Oil price shocks and domestic inflation in Thailand

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Abstract

This paper employs monthly data to examine the empirical relationship between oil price shocks and domestic inflation rate during 1993 and 2015. Three cointegration tests and the two-step approach are used. In addition, the asymmetry of oil price shocks on inflation is also investigated. The results show that real oil price measured in domestic currency is not cointegrated with consumer price index and industrial production index. Therefore, the relationship is confined to the short-run phenomenon. The results from the two-step approach estimation show that an oil price shock causes inflation to increase while oil price uncertainty does not cause an increase in 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 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, bivariate GARCH, causality
JEL Classification: E31, Q43

1. Introduction

One of interesting topics on the relationship between oil shocks and macroeconomic variables is the impact of oil price shocks on domestic inflation rate. The rise of oil price can cause the costs of production of firms to increase. Therefore, the pass-through of oil price hike is reflected in an increase in the general price level of an economy. In addition, changes in oil price in the last five decades exhibit oil price volatility that can distort the decisions 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 and thus cause 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 interest rate policy and thus did not respond to oil price shocks accurately. This resulted in 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 reduce output growth.

On the supply channel, oil price shocks can cause consumer prices to increase. This phenomenon depends on the share of 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 oil price in consumer prices. Furthermore, monetary policy has become less accommodative of oil price shocks and thus prevents 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 some factors. De Gregono and Lanerretche (2007) find that the pass-through declines because of the fall in energy intensity. However, Chen (2009) indicates that a decline in the pass-through is due to a higher degree of trade openness. 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 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 commodity.

Previous studies give the one of the main findings that oil price shocks can have an adverse impact on the US macroeconomy because they raise the level of oil prices and oil price volatility. Oil price volatility, which is measured by monthly standard deviations of daily oil prices, helps to forecast the movements in aggregate output. In addition, the asymmetric relationship between oil price shocks and output growth can be partly explained by the economy's response to oil price volatility. Federer (1996) provides evidence that support this proposition. Using a structural vector autoregressive model to analyze the response of inflation to oil prices for the G-7 countries, Cologni and Manera (2008) find the impact of oil prices on inflation in most of the G-7 countries is evidenced. Rafiq et al. (2009) examine the impact of oil price volatility measured by realized volatility, on key macroeconomic indicators of Thailand using quarterly data during 1993 and 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 oil price volatility has its impact on inflation 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 has implemented oil subsidization after the crisis.

The main purpose of the present study is to investigate the impact of oil price shocks and oil price volatility on domestic inflation in Thailand, which is a net oil-importing country. Monthly data from January 1993 to December 2015 are used. This study does not use structural vector autoregression or other methods that capture the pass-through from oil price to consumer price as used in several previous studies. In stead, the methods used are Johansen's cointegration test, Engle and Granger cointegration test and the bounds testing for cointegration. The two-step approach is used to detect the short-run impact of oil price shocks on inflation and inflation uncertainty. The main findings are: (1) There is no long-run relationship, (2) In the short-run, oil price shocks cause inflation to increase, but oil price uncertainty does not affect inflation, (3) The short-run relationship between oil price shocks and inflation is not asymmetric. Furthermore, inflation itself causes inflation uncertainty in the Thai economy. The structure of this paper is organized as the following. The next section presents the data and estimation methods that are used in the analysis. Section 3 presents 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

2.1 Data

The dataset used in this study comprises monthly data during 1993 and 2013. The rationale for using this period is that the availability of industrial production index is from 1993. In addition, monthly data give a larger sample size than 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 the 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 consumer price index, the domestic real oil price series is obtained.[1] All series are transformed into logarithmic series. The sample size comprises 276 observations.

The PP unit root tests proposed by Phillips and Perron (1988) are performed on levels and first differences of the series. The results are shown in Table 1.

Table 1
Results of PP tests for first difference of all variables: 1993M1-2015M12.

Variables	Test A	Test B
cpi	-2.705 [6]	-1.923 [6]
(Level of consumer price index)	(0.074)*	(0.640)
Δcpi	-12.212 [6]	-12.479 [5]
(Difference in consumer price index)	(0.000)***	(0.000)***
op	-1.476 [0]	-1.371 [1]
(Level of nominal domestic oil price)	(0.544)	(0.867)
Δop	-13.556 [2]	-13.624 [3]

[1] Cunado and De Gracia (2005) find that this measure of real oil price is more important than real international oil price, which does not take into account of the impact of exchange rate.

(diference in nominal domestic oil pirce)	(0.000)***	(0.000)***
ip	-1.430 [36]	-3.038 [9]
(Level of industrial production index)	(0.568)	(0.124)
Δip	-24.590 [29]	-25.475 [30]
(Difference in industrial production index)	(0.000)***	(0.000)***

Note: Test A includes intercept only while Test B includes intercept and a linear trend. The number in bracket is the optimal bandwidth. ***, ** and ** denote significance at the 1%, 5% and 10% level, respectively. The number in parenthesis is the probability of accepting the null hypothesis of unit root.

