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Crude oil price and exchange rate: Evidence from the period before and after the launch of China's crude oil futures

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ABSTRACT

This study investigates whether the relationships between China's exchange rate, domestic crude oil price, and the international crude oil price have a switch in the period before and after China's crude oil futures launched by Shanghai International Energy Exchange (INE) using the MS-VAR model. We find that, although China's oil price is strongly influenced by the international crude oil market, its effect on the international crude oil price is weak; Since the launch of INE crude oil futures in the new regime, the fluctuations in the US dollar against the RMB (USD/CNY) exchange rate has had a significant positive effect on China's crude oil prices. Placebo test results demonstrate that the launch of Brent or Oman crude oil futures, which are US dollar-dominated, do not have the same effects as the launch of INE crude oil futures. This implies that the positive impact of the USD/CNY exchange rate on the INE crude oil futures price may be transmitted to China's crude oil spot market.

1. Introduction

The RMB-denominated crude oil futures were launched by Shanghai International Energy Exchange (INE) in China on March 26, 2018. The trading volume of INE ranked top in Asia and third in the world in just 3 months. Before these, the international crude oil futures market was dominated by two competing benchmark grades in US dollars, WTI crude oil futures on the New York Mercantile Exchange (NYMEX) and Brent crude oil futures on the London Intercontinental Exchange (ICE) (Scheitrum et al., 2018). The ratio of average daily trading volume of INE crude oil futures to NYMEX's WTI crude oil futures has risen from 8.98% in the first month of launch to 29.50% in Oct 2019, while the ratio has increased from 17.99% to 52.93% compared to that of ICE's Brent crude oil futures. The growing INE trading volume is in part due to China's massive domestic market. China's oil imports have surpassed those of the United States and it has been the largest oil importer worldwide since 2015 (Lin and Xu, 2019). In 2017, before the launch of INE futures, China's crude oil imports accounted for 19.3% of the world's total oil imports. An interesting and important question that arises from this is that whether the relationship between China's crude oil price and the USD/CNY exchange rate has a structural change in the pre and post period of RMB-denominated crude oil futures.

Almost all crude oil is traded on futures markets, which implies that crude oil derivatives may be more important to the price discovery process than physical markets (Liu et al., 2015). As crude oil is dominated by US dollars, the devaluation of the US dollar is considered an important reason for the alarming increase in oil prices (Zhang et al., 2008). While crude oil is a vital resource for economic development (Wang et al., 2021; Fang et al., 2021), its prices are also influenced by fluctuations of exchange rates (Atems et al., 2015). It seems also to become a consensus that the relationship between the exchange rate and oil price is not completely linear. Beckmann and Czudaj (2013) applied the Markov-switching model to the relationship between oil prices and exchange rates and found the relationships were subject to changes over time. Basher et al. (2016) estimated the impact of oil shocks on real exchange rates using Markov-switching models and found that underlying nonlinearities between the real exchange rate and oil shocks (demand and supply) for both oil exporting and importing economies. Research on the relationship between crude oil price and the exchange rate related to China has mainly focused on the interaction between the RMB exchange rate and international crude oil price (Huang and Guo, 2007; Ju et al., 2014; Hussain et al., 2017; Ji et al., 2019). It has been found that the dependence between oil prices and the USD/CNY exchange rate is dynamic and negative. For example, Lin and Su (2020)

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found that the correlation between external oil price shocks and China's exchange rate is less significant than that in other BRICS countries. However, previous studies have rarely linked China's exchange rates to its domestic crude oil prices. Our study addressed this research gap under the opportunity of the launch of INE crude oil futures.

For INE crude oil futures, there are two points worth noting. One of the worth noting points is whether INE crude oil futures can change China's long-standing status as a price-taker in the international oil markets. Based on empirical results covering the period from January 7, 2000, to November 11, 2011, Ji and Fan (2016) found that China's crude oil market is too weak to influence other crude oil markets. They also stated that international crude oil pricing in US dollars and the largest trading volume of oil futures contracts being in the NYMEX ensure that the US holds the dominant status in the international oil market. Zhang and Wang (2014) believed that with the help of its oil futures market, China could strengthen its oil pricing power.

