Oil price shocks and domestic inflation in Thailand

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Abstract

This paper employs monthly data to examine the impact of oil price shocks on the domestic inflation rate in Thailand from 1993 to 2016. Both linear and nonlinear cointegration tests are used to examine the long-run relationship between price level, industrial production and the real price of oil. Furthermore, the two-step approach is used to examine how an oil price shock and oil price volatility affect the inflation rate. In addition, the asymmetry of oil price shocks on inflation is also investigated. The results show that price level is positively affected by the real oil price and industrial production index in the long run. The short-run analysis reveals that there is a positive relationship between an oil price shock and domestic inflation. The estimated results from the two-step approach show that an oil price shock causes inflation to increase while oil price uncertainty does not cause inflation. Furthermore, the short-run relationship between inflation and oil price shocks is not asymmetric. There is also bidirectional causality between inflation and inflation uncertainty, which might stem from monetary policy exercised by the central bank. The findings of this study will encourage the monetary authorities to formulate a more accommodative policy to respond to oil price shocks, which positively affect inflation rate. In addition, oil subsidization by the government should not be abandoned.

Keywords: Oil shocks, inflation, cointegration, VAR, bivariate GARCH, causality
JEL Classification: E31, Q43

1. Introduction

One of the interesting topics related to the relationship between oil shocks and macroeconomic variables is the impact of oil price shocks on the domestic inflation rate. The rise of oil price can cause firms' production costs to increase. Therefore, the pass-through of an oil price hike is reflected in an increase in the general price level of an economy. In addition, changes in the oil price in the last five decades exhibit oil price volatility that can distort the decisions made by economic agents. Lee and Ni (2002) find that oil price shocks affect economic performances via both demand and supply channels. Earlier studies by Mork and Hall (1980) and Mork (1989) point out that inflation induced by oil price shocks can reduce real balances, a measure purchasing power, in the economy, thus causing a recession. Bernanke et al. (1997) argue that the stagflation threat from the oil shocks in the 1970s should not be underestimated. The Federal Reserve adopted too high an interest rate policy and thus did not respond to oil price shocks accurately. This resulted in either decreased output or recession in the US. Hamilton (2003) indicates that oil shocks matter because they disrupt spending by consumers and firms on key sectors, and thus reducing output growth.

As to the supply channel, oil price shocks can cause consumer prices to increase. This phenomenon depends on the share of the oil price in the price index. Hooker (2002) examines the effects of oil price changes on inflation in the US under a Phillips curve framework that allows for asymmetries, nonlinearities and structural breaks. The results show that oil price shocks seem to affect inflation through the direct share of the oil price in consumer prices. Furthermore, monetary policy has become less accommodative of oil price shocks, thus preventing oil price changes from passing directly into core inflation. Cunado and De Gracia (2005) use quarterly data from 1975 to 2000 to examine the impact of oil price shocks on economic activities and inflation in Japan, Singapore, South Korea, Malaysia, Thailand and the Philippines. They find that the impact is more pronounced when oil prices are measured in domestic currencies. Ewing and Thompson (2007) find that oil prices lead the cycle of consumer prices in the US. The oil price pass-through into inflation in industrialized countries can decline due to certain factors. De Gregono and Lanerretche (2007) find that the pass-through declines because of the fall in energy intensity. Fukac (2011) indicates that the effect of oil price changes is stronger due to temporarily accommodating monetary policy and structural change in the US economy. Valcarcel and Wohar (2013) find that oil price-inflation pass-through may have shifted from a supply-side to a demand-side phenomenon in the US since the great moderation period. Therefore, it can affect the ability of monetary policymakers in dealing with the adverse impact of oil price shocks in the aggregate economy. Huang and Chao (2012) examine the effects of international and domestic oil prices on the price indices in Taiwan using monthly data from January 1999 to December 2011. They find that changes in international oil prices have more crucial impacts on the price indices than do changes in domestic oil prices. Chu and Lin (2013) find that oil price shocks have both long-term and short-term pass-through effects on Taiwan's producer price index. Gao et al. (2014) find that the degree of positive pass-through from oil price shocks to disaggregate US consumer prices is observed only in energy-intensive consumer price indices. In addition, the main causes of the pass-through are increases in the prices of energy-related commodities.

Many previous studies document that oil price shocks can have an adverse impact on the output because they raise the level of oil prices and oil price volatility. Oil price shocks also positively affect inflation. In addition, the asymmetric relationship between oil price shocks on output can be partly explained by the economy's response to oil price volatility. Federer (1996) provides evidence that support this proposition. Furthermore, positive and negative oil price shocks have different impacts on inflation rate. However, Farzanegan and Markwadt (2009) find that both positive and negative oil price shocks exert positive impacts on inflation in Iran. Their results also show that negative oil price shocks have a stronger short- and long-run effect on inflation compared to positive oil price shocks. Therefore, the asymmetric impacts of oil price shocks on inflation are not found. Ajmi et al. (2015) find similar results for South Africa. They use an asymmetric causality test to examine the relationship between international oil prices and price level. They find no cointegration between oil prices and price level. However, they find a causal relationship running from oil prices to price level. Furthermore, both positive and negative oil price shocks have a positive impact on price level changes even though a negative oil price shock has a stronger effect. Rafiq et al. (2009) examine the impact of oil price volatility measured by realized volatility, on key macroeconomic indicators of Thailand using quarterly data from 1993 to 2006. They find that there is unidirectional causality running from oil price volatility to economic growth, investment, unemployment and inflation. However, the results from impulse response analysis show that the impact of oil price volatility on inflation lasts for only a short time horizon. Rafiq and Salim (2014) find that oil price volatility affects output growth, but does not affect inflation in Thailand. However, the impact on output growth disappears after the financial crisis because the Thai government implemented oil subsidization after the crisis. Olofin and Salou (2017) examine the relationship between oil price and inflation for selected OPEC and EU countries. They find that the relationship between oil price and inflation is stronger in oil-exporting countries than in oil-importing countries. Moreover, oil price asymmetries seem to matter more in oil-exporting countries. Castro et al. (2016) find that the inflationary effect of oil prices remain in the Euro area because no deflationary effect of oil prices will result in a negative inflation rate.

The monetary policymakers in Thailand have tried to maintain price stability by adopting inflation targeting in 2000. The main purpose of the present study is to examine the role of oil price and its volatility in exerting an impact on inflation besides the role of monetary policy. The real price of oil is used as in the study by Cunado and Perez de Gacia (2005) who use two different definitions of oil prices. This study uses their second definition, which is the real price of oil.[1] In addition, an oil price shock is either the real domestic oil price in first differences or an oil price change. Furthermore, an increase in real oil price is defined as a positive shock while a decline in real oil price is a negative shock. This paper contributes to the existing literature by providing evidence showing that the long-run impact of oil price shocks on domestic inflation in a net oil-importing country is found from a nonlinear cointegration test. In addition, the short-run impact of oil price shocks on inflation is not asymmetric as found in some previous studies. Furthermore, oil price volatility does not cause inflation, but inflation itself causes inflation uncertainty in the Thai economy. This paper is organized as follows. The next section presents the data and estimation methods that are used in the analysis. Section 3 presents the empirical results. Section 4 discusses the results found in this study. The last section gives concluding remarks and some policy implications based on the results of this study.

2. Data and Methodology

In this section, the data and their properties are presented. The estimation methods used in the analyses are described.

2.1 Data

The dataset used in this study comprises monthly data during 1993 and 2016. The rationale for using this period is that the availability of industrial production index dates from 1993. In addition, monthly data give a larger sample size than does using quarterly data. The consumer price index, industrial production index and the US dollar exchange rate (bath/dollar) series are obtained from The Bank of Thailand’s website. The series of Brent crude oil spot price expressed in US dollar per barrel is obtained from the US Energy Information Administration. The oil price series is international oil price. By multiplying the oil price series by the US dollar exchange rate and deflating by the consumer price index, the domestic

[1] Most studies concerning the impact of oil prices on macroeconomic variables in advanced countries use different definitions of the price of oil. For example, Hamiltion (1996) uses the world price of crude oil while Cologni and Manera (2009) use the real price of oil as one of various definitions of oil shocks. Also, real oil price can reflect both the true purchasing power and the cost of production.

real oil price series is obtained.[2] All series are transformed into logarithmic series. The sample size comprises 288 observations.