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 first difference of series. It should be noted that the test for level of 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 GARCH model as well as the standard pairwise causality test described in the next sub-section.[2]

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

Table 2
Descriptive statistics: 1993M01-2015M12.

A. Level of series			
Variable	*cpi*	*op*	*ip*
Mean	4.3949	7.4089	4.9000
Median	4.3808	7.4277	4.9592
Maximum	4.6812	8.4215	5.4571
Minimum	3.9754	6.1832	4.2053
Standard deviation	0.1984	0.5887	0.3823
Skewness	-0.3157	-0.2699	-0.1141
Kurtosis	2.1310	1.7321	1.4659
JB	13.2695	21.8401	27.6652
	(0.001)	(0.000)	(0.000)
Observations	276	276	276
B. First difference of series			
Variable	Δ*cpi*	Δ*op*	Δ*ip*
Mean	0.0025	0.0016	0.0042
Median	0.0023	0.0069	0.0047
Maximum	0.0263	0.2217	0.2018
Minimum	-0.0307	-0.2900	-0.3159
Standard deviation	0.0052	0.0879	0.0399

[2] A bivariate GARCH model requires that all series be stationary.

Skewness	-0.5598	-0.6025	-1.4995
Kurtosis	10.8207	4.0110	19.2466
JB	715.1836	28.3484	3127.486
	(0.000)	(0.000)	(0.000)
Observations	275	275	275

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 0.25 percent, whereas the average monthly oil price shock is 0.16 percent and the average monthly industrial production is 0.42 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 ARCH effect.

The real domestic oil price series is plotted in Fig. 1. Starting from low oil price with some fluctuations, the impact of new oil shock in 2000 causes the price to increase. Again, the oil price reaches the peak near mid-2009. Oil price volatility plotted in Fig. 2 shows that the high volatility occurs around 2000 and again around 2009.[3]

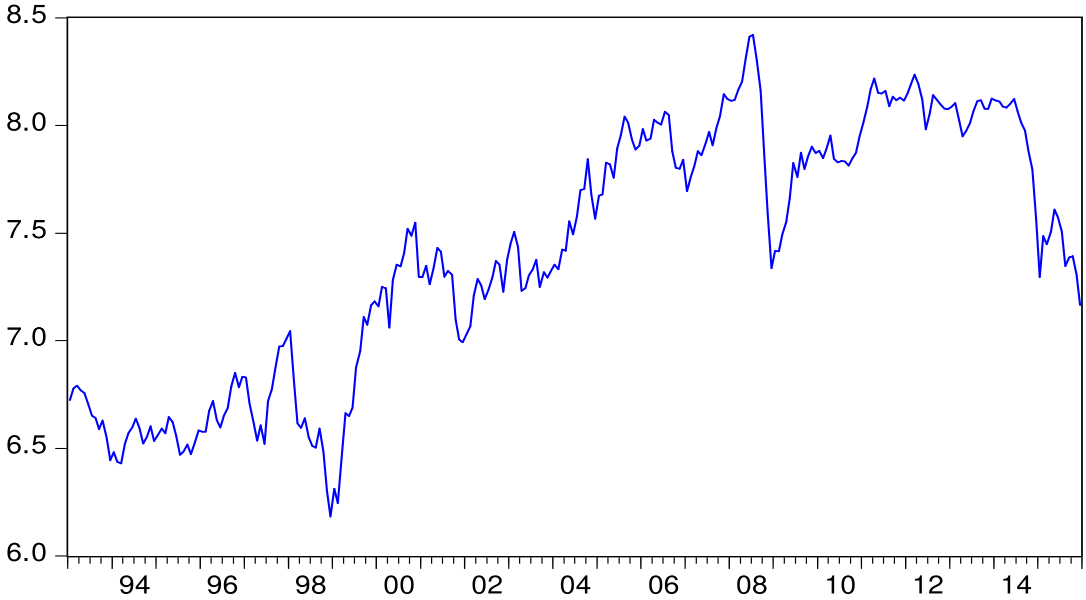

Fig. 1 Level of real oil price.