The second worth noting point is whether China's crude oil price and the USD/CNY exchange rate exhibit different relationships in pre and post period of the launch of RMB-denominated crude oil futures. With the launch of INE crude oil futures, the RMB has become the valuation currency of the world's third-largest crude oil futures market. Based on the effect of portfolio diversification, depreciation of the denominated currency will make investors switch to investing in crude oil futures assets, driving oil prices up (Coudert and Mignon, 2016). From the perspective of asset arbitrage, if the RMB depreciates against the US dollar, INE crude oil futures will be relatively cheaper, and their long position will increase. Their price will increase until there is no opportunity for arbitrage. The empirical study of Jie et al. (2021) shows that the correlations and hedging effectiveness of Chinese crude oil futures and spots are quite strong. While both spot and futures markets react simultaneously to new information (Silvapulle and Moosa, 1999), the spot price of crude oil is closely linked to INE crude oil futures, which will also increase accordingly. In other words, changes in the RMB exchange rate may directly affect the price of INE crude oil futures and thus indirectly, inducing shocks to the spot price of crude oil in China.

In this study, we regard the launch of INE crude oil futures as an exogenous shock on the crude oil markets in the sense that it breaks the existing development mode of the international crude oil futures market, which is dominated by two competing benchmark grades in US dollars. Moreover, the launch of INE crude oil futures also causes fluctuations in China's oil market for its outstanding performance. Empirically, we investigate whether the relationship between China's crude oil price, exchange rate, and the international crude oil price changed after the launch of INE crude oil futures. The Markov Regime Switching Vector Autoregression (MS-VAR) method is adopted in this paper since it is effective in dealing with asymmetry among different regimes (Ozdemir and Akgul, 2015). And more importantly, the regime variable in the MS-VAR model is treated as an exogenous stochastic process that suits the data affected by the exogenous factors (Ihle and von Cramon-Taubadel, 2008).

Specifically, we are motivated to use the MS-VAR method considering its advantages in examining the occurrence of regime switch in the dynamic relationship between China's crude oil prices, exchange rate, and international crude oil prices. First, it succeeds in studying whether the nonlinear switches of relationships between variables exist in market fluctuations compared with the traditional linear VAR model, which assumes the consistency of parameters in the sample period while ignoring the possible structural change. Second, the MS-VAR framework has been proven to be useful in cases where the data seems to be mainly driven by exogenous events (Reboredo, 2010; Basher et al., 2016). Therefore, it is a natural tool to study whether the causal links have changed over the period before and after the launch of China's crude oil futures. Third, compared with other VAR models, such as the threshold-VAR (i.e TVAR) or smooth transition-VAR with an exponential or logistic transition function (i.e STVAR), the framework of MS-VAR has the advantage that it does not require the specification of a particular variable that triggers the transition between regimes with abrupt (threshold) or smooth transition. Moreover, the smooth transition model has to estimate more parameters, which may lead to greater estimation errors.

Using the MS-VAR model, we have some findings as follows. First, fluctuations in the USD/CNY exchange rate have a significant positive impact on China's crude oil prices following the launch of the futures, indicating that the relationship between the exchange rate and China's domestic crude oil price indeed has a switch in the period before and after the launch of INE crude oil. Second, in regime 1 where the relationship between the two above variables is not significant, the trading volume of INE crude oil futures is generally lower than that of regime 2, where the exchange rate and China's crude oil price are positively correlated significantly. This indicates that the switch of the relationship between the variables is also accompanied by the change of INE crude oil futures trading volume. Third, after further tests, it is found that the launch of US dollar-denominated crude oil futures (Brent and Oman) do not have the same effects as the launch of INE crude oil futures denominated by RMB. This helps to infer that the structural change of the exchange and China's crude oil price may stem from the fact that INE crude oil futures are denominated in Chinese domestic currency.

Our study makes two contributions to the literature. First, we examine the time-varying correlation between crude oil price and exchange rate of the host country of INE crude oil futures, which is denominated in domestic currency, not in US dollars. Although there are some non-USD-denominated crude oil futures,[1] those markets have not developed to a considerable scale and are only used as hedging tools. Hence, they do not significantly correlate with (or affect, to some extent) the spot price of domestic crude oil. Our study provides a new attempt at researching the correlation of crude oil futures denominated in the domestic currency with the domestic crude oil price. We find that, in contrast to USD-denominated crude oil futures (Brent crude oil and Oman crude oil), the USD/CNY exchange rate has a significant positive impact on China's crude oil price, revealing the RMB pricing power in the crude oil market after the launch of INE crude oil futures. Second, we determine that the main change in the relation between crude oil price and the exchange rate is also closely related to the scale development of the INE crude oil futures market. Prior research on the nonlinear relationship between the exchange rate and the crude oil price has mostly consisted of qualitative analyses.

