. This is an evidence of volatility spillover in one direction. Finally, a movement in real oil price causes stock price volatility to increase.

3.3 Impulse responses

The estimate from VAR with the optimal lags of 3 gives the impulse responses of variables as shown in Figure 2.

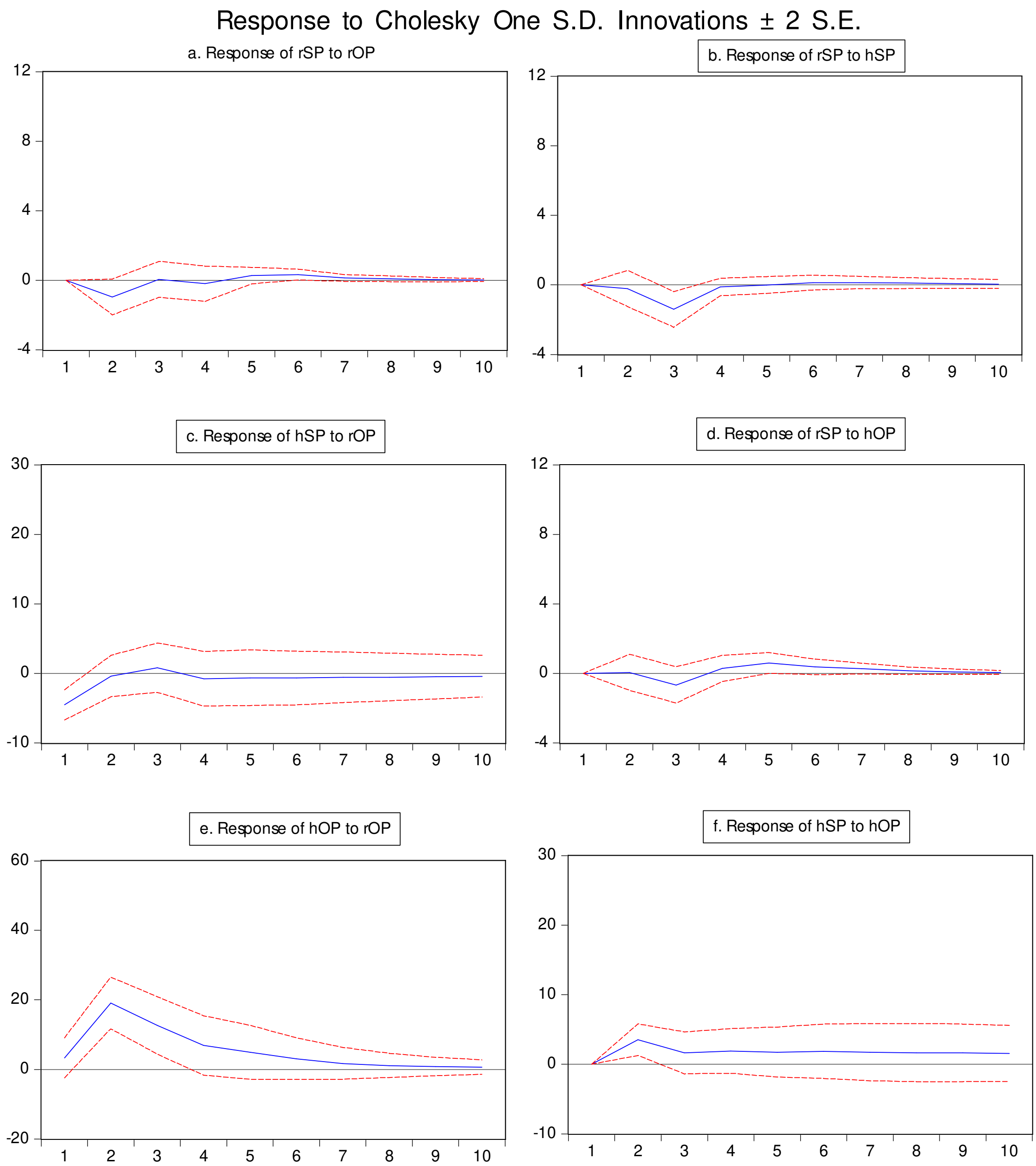


Figure 2 Impulse response from VAR

The information contained in the VAR (3) can be represented by graphs of the impulse response functions. The impulse responses illustrate the dynamic response path of a variable due to a one-period standard deviation shock to another variable. The graphs give some further evidence on the pattern of linkages between oil and stock markets. All variables of interest are shown in the figure, i. e., oil price movement and its volatility that affect stock return and its volatility. Referring to Figures 1a and 1b, the response of real stock return to oil price shock is negative but lasts for 3 months only while the response of real stock return to oil price volatility is also negative but lasts for only 4 months. The response of stock price volatility to oil price shock in Figure 1c is negative and lasts only 2 months whereas the response of real stock return to oil price volatility shock (Figure 1d) is negative but becomes positive within 4 months and dissipates within 9 months. In Figure 1e, the response of oil price volatility to oil price shock is positive and lasts for 10 months. The positive response of stock price volatility to oil price volatility shock is positive and decreases within 3 months, but never dissipates as shown in Figure 1f. The results seem to confirm those from Granger causality tests.

4. Concluding remarks

In this study, the impact of oil price volatility on the Thai stock market is investigated. The monthly data used in this study are real stock market return and oil price. The period covers May 1987 to December 2013. The estimation method used is the two stage approach, which comprises the estimation of the ccc-GARCH model to generate volatility series and the use of standard Granger causality test to determine the directions of causation. One of the main findings of this study is that there exists volatility transmission from oil to domestic stock market. The evidence that oil price shocks and oil price volatility that cause an increase in volatility of the stock market gives some implications. For risk management, portfolio managers should be aware of the impact of increasing portfolio risk caused by oil price shocks and volatility. They should diversify well enough to reduce their portfolio risk. The government can also impose some measures such as encouraging firms to improve energy efficiency and finding alternative fuels (renewable energy and natural gas). These measures can prevent large fluctuations in listed firms' profitability resulting from oil price uncertainty, which in turn can adversely affect the stock market.

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