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

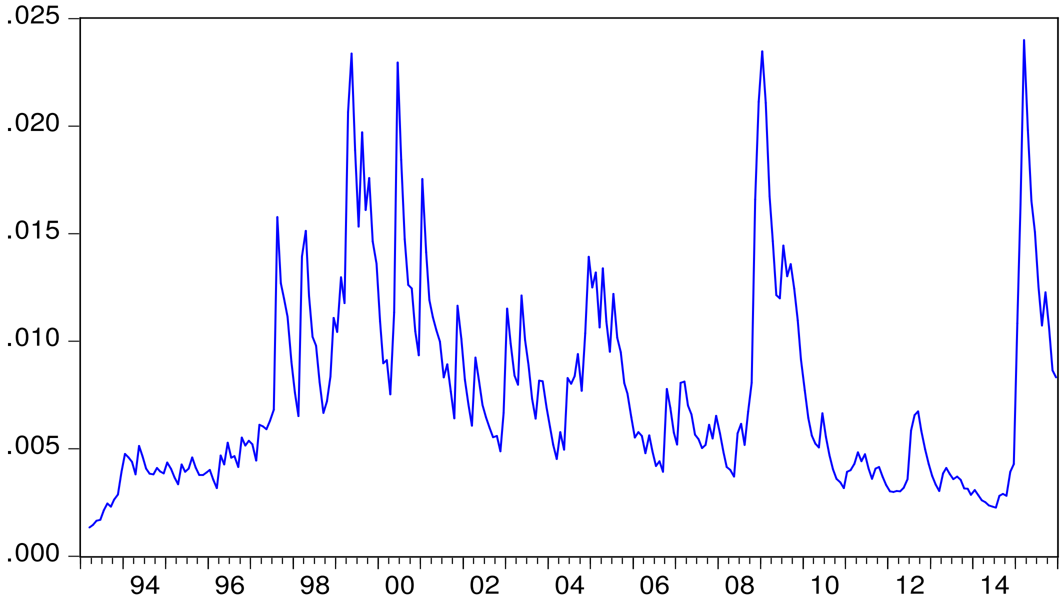

Fig. 2 Volatility of real oil price.

2.2 Estimation Methods

2.2.1 Cointegration test

The existence of cointegration between nominal oil price and consumer price index implies that there is a long-run relationship between the two variables. In a bivarite framework of cointegration analysis, two tests can be used to determine whether consumer price index is cointegrated with domestic oil price: (1) Johansen's cointegration test, (2) Engle and Granger cointegation test, and (3) the bounds testing for cointegration.

a Johansen's cointegration test

Johansen's cointegration test proposed by Johansen (1991) and Johansen and Juselius (1990) makes use of a vector autoregressive (VAR) model, and the test strictly requires that all series included in the specified VAR model be I(1) series. The VAR model for this test can be expressed as:

$$Y_t = \mu + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \ldots\ldots\ldots\ldots\ldots + \Gamma_p Y_{t-p} + e_t \qquad (1)$$

where Y is the 3x1 vector of the level of consumer price index (*cpi*), the level of real domestic oil price (*op*) series and the level of industrial production index (*ip*)[4], and Γ_1, Γ_2,….,Γ_p are the unknown parameters. This the VAR model of order *p*. The optimal order of the VAR model can be determined by Akaike Informtion Criterion (AIC). If the trace and maximum eigenvalue statistics reject the null hypothesis of no

[4] If the level of industrial production index is excluded, the Y will become the 2x1 vector in a bivariate framework.

cointegration, there will be one or more two cointegating relations. Otherwise, there will be no cointegration at all.

The existence of cointegration from Eq. (1) indicates that the relationship between consumer price index and nominal domestic oil price can be represented by the error correction model (ECM) that can be expressed as:

$$\Delta cpi_t = \varphi_0 + \varphi_1 EC_{t-1} + \sum_{i=1}^{p} \varphi_{21} \Delta cpi_{t-i} + \sum_{i=1}^{p} \varphi_{3i} \Delta op_{t-i} + \sum_{i=1}^{p} \varphi_{4i} \Delta ip_{t-1} + u_t \qquad (2)$$

where EC_{t-1} is the lagged value of the corresponding error term, which is called the error correction term (ECT), and φ_1, φ_{2i}, φ_{3i} and φ_{4i} are the regression coefficients while u_t is a random variable. For a bivariate framework for cointegration test, the lagged variable Δip_{t-1} will be excluded from the ECM.

b. Engle and Granger cointegration test

Similar to Johansen's cointegration test, this test proposed by Engle and Granger (1987) can be used by estimating the relationship between three non-stationary series: consumer price index, domestic oil price and industrial production. The relationship can be expressed as:

$$cpi_t = a + b_1 op_t + b_2 ip_t + e_t \qquad (3)$$

If domestic oil price and industrial production impose impacts on consumer price index, the coefficient b_1 and b_2 should statistically significant. The residual series, e_t, obtained from the estimation of Eq. (3) can be used to test for unit root using the Augmented Dickey-Fuller (ADF) test, which is expressed as:

$$\Delta e_t = \rho e_{t-1} + \phi \Delta e_{t-1} \qquad (4)$$

The t-statistic obtained from the estimation of Eq. (4) is the ADF statistic. This statistic is used to compare with the critical value statistic provided by MacKinnon (1991). 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 the critical value statistic leads to an acceptance of the null hypothesis of unit root and thus the absence of cointegration. For a bivariate framework, the level of industrial production index will be excluded. The ECM representations for three and two variables are similar to those of Johansen's cointegration test.