The remainder of this paper is organized as follows: Section 2 presents the methodology and data. Section 3 discusses the results. Section 4 provides some tests of the empirical results. And Section 5 includes the conclusions and policy implications.

2. Methodology and data

2.1. MS-VAR model

We select the framework of the Markov Regime Switching Vector Auto Regression (MS-VAR) model to examine whether the dynamic relationship between China's crude oil prices, exchange rate, and international crude oil prices change after the launch of INE crude oil futures. All variables are defined after taking the logarithmic difference.

The MS-VAR model is applied to examine the dynamic relationship between China's crude oil prices, exchange rate, and international crude oil prices before and after the launch of the futures. We select the Shengli crude oil prices (SLOP),[2] WTI crude oil prices (WTIOP), and USD/CNY exchange rate (USDCNY) to represent China's domestic crude oil prices,

[1] In 2001, the Tokyo Commodity Exchange (TOCOM) launched a futures contract based on Dubai crude oil and denominated in yen; in 2005 India launched the Indian rupee-denominated crude oil futures.

[2] Shengli crude oil price is the most important benchmark of the domestic spot transaction price in China.

international crude oil prices, and the exchange rate, respectively. After taking the logarithmic difference, the vector is defined as follows:

$$y_t = (\Delta \ln \mathrm{SLOP}_t, \Delta \ln \mathrm{WTIOP}_t \Delta \ln \mathrm{USDCNY}_t) \tag{1}$$

The MS-VAR model is based on the VAR model and adds a Markov chain. In recent years, the MS-VAR model has been applied to explore nonlinear relationships between economic variables (Balcilar et al., 2015; Hou and Nguyen, 2018; Chen et al., 2019).

Considering a nonlinear VAR model where time series are subject to shifts in regime[3]:

$$y_t = v(s_t) + \beta_1(s_t) y_{t-1} + \ldots + \beta_p(s_t) y_{t-p} + e_t$$

$$e_t \sim NID(0, \Sigma(s_t)) \tag{2}$$

where s_t denotes the regime variable and $v(s_t)$, $\beta_1(s_t)$, …, $\beta_p(s_t)$, $\Sigma(s_t)$ are parameter shift functions describing the dependences of the parameters v, β_1, …, β_p, Σ on the realized regime s_t. v is the intercept term, β is the coefficients and Σ is the variance of the error term (e_t).

In Eq. (2), the intercept term (v) is regime-dependent:

$$v(s_t) = \begin{cases} v_1 & if\ s_t = 1 \\ \vdots & \vdots \\ v_M & if\ s_t = M \end{cases} \tag{3}$$

and the coefficient and variance vary change as the regime shifts, or they may be stable. If the coefficient matrix $B(s_t) = (\beta_1(s_t), \beta_2(s_t), \cdots, \beta_p(s_t))'$ is regime-dependent, then:

$$B(s_t) = \begin{cases} B_1 & if\ s_t = 1 \\ \vdots & \vdots \\ B_M & if\ s_t = M \end{cases} \tag{4}$$

If $B(s_t)$ does not vary with the regime, $B(s_t) = (\beta_1, \beta_2, \cdots, \beta_p)'$ for $s_t = \{1, 2, \cdots, M\}$.

Similarly, if $\Sigma(s_t)$ is regime-dependent, we have:

$$\Sigma(s_t) = \begin{cases} \Sigma_1 & if\ s_t = 1 \\ \vdots & \vdots \\ \Sigma_M & if\ s_t = M \end{cases} \tag{5}$$

If $\Sigma(s_t)$ is not regime-dependent, $\Sigma(s_t) = \Sigma$ for $s_t = \{1, 2, \cdots, M\}$.

In MS-VAR models, the regime s_t is generated by a discrete-state homogeneous Markov chain and follows an irreducible ergodic M-state Markov process, which is defined by the transition probabilities:

$$p_{ij} = Pr(s_{i+1} = j | s_i = i)$$
$$\sum_{j=1}^{M} p_{ij} = 1, \forall i, j \in \{1, 2, \cdots, M\} \tag{6}$$

Then the ergodic M-state Markov process followed by s_t has the irreducible transition matrix:

$$P = \begin{bmatrix} p_{11} & p_{11} & \cdots & p_{1M} \\ p_{21} & p_{22} & \cdots & p_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ p_{M1} & p_{M2} & \cdots & p_{MM} \end{bmatrix} \tag{7}$$