The conventional unit root tests can have low power in the presence of structural breaks in the series. To overcome this problem, unit root tests with an unknown structural break date proposed by Zivot and Andrews (1992) are performed on both levels and first differences of the series. The results are shown in Table 1.

Table 1
Results of Zivot-Andrews tests for unit root: 1993M1-2016M12.

Variables	Test A	Break date	Test B	Break date
p (Level of consumer price index)	-3.750[1] (0.258)	2005M1	-2.792 [1] (0.955)	2014M5
Δ*p* (Difference in consumer price index)	-12.234***[0] (0.000)	2008M8	-13.575***[0] (0.000)	2008M8
ip (Level of industrial production index)	-3.336 [2] (0.480)	2002M2	-4.389 [2] (0.171)	2002M12
Δ*ip* (Difference in industrial production index)	-20.508***[0] (0.000)	2014M3	-20.594***[0] (0.000)	2014M3
o*p* (Level of real oil price)	-4.160 [1] (0.110)	1999M2	-4.531 [1] (0.272)	2014M6
Δ*op* (Difference in real oil price)	-14.250***[0] (0.000)	2008M10	-14.235***[0] (0.000)	2008M10

Note: Test A includes intercept only while Test B includes intercept and a linear trend. The numbers in bracket represent the optimal lag length determined by Schwarz information criterion (SIC),. ***, ** and ** denote significance at the 1%, 5% and 10% level, respectively. The numbers in parenthesis represent the probability of accepting the null hypothesis of unit root provided by Vogelsang (1993).

The results from unit root tests show that the degree of integration of all series is one, i.e., they are I(1) series. The null hypothesis of unit root cannot be rejected for the levels of series, but it is rejected at the 1% level of significance for the first difference of series. It should be noted that the test for the level of the consumer price index with constant only seems to reject the null hypothesis, but the level of significance is only 10%. Therefore, it can be concluded that all series are I(1). This is suitable in performing cointegration tests. The stationary property of first differences of series is also suitable in the estimate of a bivariate gerneralized autoregressive conditional heteroskedastic (GARCH) model as well as the standard pairwise causality test described in the next sub-section.[3]

[2] Cunado and De Gracia (2005) find that this measure of real oil price is more important than is real international oil price, which does not take into account of the impact of the exchange rate that influences the domestic oil price.
[3] A bivariate GARCH model requires that all series be stationary.

The basic characteristics of the level and first difference of the time series data are describe in Table 2.

Table 2
Descriptive statistics: 1993M01-2016M12.

A. Level of series			
Variable	*p*	*ip*	*op*
Mean	4.406	4.907	7.404
Median	4.389	4.977	7.411
Maximum	4.681	5.436	8.423
Minimum	3.975	4.205	6.185
Standard deviation	0.201	0.375	0.578
Skewness	-0.358	-0.198	-0.247
Kurtosis	2.112	1.475	1.780
JB	15.606	29.768	20.779
	(0.000)	(0.000)	(0.000)
Observations	288	288	288
B. First difference of series			
Variable	Δp	Δip	Δop
Mean	0.002	0.004	0.003
Median	0.002	0.004	0.010
Maximum	0.026	0.476	0.222
Minimum	-0.031	-0.446	-0.290
Standard deviation	0.005	0.056	0.089
Skewness	-0.543	-0.385	-0.577
Kurtosis	10.712	39.150	3.927
JB	725.336	15634	26.164
	(0.000)	(0.000)	(0.000)
Observations	287	287	287

Note: JB is Jarque-Bera statistic with p-value in parenthesis.

For the level of series, consumer price index domestic real oil price, and industrial production are negatively skewed, but all series do not show excess kurtosis. The Jarque-Bera statistics reveal that both series are not normally distributed. The average monthly inflation rate is 0.2 percent, whereas the average monthly oil price shock is 0.3 percent and the average monthly industrial production is 0.4 percent. All series exhibit excess kurtosis and are negatively skewed. The Jarque-Bera normality test rejects the null hypothesis of a normal distribution of all series, indicating that there may be the presence of an autoregressive conditional heteroskedastic (ARCH) effect.

Co-movement between price level and the real domestic oil price series is plotted in Fig. 1. Even though the real oil price is linked to the trend of price level, the real oil price variable fluctuates more. Starting from a low oil price with some fluctuations, the impact of a new oil shock in 2000 causes the price to increase. Again, the oil price reaches its peak near mid-2009. Oil price volatility plotted in Fig. 2 shows that high volatility occurs around 2000 and again around 2009 and 2015.[4]

[4] Real oil price volatility series are generated by a bivariate GARCH model reported in Section 3.

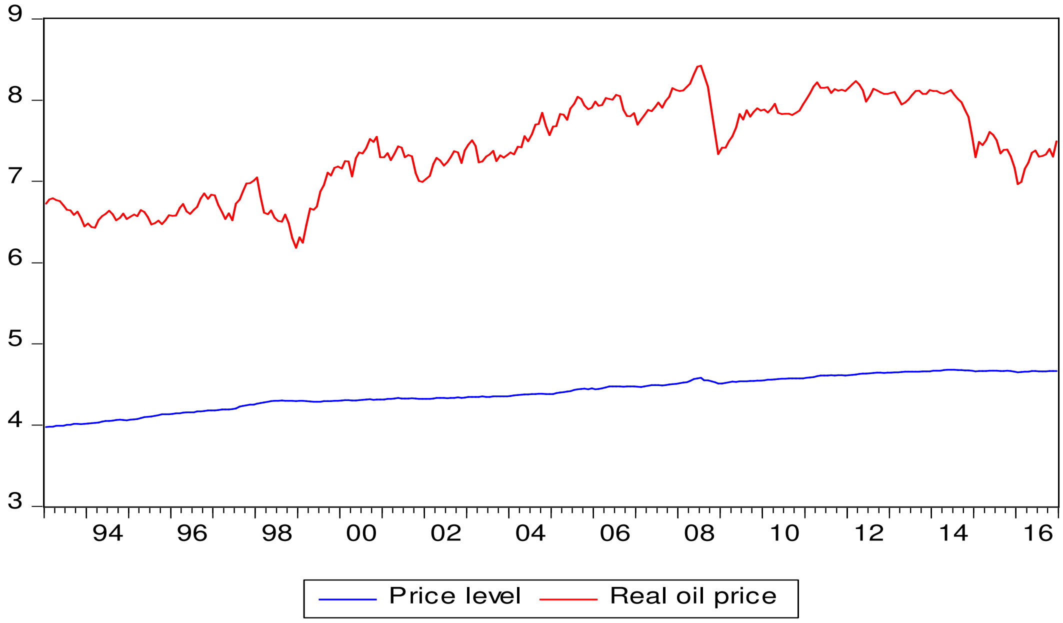

Fig. 1 Co-movement of price level with real oil price.

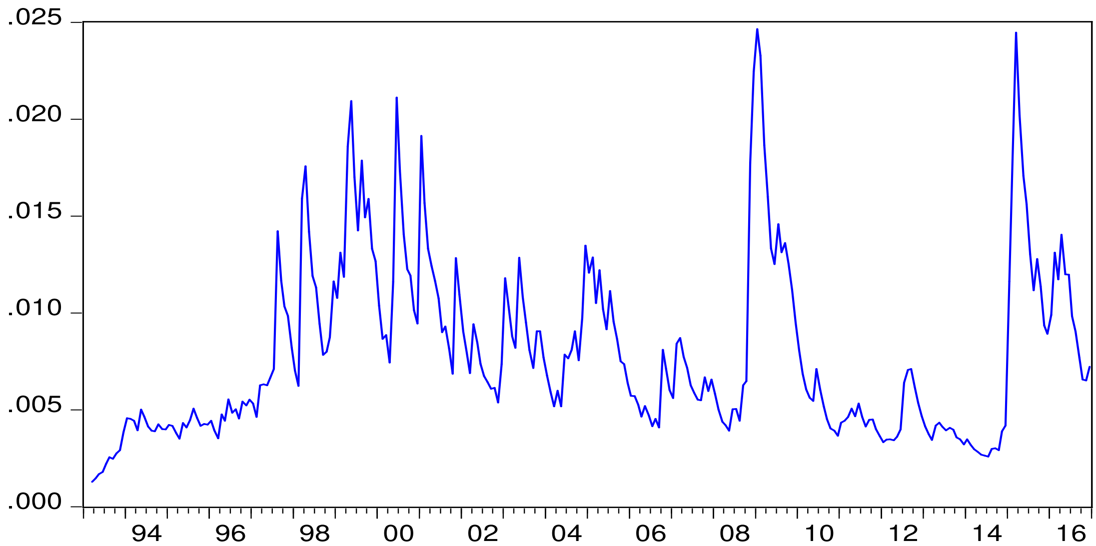

Fig. 2 Volatility of real oil price.