c. Bounds testing for cointegration

Pesaran et al. (2001) proposed an alternative procedure in testing for cointegration called a conditional autoregressive distributed lag (ARDL) model and error correction mechanism for three variables. The ARDL (:p, q, r) model is specified as:

$$\Delta cpi_t = \mu + \sum_{i=1}^{p} \alpha_i \Delta cpi_{t-i} + \sum_{j=0}^{q} \beta_i \Delta op_{t-j} + \sum_{k=0}^{r} \gamma_i \Delta ip_{t-k} + v_t \qquad (5)$$

where Δcpi is the change in consumer price index or the inflation rate, Δop is the change in nominal domestic oil price, and Δip is the change in industrial production index. The lag orders are p and q, respectively. They may be the same or different. To determine the optimal numbers of lagged first differences in the specified ARDL model, the grid search can be used to select a parsimonious model that is free of serial correlation. By adding lagged level of the two variables into Eq. (5) as expressed in Eq. (6), the computed F-statistic for detecting cointegration can be obtained.

$$\Delta cpi_t = \mu + \delta_1 cpi_{t-1} + \delta_2 op_{t-1} + \delta_3 ip_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta cpi_{t-i} + \sum_{j=0}^{q} \beta_i \Delta op_{t-j} + \sum_{k=0}^{r} \gamma_i \Delta ip_{t-k} + v_t \tag{6}$$

The computed F-statistic is compared with the critical values. If the computed F-statistic is greater than the upper bound critical F-statistic, cointegration exists. If the computed F-statistic is smaller than the lower bound F-statistic, cointegration does not exist. In case the computed F-statistic is between the upper and lower bound F-statistic, the result is inconclusive. Unlike other techniques that can be used to test for cointegration, reparameterization of the model into the equivalent vector error correction is not required. Furthermore, this procedure can an be applied to the mixed between I(0) and I(1) series resulted from unit root tests, but not for I(2) series. The results of unit root tests from Table 1 show that the order of integration of the two series does not exceed one. The ECM representation can be obtained by replacing the lagged levels of variables in Eq. (6) by the error correction term from long-run equation similar to Eq. (3). For a bivariate bounds test, the variable, *ip*, will be excluded.

2.2.2 The two-step approach

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 generalized autoregressive heteroskedastic model with constant conditional correlation (ccc-GARCH) model proposed by Bollerslev (1990) is employed to generate real exchange rate and oil price volatilities. In the second step, these generated series along with real effective exchange rate change and the rate of change in real 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. 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.[5] The system equations in a ccc-GARCH(1,1) model comprises the following five equations.

$$r_t^{cpi} = a_{1,0} + \sum_{i=1}^{p} a_{1,i} r_{t-i}^{cpi} + \sum_{i=1}^{p} b_{1,i} r_{t-i}^{op} + e_{1,t} \tag{7}$$

$$r_t^{op} = a_{2,0} + \sum_{i=1}^{p} a_{1,i} r_{t-i}^{op} + e_{2,t} \tag{8}$$

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

$$h_t^{cpi} = \mu_1 + \alpha_{1,1}\varepsilon_{t-1}^{2,cpi} + \beta_{1,1}h_{t-1}^{cpi} \tag{9}$$

$$h_t^{op} = \mu_2 + \alpha_{2,1}\varepsilon_{t-1}^{2,op} + \beta_{2,1}h_{t-1}^{op} \tag{10}$$

$$h_t^{cpi,op} = \rho_{12}(h_t^{cpi})^{1/2}(h_t^{op})^{1/2} \tag{11}$$

where r^{cpi} is the rate of change in consumer price index or inflation rate, and r^{op} is the rate of change in nominal oil price, h^{cpi} is the conditional variance of inflation rate, h^{op} is the conditional variance of nominal oil price change, and $h^{cpi,op}$ 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.

$$y_t = a_1 + \sum_{i=1}^{k}\alpha_{1i}y_{t-i} + \sum_{i=1}^{k}\beta_{1i}x_{t-i} + \eta_{1t} \tag{12}$$

and

$$x_t = a_2 + \sum_{i=1}^{k}\alpha_{2i}x_{t-i} + \sum_{i=1}^{k}\beta_{2i}y_{t-i} + \eta_{2t} \tag{13}$$

where y and x are two variables that can exhibit causal relationship. The optimal lag length is determined by AIC. 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 $\{r^{op}, r^{cpi}\}$, $\{r^{cpi}, h^{op}\}$, $\{h^{op}, h^{cpi}\}$and $\{r^{cpi}, h^{cpi}\}$. 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. In addition, impulse response analysis and variance decompositions 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.

The asymmetric impacts of oil price shocks on inflation rate can be tested using the equation specified as:[6]

$$r_t^{cpi} = \alpha_0 + \alpha_1 r_t^{op} + \alpha_2 r(+)_t^{op} + \alpha_3 r_{t-1}^{op} + \alpha_4 r_{t-1}^{cpi} + \alpha_5 (r_t^{op})^2 \tag{14}$$

where $r^{op}{}_t(+)$ is positive oil shock. If a positive oil shock has a stronger impact on inflation than a negative oil shock, the coefficient α_2 should be significantly positive. The inclusion of the lagged inflation rate in Eq. (14) gives a room for testing for possible mean reversion of inflation. The squared oil price shock is included for testing the null hypothesis that the short-run relationship between inflation and oil price shock is non-linear.