Using the transition probabilities, we can calculate the expected duration (D_j) and thus estimate how long the system will stay in a certain regime (j):

$$E(D_j) = \sum_{j=1}^{\infty} j Pr[D = j]$$

$$= 1 \times (1 - p_{ij}) + 2 \times p_{ij}(1 - p_{ij}) + 3 \times p_{ij}^2 (1 - p_{ij}) + \cdots = \frac{1}{1 - p_{ij}} \tag{8}$$

Following Basher et al. (2016), the population parameters of the MS-VAR model are estimated via maximum likelihood estimation. The maximization of the likelihood function requires an iterative estimation model to obtain autoregressive parameters and estimates of the unobservable state probability of the Markov chain. We use the Expectation Maximization (EM) algorithm. The iteration of each EM algorithm involves two steps. The first is the expectation step. This includes two algorithms, Filtering and Smoothing. We use the estimated parameter vector λ^{j-1} of the last maximization step in place of the unknown true parameter vector. This step provides an estimate of the smoothed probability $Pr(\xi | Y, \lambda^{j-1})$ of the unobservable state ξ_t, where the history of the Markov chain is recorded in. The second is the maximization step, in which an estimate of the parameter vector λ is derived as $\widehat{\lambda}$, which is a solution of the first-order conditions associated with the likelihood function. In this step, the conditional regime probabilities $Pr(\xi | Y, \lambda)$ are replaced by the smoothed probabilities $Pr(\xi | Y, \lambda^{j-1})$ derived in the last expectation step. Equipped with the new parameter vector λ, the filtered and smoothed probabilities are updated in the next expectation step, and so on, guaranteeing an increase in the value of the likelihood function at each step. Then the estimation is iterated until the maximum likelihood function value is obtained.

The conditional distribution of the total regime vector ξ is given by

$$Pr(\xi | Y) = \frac{p(Y, \xi)}{p(Y)} \tag{9}$$

The desired conditional regime probabilities $Pr(\xi_t | Y)$ can be derived by the marginalization of $Pr(\xi | Y)$. Given a specified observation set Y_τ, $\tau \leq T$, three estimated probabilities are as follows:

$\widehat{\xi_{t|\tau}}, \tau < t$: predicted regime probabilities;

$\widehat{\xi_{t|\tau}}, \tau = t$: filtered regime probabilities;

$\widehat{\xi_{t|\tau}}, t < \tau < T$: smoothed regime probabilities.

2.2. Data

The Shengli crude oil prices (SLOP), WTI crude oil prices (WTIOP), and USD/CNY exchange rate (USDCNY) are selected to represent China's domestic crude oil prices, international crude oil prices, and the exchange rate, respectively. The main MS-VAR model uses a daily dataset that includes SLOP, WTIOP, and USDCNY. The data covers 27 March 2017 to 31 October 2019. We select the price of Shengli crude oil as the representative price of China's crude oil market for two reasons. First, the Shengli Oilfield is one of China's largest oil reserves and production areas and the Shengli spot oil price is one of the most important representative prices of the crude oil market in China. Second, Shengli crude oil is the only deliverable Chinese domestic oil in the INE crude oil futures contract designated by the Shanghai International Energy Exchange. Shengli crude oil price data come from the *Wind*[4] database. The RMB exchange rate is the bilateral exchange rate quoted as the value of RMB per unit US dollar. Thus, an increase in the USDCNY indicates that the RMB depreciates against the US dollar. The exchange data come from the Central Bank of China. At the same time, the spot price of WTI crude oil is selected as the representative index data of international crude oil prices, with data collected from the US Energy Information

[3] The intercept-adjusted form of MS-VAR model is used in this paper. In fact, the MS-VAR also has a mean-adjusted form which is nearly equivalent to the intercept-adjusted one, especially in the linear VAR model. However, since these two forms has different representations, they construct different settings and meanings of the MS-VAR models. Appendix A provides more discussions about this.

[4] *Wind* is a financial information services company in China, which provides accurate and real-time information, as well as sophisticated communication platforms for financial professionals.

Table 1
Descriptive statistics of the variables.

Variable	Obs	Mean	Std. dev.	Min	Max	Sample period
lnSLOP	649	4.0466	0.1502	3.6750	4.3577	3/27/2017–10/31/2019
lnWTIOP	656	4.0527	0.1372	3.7490	4.3491	3/27/2017–10/31/2019
lnUSDCNY	634	1.9057	0.0324	1.8368	1.9585	3/27/2017–10/31/2019
INETV	390	294.7944	126.3151	15.572	719.572	3/26/2018–10/31/2019

Table 2
Unit root test results.