2.2 Estimation Methods

The methods used in the analysis comprise cointegration tests, VAR analysis and bivariate GARCH(1.1) with Granger causality.

2.2.1 Cointegration tests

The existence of cointegration between price level and real oil price implies that there is a long-run relationship between the two variables in a bivarite framework. However, industrial production can interact with both price level measured by consumer price index and real oil price. Therefore, trivariate cointegration analysis can be used to test whether there is positive long-run relationship between price level and the real domestic oil price when industrial production is treated as a control variable.

2.2.1.1 Residual-based cointegration tests with unknown breakpoints

Similar to conventional residual-based test for cointegration, this test proposed Gregory and Hansen (1996) is similar to Engle and Granger (1987) procedure in that it can be used by estimating the relationship between three non-stationary series: price level proxied by consumer price index, domestic oil price and industrial production. However, Gregory-Hansen procedure takes into account the impact of unknown level shift as well as regime shift.[5] The relationship can be expressed as:

$$p_t = a + b_1 ip_t + b_2 op_t + e_t \tag{1}$$

If real oil price and industrial production have impacts on price level (consumer price index), the coefficient b_1 and b_2 should statistically significant. The residual series, e_t, obtained from the estimation of Eq. (1) can be used to test for unit root using the Augmented Dickey-Fuller (ADF) test, which is expressed as:

$$\Delta e_t = \rho e_{t-1} + \phi \Delta e_{t-1} \tag{2}$$

The t-statistic obtained from the estimation of Eq. (2) is the ADF statistic. This statistic is used for comparison with the critical value statistic provided by Vogelsang (1993). If the ADF statistic is larger than the critical value, the null hypothesis of unit root in the residual series will be rejected. Therefore, there is cointegration or long-run relationship expressed in Eq. (1). On the contrary, the smaller value of the ADF statistic than that of the critical value leads to an acceptance of the null hypothesis of unit root and thus the absence of cointegration.

The existence of cointegration from Eq. (1) indicates that the relationship between price level, industrial production and real domestic oil price can be represented by the error correction model (ECM) that can be expressed as:

$$\Delta p_t = \varphi_0 + \lambda e_{t-1} + \sum_{i=1}^{p} \varphi_{21} \Delta p_{t-i} + \sum_{i=1}^{p} \varphi_{3i} \Delta ip_{t-i} + \sum_{i=1}^{p} \varphi_{4i} \Delta op_{t-1} + u_t \tag{3}$$

where EC_{t-1} is the lagged value of the corresponding error term, which is called the error correction term (ECT), and λ, φ_{2i}, φ_{3i} and φ_{4i} are the regression coefficients while u_t is a random variable. The sign of the coefficient of the ECT should be negative and has the absolute value of less than one. If this coefficient is statistically significant, any deviation from the long-run equilibrium will be corrected and thus the long-run relationship is stable.

[5] Zivot and Andrews (1992) also propose similar residual-based tests for cointegration with different test-statistics.

2.2.1.2 Nonlinear cointegration tests

It is important to confirm that the relationship between the three variables is not nonlinear. In case of the absence of linear cointegration between price level, industrial production and real oil price, it is possible that the long-run relationship is nonlinear and asymmetric. Therefore, the threshold autoregressive (TAR) and momentum threshold autoregressive (MTAR) models can be utilized. The two models are residual-based tests developed by Enders and Granger (1998) and Enders and Siklos (2001). The residuals from the estimate of Eq. (1) are decomposed and the test equation is expressed as:

$$\Delta e_t = I_t \rho_1 e_{t-1} + (1 - I_t)\rho_2 e_{t-1} + \sum_{i=1}^{k} \beta_i \Delta e_{t-i} + u_t \quad (4)$$

where u_t ~ iid.$(0,\sigma^2)$ and the lagged augmented term ($\Delta\hat{e}_{t-i}$) can be added to yield uncorrelated residuals of the estimates of equation (4). The Heaviside indicator function for TAR is specified in Eq. (5) while this function for MTAR is specified in Eq. (6), which are:

$$I_t = \begin{cases} 1\_if\_\Delta e_{t-1} \geq \tau \\ 0\_if\_\Delta e_{t-1} < \tau \end{cases} \quad (5)$$

and

$$I_t = \begin{cases} 1\_if\_\Delta e_{t-1} \geq \tau \\ 0\_if\_\Delta e_{t-1} < \tau \end{cases} \quad (6)$$

where the threshold value τ can be endogenously determined endogenously. According to Pertrucelli and Woolford (1984), the necessary and sufficient conditions for the stationarity of $\{e_{t-1}\}$ are $\rho_1 < 0$, $\rho_2 < 0$ and $(1+\rho_1)(1+\rho_2) < 1$. The long-run equilibrium value of the error term should be zero when these conditions are met. Ender and Siklos (2001) propose two test statistics for the null hypothesis of no cointegration, i.e., t-Max and the F statistic called Φ. If cointegration exists, the t-Max and Φ statistics should be larger than the 5% critical values. However, the Φ statistic has substantially more power than the t-Max statistic for testing the null hypothesis of $\rho_1 = \rho_2 = 0$ or no cointegration. The main drawback of the Φ statistic is that it can lead to the rejection of the null hypothesis when only one of the rho coefficients is negative.

If the evidence indicates the existence of linear cointegration between price level, industrial production and real oil price, the time series dynamics of the relationship between the three variables can be explored by a vector autocorrelation mechanism (VECM). The VECM can be expressed as:

$$\Delta p_t = \varphi_0 + \lambda_1 e_{t-1} + \sum_{i=1}^{p} \varphi_{21} \Delta p_{t-i} + \sum_{i=1}^{p} \varphi_{3i} \Delta ip_{t-i} + \sum_{i=1}^{p} \varphi_{4i} \Delta op_{t-1} + u_{1t} \quad (7)$$

and

$$\Delta p_t = \tilde{\varphi}_0 + \lambda_2 e_{t-1} + \sum_{i=1}^{p} \tilde{\varphi}_{21} \Delta p_{t-i} + \sum_{i=1}^{p} \tilde{\varphi}_{3i} \Delta ip_{t-i} + \sum_{i=1}^{p} \tilde{\varphi}_{4i} \Delta op_{t-1} + u_{1t} \quad (8)$$

where P is the lag order, λ_1 and λ_2 are the coefficients showing the speeds of adjustment.[6] The short-run dynamics allow for testing the alternative hypothesis pertaining to the short-run

[6] The speed of adjustment is $\lambda_1 = I_t \rho_1$ in the first regime and $\lambda_2 = (1 - I_t)\rho_2$ in the second regime while I_t in equation (5) is used for the TAR model and is I_t in Eq. (6) is used for the MTAR model.

relationship between price level, industrial production and real oil price. The coefficients of the lagged differences for industrial production and for real oil price show the short-run impacts of the two variables on the first difference of price level while the coefficients of the asymmetric errors correction terms are the speeds of adjustment toward the long-run equilibrium. Eqs. (7) and (8) can also be used to test for short-run causality between industrial production, real oil price and price level.