[6] This type of least square equation is used in finance to test for asymmetry in the relationship (see Ederington and Guan, 2010, for example).

3. Results

The model expressed in Eq. (1) is used for testing the existence of long-run relationship between consumer price index (cpi) and nominal domestic oil price.[7] The results from bounds testing for cointegration are shown in Table 2.

The results in Table 2 show that there is no cointegration because both trace and maximum eigenvalue tests are smaller than the 5% critical values for three-variable tests in Panel A. For two-variable test results in Panel B, the trace test indicates one cointegrating equation while the maximum eigenvalue test indicates no cointegration. Therefore, it is not clear whether there is a long-run relationship between consumer price index and domestic oil price. Without the presence of cointegration, the estimation of ECM representation expressed in Eq. (2) is not valid.

Table 2
Results of Johansen's cointegration test.

A. Three variables: *cpi*, *op* and *ip*			
Trace test			
No. of cointegrating vectors	Trace statistic	5% critical value	p-value
None	25.992	29.797	0.129
At most 1	11.448	15.495	0.185
At most 2	2.422	3.841	0.120
Max eigenvalue test			
No. of cointegrating vectors	Max-eigenvalue statistic	5% critical value	p-value
None	14.543	21.132	0.322
At most 1	9.026	14.265	0.284
At most 2	2.422	3.841	0.120
B. Two variables: *cpi* and *op*			
Trace test			
No. of cointegrating vectors	Trace statistic	5% critical value	p-value
None*	15.760	15.495	0.046
At most 1	3.575	3.841	0.059
Max eigenvalue test			
No. of cointegrating vectors	Max-eigenvalue statistic	5% critical value	p-value
None	12.184	14.265	0.104
At most 1	3.575	3.841	0.059

Note: MacKinnon et al. (1999) p-value in parenthesis, * denotes rejection of the null hypothesis at the 5% level.

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

The results of Engle-Granger cointegration test in Eqs. (3) and (4), are reported in Table 3.

Table 3
Long-run coefficient and unit root test of the residual series.

A. Three-variable cointegration test: Dependent variable is cpi_t			
Independent variable	Coefficient	t-statistic	p-value
op_t	-0.011	-0.745	0.457
ip_t	0.510	22.426	0.000
Adj. R^2 = 0.907			
ADF statistic = -2.073, 5% Critical value = -3.760			
B. Two-variable cointegration test: Dependent variable is cpi_t			
Independent variable	Coefficient	t-statistic	p-value
op_t	0.290	27.851	0.000
Adj. R^2 = 0.738			
ADF statistic = -1.162, 5% Critical value = -3.350			

Note: Critical values are provided by MacKinnon (1991).

There seems to be a positive long-run relationship between consumer price index and domestic oil price and industrial production index in Panel A of Table 3. However, the residual based-test for cointegration shows that the absolute value of the ADF statistic is smaller than the critical value at the 5% level of significance. Therefore, the null hypothesis of no cointegration cannot be rejected. By excluding industrial production index in cointegration test as shown in Panel B of Table 3, the result shows that the ADF statistic is -1.162, which is smaller than the 5% critical value. Therefore, it can be concluded that there is no long-run relationship.

For the bounds testing for cointegration, the least squares estimation of Eqs. (5) and (6) are performed. The results are reported in Table 4.[8]

Table 4
Results from bounds testing for cointegration.

Model	Computed F	ARDL model	$\chi^2_{(2)}$
a. *cpi* vs. *op* and *ip*	4.84	(1,1,1)	2.68 (p=0.26)
b. *cpi* vs. *op*	4.88	(1,1)	2.62 (p=0.27)

c 5% Upper bound and lower bound ound critical values = (4.85, 3.79) for three-variable test.
5% Upper bound and lower bound ound critical values = (5.73, 4.94) for two-variable test.

Note: The LM test for serial correlation in the specified ARDL models is represented by $\chi^2_{(2)}$. Three variables: *cpi*, *op* and *ip* are the logs of CPI, real oil price and industrial production index, respectively. Critical values are from Pesaran et al. (2001) in Table CI (iii) Case III.

[8] The PP tests for unit root might have low power. In fact, the variables might have level relationship if they are mixed between I(1) and stationary series. Therefore, this procedure can be employed to reexamine long-run relationship.