	Original series		First-order differences	
	ADF	PP	ADF	PP
lnSLOP	−1.933 (0.3166)	−2.093 (0.2475)	−11.822* (0.000)	−24.688* (0.0000)
lnWTIOP	−1.799 (0.3812)	−2.034 (0.2717)	−12.134* (0.0000)	−26.639* (0.0000)
lnUSDCNY	−0.733 (0.8381)	−0.499 (0.8921)	−10.753* (0.0000)	−21.484* (0.0000)

Note: The original hypothesis of the ADF and PP tests is "the sequence is non-stationary." The numbers in the table are t statistics, and *p*-values are reported in parentheses. * Rejects the null hypothesis at the 1% significance level.

Table 3
The EG-ADF cointegration tests of three variables.

Dep. variable	Resd. sequence	Test-statistics	Mackinnon critical value (MacKinnon, 1990, 2010)[a]		
			1%	5%	10%
lnSLOP	resd_1	−2.463			
lnWTIOP	resd_2	−2.499	−4.318	−3.755	−3.463
lnUSDCNY	resd_3	−1.889			

[a] Since the distributions of the EG-ADF test statistics are non-standard, the critical value of the ordinary ADF test is not suitable here. MacKinnon (1990, 2010) has computed response surface regressions which provide critical values for all the cases.

Administration (EIA). Considering that our sample period covers the pre and post period of the launch of INE crude oil futures, we also provide the information of daily trading volume of INE crude oil futures, which is taken from the *Wind* database, and its unit is 1000 contracts.[5]

Descriptive statistical analysis results of the variables are shown in Table 1. It can be preliminarily judged through the descriptive statistics that Shengli crude oil exhibits the highest price volatility, while WTI crude oil futures prices and the US dollar to RMB exchange rate are relatively weak.

3. Empirical results

3.1. Unit root tests

To ensure the validity of our analyses, we carry out augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests to perform a unit root test. For ADF tests, 3 lags are chosen. All of the unit root tests are conducted with intercept and without trend. The results for each sequence are shown in Table 2. It is found that the original variable data contains a unit root. However, after taking the first-order difference, the ADF and PP statistics clearly show that all first-order differences in sequences are stable.

3.2. Cointegration tests

As the representation theorem provided by Engle and Granger (1987) stated, a VAR model in levels is equivalent to its error correction representation when the time series have unit roots and are cointegrated. Therefore, the presence of cointegration among the levels of the used variables would result in misspecification of the VAR model in first differences as it omits the error correction dynamics. To verify whether the cointegration exists among the levels of three variables in the sample period, we conduct a test for cointegration before using the MS-VAR model in the first difference by adopting two approaches.

The extended EG-ADF test proposed by Engle and Granger (1987) is first used in the cointegration test. The test follows the very simple intuition that if variables are cointegrated, then the residual of the cointegrating regression should be stationary. The EG-ADF test is carried out in two steps considering that there is a single cointegrating vector. For nonstationary sequence $\{y_t, x_t\}$ which is integrated of order one (i.e. I(1)), OLS is used to establish a regression for the variables and estimate the normalized cointegrating vector in the first step. In the second step, the residual sequence $\{z_t\}$ is calculated according to the regression equation, and the ADF test is performed on $\{z_t\}$. If $\{z\}$ is stable, there is a cointegration relationship between the I(1) sequence $\{y_t, x_t\}$; Otherwise, there is no cointegration between them. In the extended EG-ADF test suitable for multi-variables, it is considered that there is no cointegration among the variables when the stable residual sequence can't be obtained after all variables have been tested as dependent variables.

The result of the extended EG-ADF test is reported in Table 3. The test is conducted with intercept and without trend. And 3 lags are chosen according to the Akaike information criterion (AIC) and Bayesian Information Criterion (BIC). It can be found that no matter which variable is treated as the dependent variable, the statistic of the EG-ADF test is less than the critical value at all levels. This indicates that the residual sequence $\{z_t\}$ is not stationary in the three cases, which means there is no cointegration relationship among $\{lnSLOP_t, lnWTIOP_t, lnUSDCNY_t\}$ during the sample period.