2.2.2 Short-run analysis and the role of oil price volatility

The two-step approach is employed to explain the relationship between nominal oil price and its uncertainty (or volatility) as well as inflation and its uncertainty. In the first step, a bivariate GARCH(1,1) model with constant conditional correlation (ccc-GARCH) model proposed by Bollerslev (1990) is employed to generate inflation uncertainty and oil price volatility. In the second step, these generated series along with the inflation rate and the series of real oil price changes are 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, it can be argued that the main advantage of the two-step procedure is that it provides room for the ability to establish causality between variables.[7] The system equations in a ccc-GARCH(1,1) model comprises the following five equations.

$$\Delta p_t = a_{1,0} + \sum_{i=1}^{p1} a_{1,i}\Delta p_{t-i} + \sum_{i=1}^{p2} b_{1,i}\Delta op_{t-i} + e_{1,t} \tag{9}$$

$$\Delta op_t = a_{2,0} + \sum_{i=1}^{p1} a_{2,i}\Delta op_{t-i} + \sum_{i=1}^{p2} b_{2,i}\Delta p_{t-i} + e_{2,t} \tag{10}$$

$$h_t^{\Delta p} = \mu_1 + \alpha_{1,1}\varepsilon_{t-1}^{2,\Delta p} + \beta_{1,1}h_{t-1}^{\Delta p} \tag{11}$$

$$h_t^{\Delta op} = \mu_2 + \alpha_{2,1}\varepsilon_{t-1}^{2,\Delta op} + \beta_{2,1}h_{t-1}^{\Delta op} \tag{12}$$

$$h_t^{\Delta p,\Delta op} = \rho_{12}(h_t^{\Delta p})^{1/2}(h_t^{\Delta op})^{1/2} \tag{13}$$

where Δp is the change in price level or inflation, and Δop is the change in real oil price or oil price shock, $h^{\Delta p}$ is the conditional variance of inflation, $h^{\Delta op}$ is the conditional variance of real oil price change, and $h^{\Delta p,\Delta op}$ 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 equations.

$$y_t = a_1 + \sum_{i=1}^{k} \alpha_{1i}y_{t-i} + \sum_{i=1}^{k} \beta_{1i}x_{t-i} + \eta_{1t} \tag{14}$$

and

$$x_t = a_2 + \sum_{i=1}^{k} \alpha_{2i}x_{t-i} + \sum_{i=1}^{k} \beta_{2i}y_{t-i} + \eta_{2t} \tag{15}$$

[7] The current value of one variable might not affect the current value of another variable, but some of its lags might do.

where y and x are two variables that can exhibit causal relationship. The optimal lag length is determined by SIC. If any independent variable causes the dependent variable, there should be at least one significant coefficient of that lagged independent variable. This also indicates that the F-statistic in the standard causality test must show significance for each pair of variables. In the present study, the causal relationship of the pairs of variables that will be focused are {Δop, Δp}, {Δop, $h^{\Delta op}$}, {$h^{\Delta op}$, Δp}, {Δp, $h^{\Delta p}$}, {$h^{\Delta p}$, Δop} and {$h^{\Delta op}$, $h^{\Delta p}$}. It should be noted that all variables in the test must be stationary. A VAR model is used to detect the sign of lagged variables. In addition, impulse response functions (IRFs) and variance decompositions (VCDs) can be obtained from the specified VAR model to detect the response of each variable to a shock and the impact of each variable on other variables.

3. Empirical Results

This section reports the results from cointegration tests and short-run dynamics, IRFs and VCDs, and Granger causality tests.

3.1 Long-run relationship and short-run dynamics

The model expressed in Eq. (1) is used for testing the existence of a long-run relationship between price level (p), industrial production (ip) and real domestic oil price (op).[8] The results from Gregory-Hansen testing for cointegration are shown in Table 3.

The results in Table 3 show that there is no cointegration because both the model with level shift and the model with regime shift are smaller than the 5% critical values for the three-variable model. Zivot and Andrew (1992) tests give the Za* statistic = 43.247 for the level shift model and Zt* statistic = -4.849 for the regime shift model, which are smaller than the critical values of -46.98 and -5.29 respectively. The break date is 1997M6 for the level shift model, which is almost the same as the impact of the 1997 Asian financial crisis. Without the presence of cointegration, the estimation of ECM representation expressed in Eq. (3) is not valid.

Table 3
Results of Gregory-Hansen cointegration tests.

Model	t-statistic	lag	Break date
1. Level shift	-3.416	2	1996M12
2. Regime shift	-3.317	2	2002M7

Note: The 5% critical values with the three-variable model provided by Gregory and Hansen (1996) are -5.29 and -5.50 for the model with level shift and the model with regime shift, respectively.

Even though the results of Gregory-Hansen cointegration tests suggest that there is no linear cointegration between the three variables, it is still possible that the long-run relationship can be nonlinear. The TAR and MTAR models are estimated. Firstly, the long-run relationship is estimated with a dummy variable determined by the Zivot-Andrews model with level shift. Secondly, the residual series is obtained from the estimated equation with the 1997 financial crisis dummy reported in Table 3 being used to test for threshold cointegration.

[8] International oil price should not be suitable because it does not take into account the role of the nominal exchange rate of an oil-importing economy.

Table 4
Long-run coefficients of the estimated models.

Dependent variable is p_t			
Independent variable	Coefficient	t-statistic	p-value
D_t	0.113***	9.437	0.000
ip_t	0.388***	17.095	0.000
op_t	0.053***	3.910	0.000
Adj. R^2 = 0.914			

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

There seems to be a positive long-run relationship between price level, industrial production and real oil price. A one percent increase in industrial production causes the price level to rise by 0.39 percent and vice versa. Since the industrial sector comprises many manufacturing firms, which are energy intensive, the reduction of oil use cannot be avoidable. Therefore, firms in the manufacturing sector can adjust themselves to oil price shocks in the long run. For the real price of oil, the positive relationship between price level and real oil price is not surprising. A one percent increase in the real oil price causes the price level to rise by 0.05 percent in the long run. The claimed positive impact of the real oil price on the general price level will be valid if threshold cointegration is found. The impact of level shift is significantly positive.

In testing for threshold cointegration, the results are obtained from the estimation of Eq. (4) by estimating Eq. (1), which includes the 1997 Asian financial crisis dummy variable as suggested by the Zivot-Andrews cointegration test to obtain the residual series. The results from the estimated TAR and MTAR models are reported in Table 5.

Table 5
Results of Threshold cointegration.

	TAR	MTAR
ρ_1	-0.213 (0.044)	0.035 (0.061)
ρ_2	-0.069 (0.047)	-0.210 (0.037)
τ	0.043	0.015
κ	1	1
t-Max	-1.489 [-2.090]	0.571 [-2.278]
Φ	12.884**[8.306]	16.465**[9.539]
F-Equal	5.240 [6.055]	12.001**[8.190]

Note: Standard deviation is in parenthesis, the number in bracket represent the 5% critical value, ** and * indicate significance at the 5% and 10% level, respectively, τ is the threshold value, κ is the number of lagged augmented term, Φ is the F $\rho_1 = \rho_2 = 0$, and F-Equal is F $\rho_1 = \rho_2$.

The results reported in Table 5 show that the estimated ρ_1 and ρ_2 are negative with the absolute value of less than one and $(1+\rho_1)(1+\rho_2)$ is equal to 0.811 for the TAR model. However, for the MTAR model, ρ_1 is positive and ρ_2 is negative. Therefore, the convergence condition is not met for the MTAR model. The Φ statistic is 12.884 and 16.465 for the TAR and MTAR models, respectively, while the simulated critical values at the 5% level are 8.306

and 9.539 for the TAR and MTAR models, respectively. For the TAR model, the null hypothesis of no threshold cointegration is rejected at the 5% level of significance while the null hypothesis is rejected at the 5% level for the MTAR model. Based on the MTAR model, there is nonlinear cointegration between price level, industrial production and the real price of oil. However, the null hypothesis of no asymmetric adjustment toward the long-run equilibrium cannot be rejected because the F-Equal statistic is smaller than the critical value at the 5% level of significance for the TAR model while the null hypothesis of no asymmetric adjustment is rejected for the MTAR model. According to Enders and Siklos (2001), the Φ statistic can lead to a rejection of the null hypothesis of no cointegration when only one of the rho coefficients is negative, but the convergence condition is not met as in the case of the MTAR model. Thus it can be concluded that there is nonlinear cointegration between the three variables under the TAR estimate without asymmetric adjustment.[9] The tests are also conducted for the TAR and MTAR models at the 10% level of significance, the results show that only the TAR model meets the convergence or stationary condition. The Φ statistic is 12.84 and is larger than the simulated 10% critical value of 7.40. Also, the F-Equal statistic is 5.24 and is larger than the 10% critical value of 4.55. Using the lower level of significance, threshold cointegration with asymmetric adjustment holds under the estimated TAR model because the estimated statistics are larger than their respective critical values, and thus the null hypotheses of no cointegration and no asymmetric adjustment are rejected.

The results from two types of cointegration tests reveal that there is no long-run relationship between price level, industrial production and domestic real oil price in Gregory and Hansen (1996) and Zivot and Andrew (1992) tests. However, the TAR model shows the presence of asymmetric adjustment in the nonlinear long-run relationship at the 10% level of significance. The short-run dynamics will depend on the symmetric ECM framework specified in Eq. (3) when nonlinear cointegrattion without asymmetric adjustment is found in the TAR model at the 5% level of significance. If a lower level of significance at the 10% level is accepted, the short-run dynamics of asymmetric adjustment specified in Eqs. (7) and (8) are used. The results of symmetric adjustment specified in Eq. (3) are reported in Table 6.