In order to determine the optimal lag length of Eq. (5), the AIC suggest the lag of two. However, reducing the lag to one improves the test results. The results from bounds tests in Table 4 indicate that trivariate cointegration test gives the computed F-statistics of 4.84, which is between the upper and lower bounds critical values of 4.85 and 3.79 at the %5 level of significance. Therefore, it can be concluded that the result is inconclusive. For the bivariate test, the computed F-statistic is -4.88, which is smaller than the lower bound critical value of the 5% level of significance. Therefore cointegration does not exist. In other words, the test suggests that there is no long-run equilibrium relationship between the consumer price index and oil prices. When industrial production index series is also included in the test, the results the result becomes inconclusive.

The results from three techniques of cointegration tests reveal that there is no long-run relationship between consumer price index and domestic real oil price, which is the main focus of the analysis in this paper. This phenomenon suggests that the impact of an oil shock to a change in consumer price index or inflation rate is confined to the short-run relationship. In analyzing short-run relationship, the two step approach explained in the previous section is utilized. First, a bivariate GRACH model is estimated to obtain volatility series. The next step is to employ Granger causality and an unrestricted VAR model to examine short-run causality and the use of impulse response functions as well as variance decompositions 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 first differences of the two series are stationary and is thus suitable for the estimation.

The bivariate GARCH estimation for the system equations (7) to (11) to obtain volatility or uncertainty series are reported in Table 6. The series, calculated as the rates of change, are also stationary.

Table 6 Results from the bivariate ccc-GARCH(1,1) estimation.

Mean equations:

$$r_t^{cpi} = 0.126^{***} + 0.186^{**} p_{t-1}^{cpi} + 0.999^{***} r_{t-1}^{op}$$

(4.114) (2.246) (3.916)

$$r_t^{op} = -0.001 + 0.145^{**} r_{t-1}^{op}$$

(-0.181) (2.129)

(t-statistic in parenthesis)

Variance and covariance equations:

$$h_t^{cpi} = 0.022^{***} + 0.318^{***} \varepsilon_{t-1}^{2,cpi} + 0.640^{***} h_{t-1}^{cpi}$$

(2.953) (3.636) (8.140)

$$h_t^{op} = 0.001^{*} + 0.185^{***} \varepsilon_{t-1}^{2,op} + 0.772^{***} h_{t-1}^{op}$$

(1.692) (2.808) (11.581)

$$h_t^{p,op} = 0.259^{***} (h_t^{p})^{1/2} (h_t^{op})^{1/2}$$

(4.083)

(t-statistic in parenthesis)

System diagnostic test:

Q(4) =14.529 (p-value=0.559)

Note: The variables, r^{cpi} and r^{op}, stands for the percentage rates of change in consumer price index and nominal oil price, respectively. The conditional variances, h^{cpi} for inflation rate and h^{op} for nominal oil price. The conditional covariance is $h^{p,op}$. ***, ** and * denotes significance at the %1, %5 and %10, respectively. Q(k) is the Box-Pierce statistic test for the residuals obtained from system residual Portmanteau tests for autocorrelations.

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 independent of inflation rate.[9]

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 change, respectively. Referring to Panel A, the inflation rate is positively affected by the one-period lag of oil price change. In Panel B, oil price change is positively 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_1 and β_1). The sum of the coefficients of the ARCH and GARCH terms for inflation rate is 0.958 whereas the sum of coefficients for the rate of oil price change is 0.957. These results show that the GARCH variance series as measures of volatility or uncertainty is stationary. The constant conditional correlation in Panel C is 0.259, which is low and statistically significant.[10] The system diagnostic test using residual portmanteau test for autocorrelation accepts the null of no autocorrelation as indicated by Q(4) statistic. Therefore, the system equations are free of serial correlation. The volatility series are generated so as to examine their impacts on inflation and volatility in the standard Granger causality test. The results of pairwise Granger causality test are reported in Table 7.

Table 7 Results of pairwise Granger causality test

Hypothesis	F-statistic	Lag length
r^{op} does not cause r^{cpi}	2.922 **(+)	4
r^{cpi} does not cause r^{op}	1.601 (+)	4
h^{op} does not cause r^{op}	6.479***(-)	4
h^{op} does not cause r^{cpi}	2.106* (-)	4
h^{op} does not cause h^{cpi}	0.963 (+)	4
r^{cpi} does not cause h^{cpi}	5.460*** (+)	4
h^{cpi} does not cause r^{cpi}	5.498*** (-)	4

Note: op and op stands for the percentage rates of change in consumer price index and nominal oil price, respectively. The conditional variances, h^p for inflation rate and h^{op} for nominal oil price. ***, ** and * denotes significance at the 1%, 5% and 10%, respectively. The lag length in the pairwise causality test is determined by AIC.

[9] The country is a small oil-importing country. Therefore, its inflation rate should not affect world oil price.

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

The results in Table 7 show that an oil price shock tends to cause the inflation rate to increase while inflation does not cause an oil shock. In addition, oil price volatility tends to cause the inflation rate to decrease, but is statistically significant at the 10% level only. Oil price volatility significantly causes an oil price shock to decrease. Therefore, this effect can partly reduce the size of oil price shock when oil price volatility rises. Furthermore, oil price uncertainty does cause inflation uncertainty. Finally, there exist bidirectional causality between inflation and inflation uncertainty. It is obvious that inflation causes higher inflation uncertainty, but inflation uncertainty causes inflation to decrease. The latter impact might stem from the sound implementation of monetary policy.