Considering that the extended EG-ADF method is conducted in two steps and the estimation error in the first step will be carried to the second, we further adopt the trace test proposed by Johansen (1988, 1991) for the Vector Error Correction Model (VECM) context. Different from the EG-ADF test based on the residual sequence calculated by the OLS regression, the Johansen Test uses a maximum likelihood

[5] Before the launch of INE crude oil futures (3/26/2018), the value of INE crude oil futures trading volume was zero for there was no trading volume in INE crude oil futures market.

estimation strategy to make it possible to estimate all cointegrating vectors for more than two variables with unit roots.

For the vector autoregression (VAR) in levels with the constant suppressed:

$$y_t = \sum_{i=1}^{k} \phi_i y_{t-i} + \varepsilon_t, k > 1 \tag{10}$$

Whose vector error correction representation can be written as:

$$\triangle y_t = \Pi y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \triangle y_{t-i} + \varepsilon_t \tag{11}$$

$$\Pi = \sum_{i=1}^{k} \phi_i - I, \Gamma_i = -\sum_{j=i+1}^{k} \phi_j \tag{12}$$

The basic idea of the Johansen cointegration test is to determine whether the coefficient matrix Π contains linearly independent cointegration vectors. That is, to test whether the rank of Π is 0. It is concluded that there is no cointegration relationship if $rank(\Pi) = 0$.

Table 4 reports the results of the Johansen cointegration test with intercept and without trend. 3 lags are chosen in the test according to the AIC and BIC. It is shown that the trace statistic can't reject the null hypothesis of $rank(\Pi) = 0$. This further confirms that there is no cointegration relationship among $\{lnSLOP_t, lnWTIOP_t, lnUSDCNY_t\}$ during the period studied in this article. In fact, the large and high-frequency fluctuations of crude oil prices have become a common phenomenon in the crude oil market. And the relationship between exchange rate and crude oil prices always exhibits dynamic changes over time due to the influence of complex factors from the spot market, economic fundamentals and financial markets (Beckmann and Czudaj, 2013; Basher et al., 2016).

We then conclude that all variables integrated of first-order have no cointegration. Referring to Shrestha and Bhatta (2018), we use all three variables in the first differences to estimate the MS-VAR model to guarantee validity.

3.3. Choice of MS-VAR model and nonlinear test

According to the Akaike information criterion (AIC) and Schwarz criterion (SC), the lag order of vector autoregression in the first difference is selected to be 2. The number of regimes is chosen to be 2 since we are interested in the relation switch of the variables in the pre and post period of the launch of the INE crude oil futures. This is also supported by the HQ (i.e Hannan-Quinn criterion), and SC in the MS-VAR analysis process. We choose the optimal MSIAH(2)-VAR(2), a two-regime, second-order autoregressive model, assuming that the intercept, regression parameters, and variance dependence on the system. The nonlinear test statistic LR of this model is 255.6552, significantly rejecting the null hypothesis of the linear model, which indicates that the MSIAH(2)-VAR (2) model can be used to effectively examine the nonlinear relationships between those three variables (SLOP, WTIOP, and USDCNY). The information criteria for model selection are summarized in Appendix A (Table A.2).

Table 4
The Johansen cointegration tests of three variables.

Maximum rank	LL	Eigenvalue	Trace statistic	5% Critical value
0	5961.4637		29.2759*	29.68
1	5972.0764	0.03487	8.0503	15.41
2	5975.2988	0.01072	1.6056	3.76
3	5976.1016	0.00268		

Note: LL is the log-likelihood function.

3.4. Regime state and parameter analyses

The graph of the filtered probabilities, smoothed probabilities, and predicted probabilities (as shown in Fig. 1) captures the characteristics of the regime switching associated with fluctuations in Shengli crude prices, WTI crude oil price, and USD/CNY exchange rate from 27 March 2017 to 31 October 2019. Before the INE crude oil futures were launched (26 March 2018), regime 2 emerged very infrequently, and the market remained in regime 1 for a long time. There was no significant regime switching characteristics during that period. However, after the launch of the futures, the model system entered regime 2 for a long time, and regime 2 emerged more frequently during that period.

Table 5 summarizes the transition probabilities between the two regimes and the expected duration of the regimes. The expected duration of regime 1 is significantly larger than that of regime 2. If the INE crude oil futures had not been launched, regime 1 would have been the normal state. The probability of transitioning from regime 2 to 1 is only 23.8%. Therefore, the conversion from regime 1 to regime 2 after the launch of the futures is not normal.