Table 6
Results of short-run dynamics.
Dependent variable: Δp_t

Variable	Coefficient	Standard Error	t-statistic	p-value
$\hat{e}_{t-1}$	-0.016***	0.061	-2.611	0.010
Δp_{t-1}	0.238***	0.061	3.884	0.000
Δp_{t-2}	0.104*	0.060	1.719	0.087
Δip_{t-1}	-0.003	0.005	-0.488	0.626
Δip_{t-2}	-0.002	0.005	-0.289	0.773
Δop_{t-1}	0.011***	0.003	3.071	0.002
Δop_{t-2}	-0.006*	0.004	-1.750	0.081
Intercept	0.002***	0.001	4.720	0.000

Adjusted $R^2 = 0.142$, $F = 7.715$
Serial correlation test: $\chi^2_{(2)} = 1.608$ (p-value = 0.448)
ARCH test: $\chi^2_{(1)} = 1.147$ (p-value = 0.234)

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

[9] This is the main drawback of the Φ statistic because it can lead to the rejection of the null hypothesis when only one of the rho coefficients is negative. It does not seem to be an exceptional case for this dataset when applied to the MTAR model.

The lag length for symmetric adjustment shown in Table 6 is two determined by HQ information criterion because SIC indicates that the lag should be zero. The estimated short-run equation passes important diagnostic tests, i.e., the no serial correlation in the residuals and no ARCH effect. The coefficient of the error correction term has a correct sign with the absolute value of 0.016, which is less than one and significant at the 1% level. Therefore, any deviation from long-run equilibrium will be corrected. However, the coefficients of lagged changes in industrial production are insignificant. Using the Wald F test, $F_{2,277} = 0.143$ with p-value = 0.867, short-run causality running from changes in industrial production to inflation is not found. On the contrary, positive short-run causality running from oil price shocks to inflation is found at the 1% level of significance because the Wald $F_{2,\,277} = 5.774$ with p-value = 0.004, which leads to a rejection of the null hypothesis of no causality.

When a lower level of significance is accepted for the TAR model, the asymmetric adjustments of the higher and lower regimes are reported in Table 7.

Table 7

Results from the estimated ECMs from the TAR Model.

	Higher regime (Above threshold)	Lower regime (Below threshold)
	Δp_t	Δp_t
$\hat{e}_{t-1}$	-0.011	-0.022***
	(0.244)	(0.001)
Δp_{t-1}	0.240	0.244**
	(0.062)	(0.061)
Δp_{t-2}	0.104*	0.106*
	(0.061)	(0.060)
Δip_{t-1}	-0.001	0.001
	(0.005)	(0.005)
Δip_{t-2}	-0.001	0.002
	(0.005)	(0.005)
Δop_{t-1}	-0.011***	0.010***
	(0.004)	(0.003)
Δop_{t-2}	-0.006*	-0.006
	(0.004)	(0.004)
Intercept	0.002***	0.001***
	(0.001)	(0.007)
Adjusted R^2	0.125	0.142
F-Statistic	6.806	7.726
% of sample	15%	85%
Diagnostics:		
$\chi^2_{(2)} = 0.440$		$\chi^2_{(2)} = 1.688$
(prob. = 0.802)		(prob. = 0.403)
$\chi^2_{(1)} = 1.398$		$\chi^2_{(1)} = 1.611$
(prob. = 0.237)		(prob. = 0.204)

Note: Standard error is in parenthesis. ***, **and *indicate significance at the 1%, 5% and 10% level, respectively. The statistic $\chi^2_{(2)}$ is used to test for serial correlation and $\chi^2_{(1)}$ is used to test for the ARCH effect.

The estimated ECMs pass two important diagnostic tests, i.e., there are no serial correlation in the residuals and no ARCH effect. For lagged residuals above the threshold value, the coefficient of the error correction term has the expected sign and size. However, this coefficient is not statistically significant, and thus any deviation from the long-run equilibrium will not be corrected. The Wald F = 0.006 with p-value = 0.994 accepts the null hypothesis that lagged changes in industrial production do not cause inflation. In addition, the null hypothesis that lagged oil price shocks do not cause inflation is rejected at the 1% level of significance since the Wald F = 5.896 with p-value = 0.003. The causality results suggest that there is no causality running from changes in industrial production to inflation while there is negative causality running from oil price shocks to inflation in the higher regime. For the lower regime when lagged residuals are below the threshold value, the coefficient of the error correction term has a negative sign with the absolute value of less than one and is significant at the 1% level. This indicates that any deviation from the long-run equilibrium will be rapidly corrected. In the Granger causality sense, there is no short-run causality running from lagged changes in industrial production to inflation because the Wald F = 0.293 with p-value = 0.911. However, there is positive short-run causality running from lagged oil price shocks to inflation since the Wald F = 5.641 with p-value = 0.004, which leads to a rejection of the null hypothesis of no causality at the 1% level of significance.

It should be noted that the results from the estimated ECM in the lower regime are similar to the results of symmetric ECM reported in Table 5 because the lower regime comprises approximately 85% of the whole sample. Overall, the results suggest that there is a positive causality running from oil price shocks to inflation in the short run.

3.2 Short-run relationship and the role of oil price volatility

In analyzing the short-run relationship, the two step approach explained in the previous section is utilized. First, a bivariate GRACH model is estimated to obtain two volatility series. The next step is to employ the standard Granger causality test and an unrestricted VAR model to examine short-run causality and the use of IRFs as well as VCDs to examine the interactions among variables of interest.

In performing a bivariate GARCH estimate, the unit root statistics for the full sample period reported in Table 1 show that the first differences of the two series are stationary and thus suitable for the estimation.

The bivariate GARCH estimation for the system equations (9) to (13) to obtain volatility or uncertainty series are reported in Table 8. The two series, Δp and Δop, are stationary as required. The assumption of constant conditional correlation facilitates the simplicity of the system estimation. The model performs quite well in the dataset. The mean equation for domestic inflation rate is assumed to be dependent on the lag of domestic oil price change while the mean equation for domestic oil price change is assumed to be dependent on inflation rate.[10]

[10] Even though the country is a small oil-importing country, its inflation rate should not affect the world oil price. However, the oil price series is converted to real domestic oil price. Therefore, it is possible that inflation and oil price shocks will be interdependent.

Table 8 Results from the bivariate ccc-GARCH(1,1) estimation.

Mean equations:

$$\Delta p_t = 0.001^{***} + 0.201^{**}\Delta p_{t-1} + 0.009^{***}\Delta op_{t-1}$$
(3.99) (2.71) (3.74)

$$\Delta op_t = -0.007 + 0.139^{**}\Delta op_{t-1} + 1.245^{*}\Delta p_{t-1}$$
(-1.24) (2.03) (1.67)

(t-statistic in parenthesis)

Variance and covariance equations:

$$h_t^{\Delta p} = 0.001^{***} + 0.331^{***}\varepsilon_{t-1}^{2,\Delta p} + 0.635^{***}h_{t-1}^{\Delta p}$$
(2.98) (3.83) (8.61)

$$h_{t-1}^{\Delta op} = 0.001^{**} + 0.172^{***}\varepsilon_{t-1}^{2,\Delta op} + 0.781^{***}h_{t-1}^{op}$$
(1.98) (2.64) (12.39)

$$h_t^{\Delta p,\Delta op} = 0.289^{***}(h_t^{\Delta p})^{1/2}(h_t^{\Delta op})^{1/2}$$
(4.72)

(t-statistic in parenthesis)

System diagnostic test:

Q(4) =11.403 (p-value = 0.784)

Note: The variables, Δp and Δop, stand for changes in price level and oil price shock, respectively. The conditional variances are: $h^{\Delta p}$ for inflation rate and $h^{\Delta op}$ for oil price shock. The conditional covariance is $h^{\Delta p,\Delta op}$. ***, ** and * denotes significance at the 1%, 5% and 10%, respectively. Q(k) is the statistical test for the residuals obtained from system residual Portmanteau tests for autocorrelations, where k is the lag length.