The estimate of VAR(4) model allows for performing an analysis of impulse response function and variance decompositions. The results of impulse response analysis are shown in Fig. 3. The figure shows the impulse response functions from the Monte Carlo simulated at 95 percent intervals. The response of inflation rate (r^{CPI}) to a shock in oil price (r^{OP}) shows that inflation increases in the next month following the contemporaneous effect of that shock. This impact starts to decay to the negative impact and the whole impact is incorporated within four months. The response of inflation to a shock in oil price volatility (h^{OP}) shows that inflation decreases and starts to increase and incorporated with in three months. The response of inflation uncertainty (v^{CPI}) to a shock in oil price start in two months and the impact starts to increase but decays later on. Finally, the response of inflation uncertainty to a shock in oil price volatility starts to increase in the next month, but decays and the impact becomes negative after four and half months.

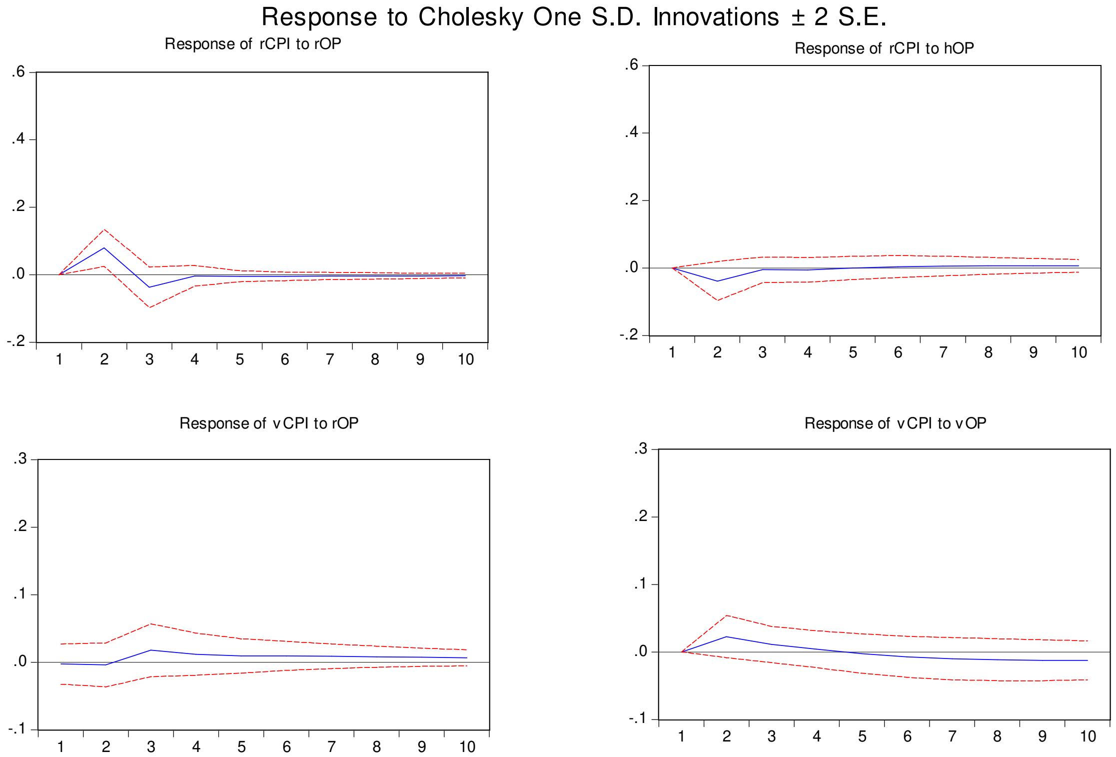

Fig. 3 Impulse response functions

Variance decompositions shown in Fig. 4 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. Variance decompositions are presented in Fig. 3. The dashed lines represent the Monte Carlo simulated at 95 percent confidence intervals. 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.