Table 6 shows the characteristic descriptive statistics for the INE crude oil futures market and the variables studied for the two regimes. Whether in regime 1 or regime 2, the volatility of the Shengli crude oil price is smaller to that of WTI crude oil. Notably, the trading volume is significantly higher in regime 2 than in regime 1. The 90% quantile of the INE crude oil futures trading volume in regime 1 of the MSIAH (2)-VAR (2) model is 352,3528 contracts. This shows that the trading volume of INE crude oil futures is under 352,3528 contracts most of the time in regime 1. While the average trading volume of the INE crude oil futures in regime 2 is 344,4751 contracts, about 1.3 times the average level in regime 1. This indicates that the regime switching is also accompanied by the increase of INE crude oil futures trading volume.

Table 7 shows the coefficients and t-value of the Shengli crude oil price equation and WTI crude oil price according to the MSIAH(2)-VAR (2) model regression results. These results fully demonstrate the differences between the two regimes. There are two notable and important points: First, whether in regime 1 or regime 2, fluctuations in the WTI crude oil price have a significant positive impact on the price of Shengli crude oil, indicating that China's crude oil market has always passively accepted the impact of WTI crude oil prices. Second, fluctuations in the USD/CNY exchange rate have a negative but not significant impact on the price of the Shengli crude oil in regime 1, but the impact becomes positive and significant in regime 2. The complete coefficient regression results are shown in Appendix B (Table B.1).

The first point answers the question about whether China's long-standing status as a price-taker in the international oil markets changed after the launch of INE crude oil futures. Although INE crude oil futures gained the third-largest trading scale in the world shortly after its launch, it does not yet have sufficient crude oil pricing power for China. INE crude oil futures have shown a certain pricing efficiency in China. However, because its price may be deeply affected by the international crude oil spot and futures markets (Yang et al., 2019), the Chinese market remains very passive globally. The acquisition of crude oil pricing power is a long-term process. Consistently, Yang et al. (2019) and our statistical results both indicate that the current INE crude oil futures have not yet changed China's passive status in the international crude oil market.

The second point shows interesting facts after the launch of INE crude oil futures. The most prominent feature of regime 2 is that the USD/CNY exchange rate has a significant positive impact on China's domestic crude oil price. Combined with regime state analyses in Fig. 1, the regime probabilities trended to regime 2 after the launch of INE crude oil futures. This is consistent with our theoretical analyses: after the launch of the INE crude oil futures, the positive spillover effect of USD/CNY exchange rate on the price of Chinese crude oil is significantly enhanced.

Fig. 2 presents the impulse response results of Shengli oil prices to

Fig. 1. Regime probabilities of the MSIAH(2)-VAR(2) model.

Table 5
Expected duration and regime transition probabilities.

	Duration	Regime 1	Regime 2
Regime 1	7.59	86.82%	13.18%
Regime 2	4.20	23.80%	76.20%

one standard deviation of USD/CNY exchange rate in regime 1 (the left curve) and regime 2 (the right curve). In regime 1, one standard shock of USD/CNY exchange rate has no statistically significant impact on Shengli oil prices. While in regime 2, when the USD/CNY exchange rate is given a standard deviation, the first period on Shengli oil prices has a strong positive impact. From the second period, the impact of the USD/CNY exchange rate on Shengli oil prices shows a positive and negative volatility phenomenon, and the entire duration period lasts about 5 days.

Fig. 3 reflects the impulse response results of the USD/CNY exchange rate to one standard deviation of Shengli oil prices in regime 1 (the left curve) and regime 2 (the right curve). Both in regime 1 and regime 2, one standard deviation Shengli oil price shock had no statistically significant impact on the USD/CNY exchange rate. This shows that the impact of Shengli crude oil price fluctuation on the exchange rate is small before and after the launch of China's crude oil futures.

Table 6
Characteristic statistics of the two regimes.

	Variable	Mean	Std. dev.	Min	Max	10% Quantile	90% Quantile
Regime 1	INETV	259.2570	86.9068	55.1640	554.9260	156.0154	352.3528
	DlnUSDCNY	0.0001	0.0012	−0.0033	0.0031	0.0001	0.0020
	DlnWTIOP	0.0038	0.0109	−0.0235	0.0332	0.0013	0.0193
	DlnSLOP	0.0024	0.0149	−0.0535	0.0411	0.0027	0.0250
Regime 2	INETV	344.4751	157.1274	75.9540	712.9560	255.2970	606.4846
	DlnUSDCNY	0.0001	0.0038	−0.0097	0.0090	0.0003	0.0066
	DlnWTIOP	−0.0049	0.0379	−0.0872	0.1350	0.0045	0.0580
	DlnSLOP	−0.0014	0.0314	−0.0989	0.0840	0.0069	0.0511

Table 7
Coefficients of the Shengli crude oil price and WTI crude oil price equations in the MSIAH(2)-VAR(2) model.