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 inflation rate and oil price changes, respectively. Referring to Panel A, the inflation rate is positively affected by the one-period lagged oil price changes. In Panel B, oil price change is positively affected by its one-period lag and lagged inflation. The coefficients in the two conditional variance equations are non-negative. Both conditional variance equations give significant ARCH and GARCH terms (α_1 and β_1). The sum of the coefficients of the ARCH and GARCH terms for inflation rate is 0.966 whereas the sum of the coefficients for the rate of oil price change is 0.953. These results show that the GARCH variance series as measures of volatility or uncertainty is stationary. The constant conditional correlation in Panel C is 0.289, which is low and statistically significant.[11] The system diagnostic test using residual portmanteau test for autocorrelation accepts the null of no autocorrelation as indicated by the Q(4) statistic. Therefore, the system equations are free of serial correlation. The volatility series are generated to examine their impacts on inflation and volatility in the standard Granger causality test. The results of a pairwise Granger causality test are reported in Table 9. The results in Table 9 show that an oil price shock tends to cause the inflation rate to increase while inflation also causes an oil price shock to rise. Also, an oil price shock causes higher oil price volatility. In addition, oil price volatility tends to cause oil price shocks to decrease. Oil price volatility significantly causes an oil price shocks to decrease. However, oil price volatility does not cause inflation uncertainty but inflation uncertainty causes oil price volatility to increase. In addition, inflation uncertainty causes oil price shocks to decrease. Therefore, this effect can partly reduce the size of oil price shock when oil price volatility rises. Furthermore, inflation causes oil price volatility to decrease, but oil price shocks do not

[11] This result shows that inflation and oil price change series are positively correlated.

cause inflation uncertainty. Even though inflation uncertainty does not cause oil price volatility, inflation uncertainty causes oil price shocks to decrease. Finally, oil price volatility does not cause inflation.

Table 9 Results of pairwise Granger causality test

Hypothesis	F-statistic	p-value
Δop does not cause Δp	9.640**(+)	0.002
Δp does not cause Δop	3.878** (+)	0.050
Δop does not cause $h^{\Delta op}$	13.083***(-)	0.000
$h^{\Delta op}$ does not cause Δop	7.313* (-)	0.007
$h^{\Delta op}$ does not cause $h^{\Delta p}$	0.232 (+)	0.631
$h^{\Delta p}$ does not cause $h^{\Delta op}$	8.908*** (-)	0.003
$h^{\Delta p}$ does not cause Δop	10.965***(-)	0.001
$h^{\Delta p}$ does not cause Δp	5.891**(-)	0.016
Δp does not cause $h^{\Delta op}$	3.131*(-)	0.078
Δop does not cause $h^{\Delta p}$	1.160 (-)	0.282
$h^{\Delta p}$ does not cause Δop	10.691***(-)	0.001
$h^{\Delta op}$ does not cause Δp	1.016 (-)	0.314

Note: Δp and Δop stand for inflation and oil price shocks, respectively. The conditional variances, $h^{\Delta p}$ for inflation rate and $h^{\Delta op}$ for oil price shocks. ***, ** and * denotes significance at the 1%, 5% and 10% level, respectively. The + sign indicates positive causation while the – sign indicates negative causation. The lag length in the pairwise causality test is 1 determined by HQ.

It should be noted that inflation is positively affected by oil price shocks, but it is not affected by oil price volatility.

The estimate of VAR(1) model allows for performing an analysis of IRFs and VDCs. The results of impulse response analysis are shown in Fig. 3. The figure shows the IRFs from the Monte Carlo simulated at 95 percent intervals. The response of inflation rate (Δp) to a shock in oil price (Δop) shows that inflation significantly increases in the next month following the contemporaneous effect of that shock. This impact starts to decay and the whole impact is incorporated within four months. The response of inflation to a shock in oil price volatility ($h^{\Delta OP}$) shows that inflation decreases until the 4th month and starts to recover and is incorporated in the 12th month. The response of inflation to a shock in oil price volatility starts in the 2nd month and the negligible impact starts to increase but decays later on. For the oil price shock variable, the response of a shock in oil price to inflation starts in the next month, i. e., inflation has a significantly positive impact on the real price of oil but decays and is incorporated in the 4th month. Oil price shocks respond negatively to inflation uncertainty in the 2nd month and the impact subsides and is incorporated in the 6th month. On the contrary, oil price shocks respond positively to oil price volatility. The positive impact occurs in the 2nd month and starts to decay later on. The impact of inflation on inflation uncertainty is positive but becomes negligible after the 2nd month while its slight impact on oil price shocks is negative and incorporated in the 8th month. The impact of inflation uncertainty on oil price volatility is negative, but the impact is very slight and last until the 12th month. As for oil price volatility, this variable responds negatively to both inflation and oil price shocks. Even though the impacts subside within few months but they never dissipate. Finally, the positive response of oil price volatility to inflation uncertainty is significant in the 4th month and reaches its peak in the 7th month. Even though the impact subsides later on, it never dissipates.

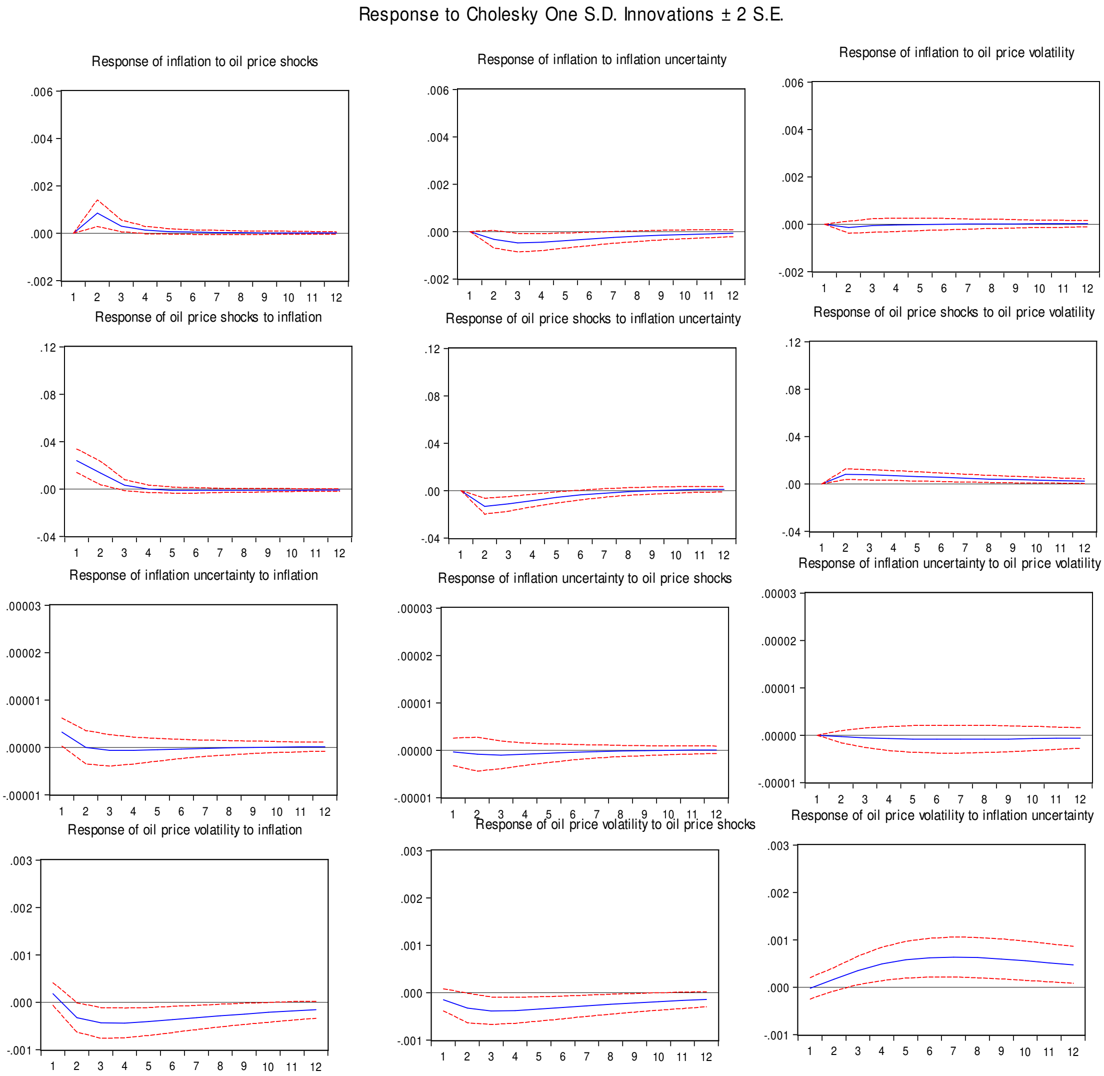

Fig. 3 Impulse response functions including volatility series.