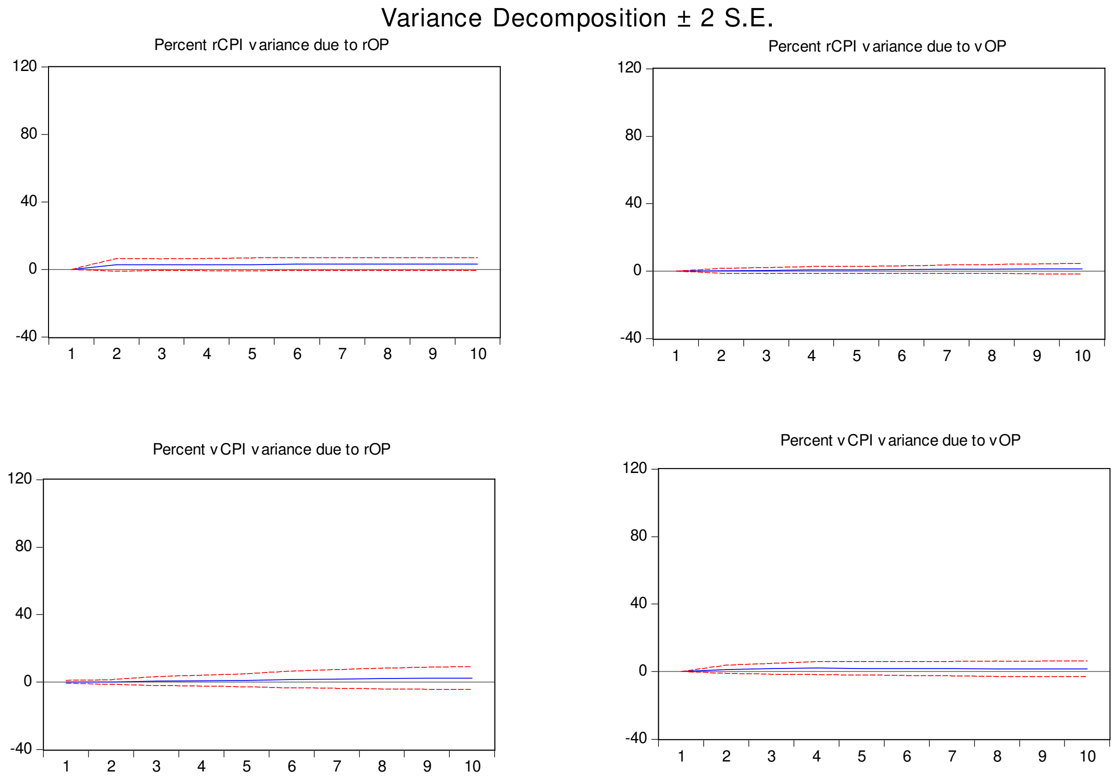

Fig. 4 Variance decompositions

The results of estimation of equation (14) for testing asymmetric impact of oil price shocks on inflation are reported in Table 8.

Table 8
Asymmetric impact of oil price shocks on inflation.

Dependent variable: r_t^{cpi}			
Variable	Coefficient	t-statistic	p-value
r_t^{op}	0.018	1.179	0.239
$r_t^{op}(+)$	-0.002	-0.067	0.946
r_{t-1}^{op}	0.006*	1.709	0.089
r_{t-1}^{cpi}	0.182***	3.145	0.002
$(r_t^{op})^2$	-0.001	-1.145	0.254
Intercept	0.252***	4.061	0.000

Note: r^{op} denotes an oil price shock, and $r^{op}(+)$ denotes positive oil price shock. ***, **, and * indicate significance at the 1%, 5% and 10%, respectively.

The results in Table 8 suggest that there is no asymmetric impact of oil price shock on inflation because the coefficient of positive oil price shock variable is not statistically significant. Inflation rate seems to merely respond to the lagged oil price shock at the 10% level of significance. The coefficient of the squared oil price shock is insignificant, which does not indicate the presence of non-linear relationship. However, inflation seems to exhibit mean reversion. Instead, the significance of the coefficient of lagged inflation suggests that it is possible that inflation is mean-reverting.

4. Discussion

Previous studies find that oil price shocks pass through domestic inflation. Furthermore, there is a non-linear adjustment between oil price changes and price indices. The present study reveals that domestic oil price shocks Granger cause domestic inflation and this result is contradictory to the finding by Huang and Chao (2012) who find that international oil price plays more important role than domestic oil price on price indices. Even though oil price uncertainty does not affect inflation, inflation itself positive causes inflation uncertainty, which supports Friedman (1977) hypothesis. On the contrary, inflation uncertainty lowers inflation rate, which is contradictory to Cukierman and Meltzer (1986) 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 present study is that the relationship is confined to the short run, which is in line with one of the main findings by Cunado and De Gracia (2005) who use quarterly data in their analyses. However, the asymmetric impacts of oil price shocks on inflation cannot be found.

5. Concluding Remarks and Policy Implication

This study investigates the impact of oil price shocks on domestic inflation in Thailand. Monthly data from January 1993 to December 2013 are used. This study does not use structural vector autoregression or other methods that capture the pass-through from oil price to consumer price as used in many previous studies. In stead, the methods used are three techniques to test for cointegration and the two-step approach to detect the impact of oil price shocks on inflation and inflation uncertainty. In addition, the simple regression is also used to test for asymmetric impacts of oil price shocks on inflation in the short-run. The main findings are that (1) oil price shocks, defined as movements in real oil price, positively cause inflation to increase, but oil price uncertainty merely and marginally causes inflation to decrease, (2) inflation itself positively causes inflation uncertainty in the Thai economy. The implication based upon the results of this study is that besides 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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