VDCs shown in Table 10 can be used to ascertain how important the innovations of other variables are in explaining the fraction of each variable at different step ahead forecast variances. The results of this analysis provide evidence for the independency of an oil price shock and other variables. An oil price shock has a significantly positive impact on inflation and inflation uncertainty. Furthermore, oil price volatility has a slight impact on inflation, but no impact on inflation uncertainty.

Table 10
Variance decompositions of Δp, Δop, $h^{\Delta p}$, and $h^{\Delta op}$.

Month	Δp	Δop	$h^{\Delta p}$	$h^{\Delta op}$
Variance decomposition of Δp				
1	100.00	0.00	0.00	0.00
2	96.77	2.75	0.41	0.07
4	94.83	3.06	2.02	0.09
8	93.59	3.05	3.13	0.09
12	93.40	3.04	3.47	0.09
Variance decompositions of Δop				
1	8.09	91.91	0.00	0.00
2	9.96	86.77	2.36	0.90
4	9.68	83.27	4.79	2.25
8	9.55	81.51	5.36	3.58
12	9.55	81.08	5.36	4.01
Variance decompositions of $h^{\Delta p}$				
1	1.70	0.02	98.28	0.00
2	1.08	0.09	98.81	0.01
4	0.87	0.21	98.84	0.08
8	0.80	0.24	98.68	0.22
12	0.79	0.24	98.56	0.40
Variance decompositions of $h^{\Delta op}$				
1	0.83	0.60	0.01	98.56
2	1.98	1.88	0.43	95.71
4	4.50	3.58	3.44	88.48
8	5.91	4.51	11.29	78.29
12	6.07	4.63	15.99	73.31

Note: Δp is inflation rate, Δop is oil price shocks, $h^{\Delta p}$ is inflation uncertainty, and $h^{\Delta op}$ is oil price volatility.

Inflation explains only its own variances in the first month. It explains approximately 3% of the variances of oil price shocks in the 4th month and only 2% and 1% of inflation uncertainty and oil price volatility, respectively. The oil price shock variable explains 8% of the variances of inflation, but it does not explain the variances of inflation uncertainty and of oil price volatility in the first month. This variable explains more than 9% of the variances of inflation for the remaining months, and it explains 5% and 2% of the variances of inflation uncertainty and oil price volatility in the 4th month. It explains 5% and 4% of the variance of inflation uncertainty and oil price volatility in the 12th month. Inflation uncertainty explains almost 2% of the variance of inflation in the first month. From the 2nd month onward, it slightly explains the variances of other variables. Finally, oil price volatility explains its own variances in the first month. It explains 16% of the variances of inflation uncertainty in the 12th month and only 6% and almost 5% of the variances of inflation and oil price shocks.

3.3 Symmetric responses between real oil price and inflation

One of the important aspects of the relationship between inflation and oil price shocks is whether the short-run relationship is either symmetric or asymmetric. Following Mork (1989 procedure, oil price shocks are separated as positive and negative components. The asymmetric causality is tested and the results are reported in Eq. (16).

$$\Delta p_t = 0.002^{***} + 0.247^{***}\Delta p_{t-1} + 0.013^{**}\Delta op_{t-1}^{+} + 0.010^{**}\Delta op_{t-1}^{-} \quad (16)$$

(5.52) (4.19) (2.55) (1.98)

Adj. $R^2 = 0.117$, $F = 13.652$, $\chi_{(2)}2 = 3.903$ (p-value = 0.142)

(t-statistic in parenthesis).

The null hypothesis to be tested is that the coefficients of lagged positive oil price shocks (op^+) and lagged negative oil price shocks (op^-) are the same. The lag length is determined by HQ because SIC gives zero lag length. The estimated equation possesses no serial correlation. The results show that both positive and negative oil price shocks positively causes inflation. The Wald F test for the null hypothesis that the coefficients of positive and negative oil price shocks are the same is accepted, i.e., F = 0.259 with p-value = 0.611. Therefore, the impacts of positive and negative oil price shocks are not asymmetric. This results is consistent with the evidence found by Ajmi et al. (2015) for South Africa.

An unrestricted VAR model can be utilized to examine inflationary effects of both positive and negative oil price changes.[12] For this purpose, stationary series of price level changes along with positive and negative oil price changes enter into the specified VAR model. The lag length of one is determined by HQ. The estimated VAR models show that the coefficient of lagged positive oil price shock is 0.018, which is significant at the 1% level while the coefficient of a lagged negative oil price shock is 0.013, which is significant at the 5% level. Fig. 4 shows the IRFs of positive oil price shock and inflation.

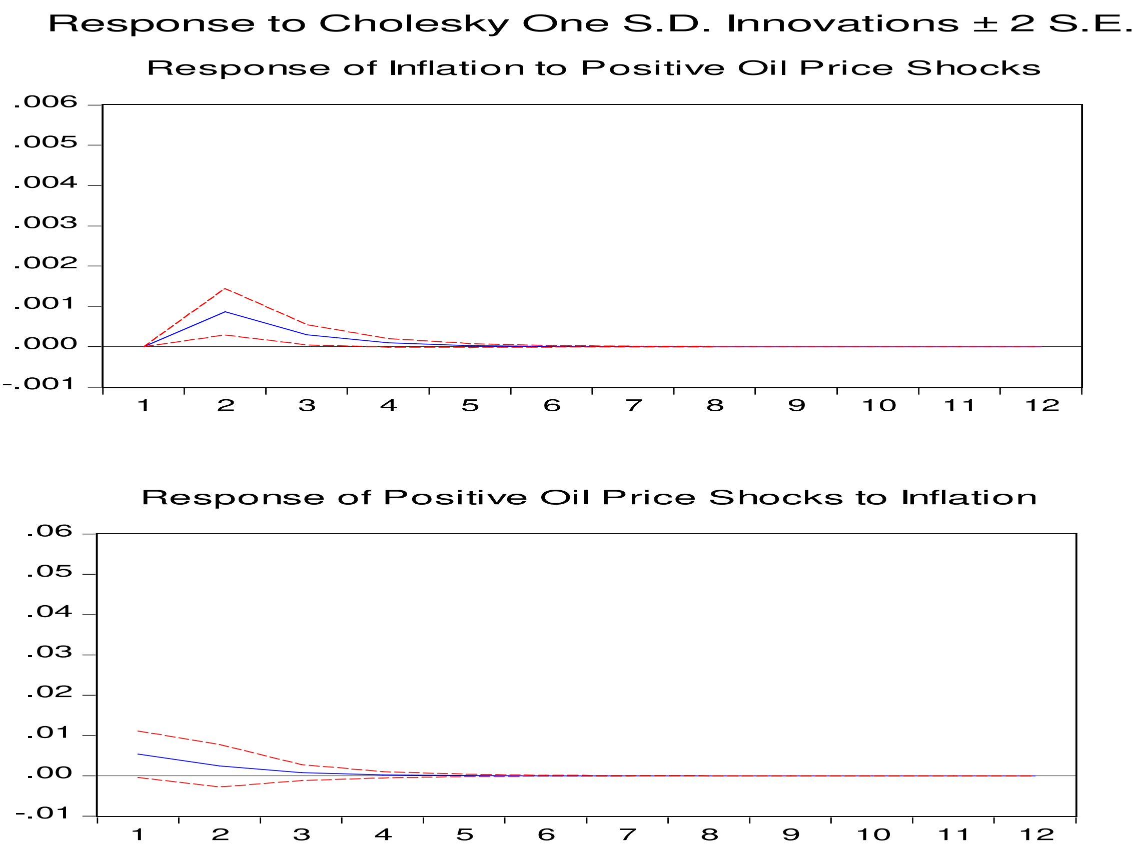

Fig. 4 Positive oil price shock and inflation

[12] Again, following Mork (1989), the oil price change series are separated into positive and negative components.

The response of inflation to initial positive oil price shocks is significantly positive after the first month of the shocks. The peak is reached in the 2nd month. The impact of the shock dissipates in the 5th month. The shocks in inflation significantly causes the real oil price to decease and the impact dissipates in the 4th month. Fig. 5 shows the IRFs of negative oil price shock and inflation. The impact of negative oil price shocks is similar to the impact of positive oil price shocks.

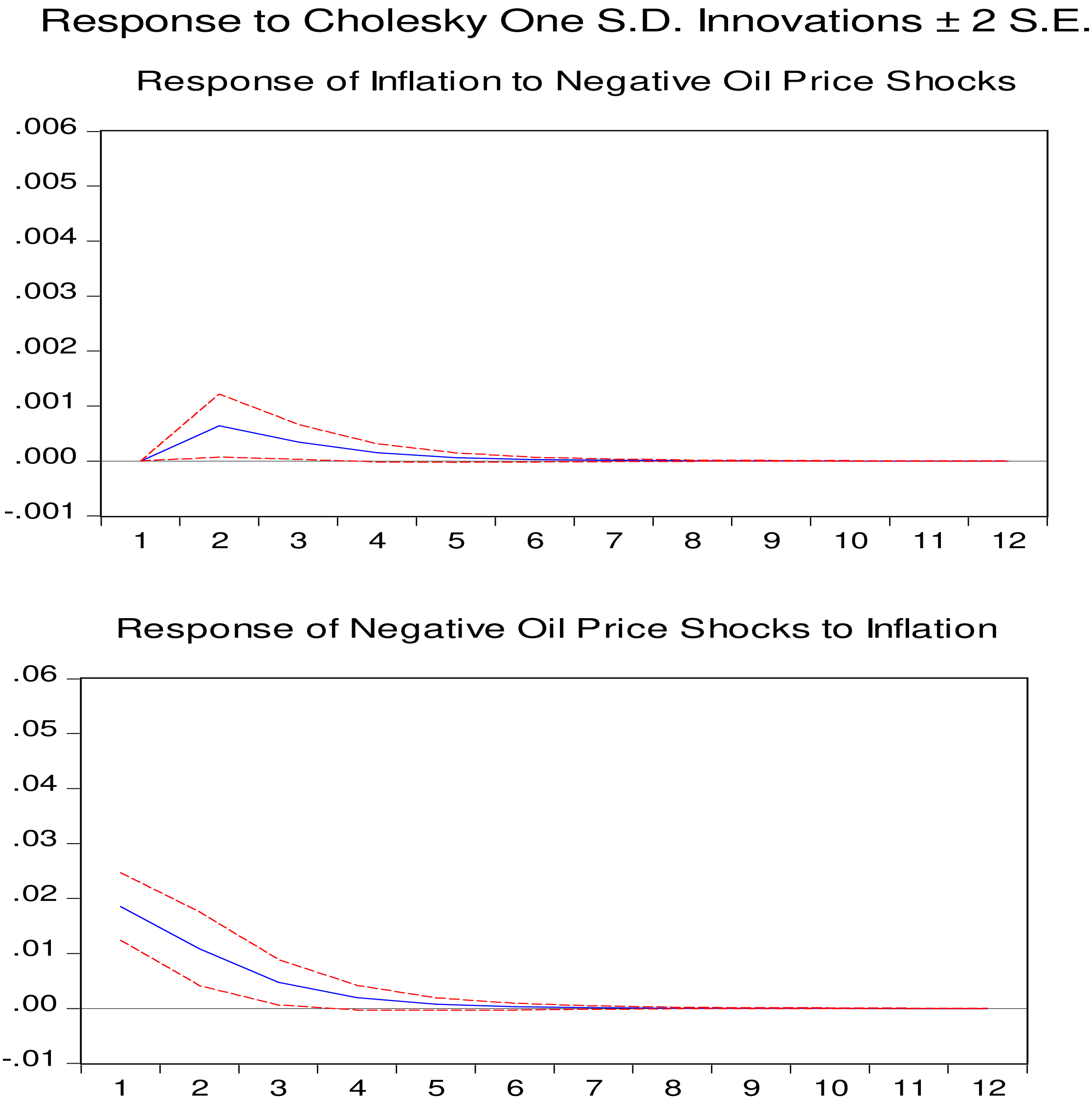

Fig. 5 Negative oil price shock and inflation

The results from impulse response analysis suggest that there seem to be no asymmetric impacts of oil price shock on inflation because the coefficients of positive and negative oil price shock variables are not quite different. The inflation rate seems to respond to the lagged positive and negative oil price shocks in a similar manner. However, the impact of inflation on negative oil price shock seems to be more pronounced than the impact on positive oil price shock. The results appear to be in line with the findings of Fazanegan and Markwardt (2009) and Ajmi et al. (2015).

Table 11 reports variance decompositions of positive and negative oil price shocks in inflation.

Table 11
Variance decompositions of positive and negative oil price shocks.

Month	Δp+	Δop+	Δp-	Δop-
Variance decompositions of inflation				
1	100.00	0.00	100.00	0.00
4	96.85	3.12	97.95	2.05
8	96.85	3.15	97.94	2.06
12	96.85	3.15	97.94	2.06
Variance decompositions of oil price shocks				
1	1.26	98.74	11.59	88.41
4	1.56	98.44	14.57	85.43
8	1.56	98.44	14.58	55.42
12	1.56	98.44	14.58	85.42

Note: Δp+ denotes inflation affected by positive oil price shocks (Δop+), and Δp- denotes inflation affected by negative oil price shocks (Δop-).

Both positive and negative oil price shocks affect the volatility of inflation in the model to somewhat similar degrees. For fluctuations of oil price shocks, inflation affects volatility of negative oil price shocks to stronger degree than it affects positive oil price shocks. Therefore, it cannot be concluded that the impacts of positive and negative oil price shocks on inflation are asymmetric.

4. Discussion

Previous studies find that oil price shocks affect domestic inflation. Furthermore, there is a non-linear adjustment between oil price changes and price indices. The present study uses two techniques of cointegration analysis to examine the long-run relationship between price level, industrial production and real oil price. The presence of cointegration is not found in linear cointegration tests with structural breaks. However, cointegration is found when using a threshold cointegration test that includes the 1997 financial dummy variable. The short-run dynamics reveal that the adjustment toward long-run equilibrium is observed only in the regime below the threshold value. The results of short-run analysis reveal that domestic oil price shocks Granger cause domestic inflation and this result is contradictory to Huang and Chao (2012) who find that international oil price plays a more important role than does domestic oil price on price indices. In addition, oil price volatility does not cause inflation as in the study by Rafiq and Salim (2014). Even though oil price uncertainty does not affect inflation, inflation itself positively causes inflation uncertainty, which supports Friedman (1977)'s hypothesis. On the contrary, inflation uncertainty lowers the inflation rate, which is contradictory to Cukierman and Meltzer (1986)'s hypothesis. However, the impact of oil price shocks on inflation might surpass the negative impact of inflation uncertainty on inflation. Therefore, the inflation induced by oil price shocks should not be ignored by the monetary authorities. The main finding in the short run that oil price shocks cause inflation is in line with one of the main findings of Cunado and De Gracia (2005) who use quarterly data in their analyses. However, the evidence that the impacts of oil price shocks are not asymmetric is consistent with the findings of Fazanegan and Markadt (2009) and Ajmi et al. (2015).

5. Concluding Remarks and Policy Implications

This study investigates the impact of oil price shocks on domestic inflation in Thailand. Monthly data from January 1993 to December 2016 are used. This study employs various techniques to capture the impact of oil price shocks on inflation. Both linear and nonlinear cointegration tests with structural breaks are adopted to detect the long-run relationship between price level, industrial production and the real price of oil. In the short-run, the two-step approach is also adopted to examine the impact of oil price shocks on inflation and inflation uncertainty. In addition, an asymmetric causality test is also used to test for asymmetric impacts of oil price shocks on inflation.

The main findings are threefold. Firstly, one threshold cointegration between price level, industrial production and real domestic oil price is found in the threshold autoregressive model. Both industrial production and real oil price have positive impacts on price level. In addition, asymmetric adjustments toward long-run equilibrium are found at the low level of significance. Secondly, oil price shocks positively cause inflation, but oil price volatility does not significantly cause inflation. Furthermore, inflation itself positively causes inflation uncertainty. This finding is also confirmed by impulse response analysis and variance decompositions. Finally, the presence of asymmetric impacts of oil price shock on inflation is not found in the Thai economy. The implications based upon the results of this study are that, besides the inflation-targeting that has been implemented by the monetary authorities, monetary measures should also be designed to accommodate inflation induced by oil price shocks. The oil fund as subsidization should not be discarded.

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