	DlnSLOPt		DlnWTIOPt	
	Regime 1	Regime 2	Regime 1	Regime 2
Const	0.000895 (1.4950)	0.000346 (0.2222)	0.002258** (2.7008)	−0.003901* (−1.8059)
DlnSLOPt-1	−0.433326*** (−7.5934)	−0.283768*** (−3.8098)	−0.037269 (−0.5246)	0.003257 (0.0335)
DlnSLOPt-2	−0.120981*** (−3.4087)	−0.052085 (−0.7904)	−0.041535 (−0.8872)	0.007195 (0.0825)
DlnWTIOPt-1	0.858739*** (20.0690)	0.573871*** (9.3130)	0.071954 (1.3015)	−0.201288** (−2.5591)
DlnWTIOPt-2	0.286305*** (5.2158)	0.455403*** (5.7412)	−0.031128 (−0.4766)	0.078262 (0.7617)
DlnUSDCNYt-1	−0.231532 (−0.6563)	1.227560** (2.1372)	−0.626081 (−1.3753)	0.012727 (0.0168)
DlnUSDCNYt-2	0.234845 (0.6759)	−0.345722 (−0.5490)	0.455128 (1.1053)	0.503800 (0.6271)
SE	0.009942	0.021090	0.013600	0.028004

Note: T-statistics are shown in parentheses. *, ** and *** denote 10%, 5% and 1% significance levels, respectively.

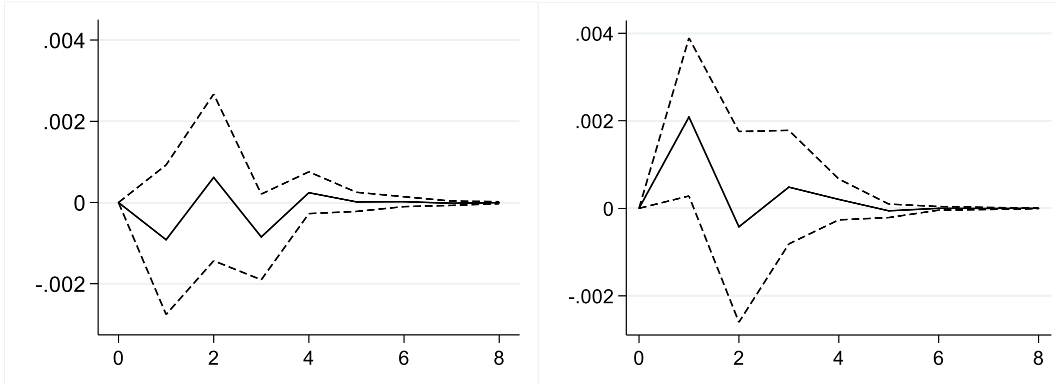

Fig. 2. Response curves of Shengli oil prices to USD/CNY exchange rate.

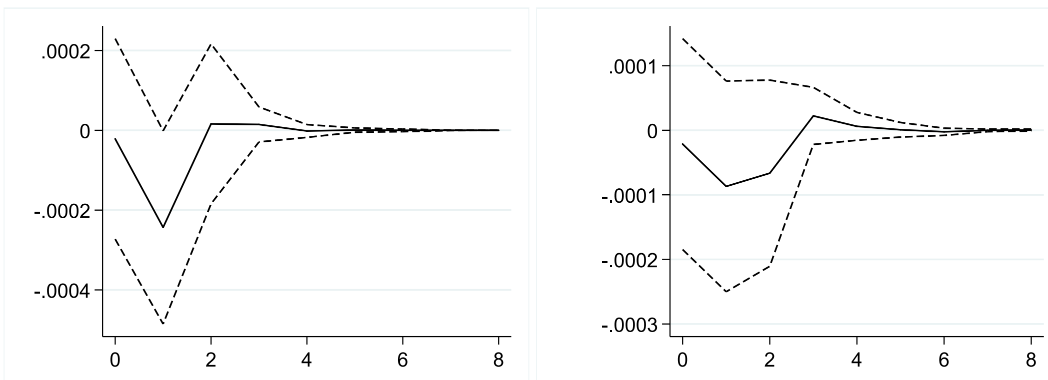

Fig. 3. Response curves of USD/CNY exchange rate to Shengli oil prices.

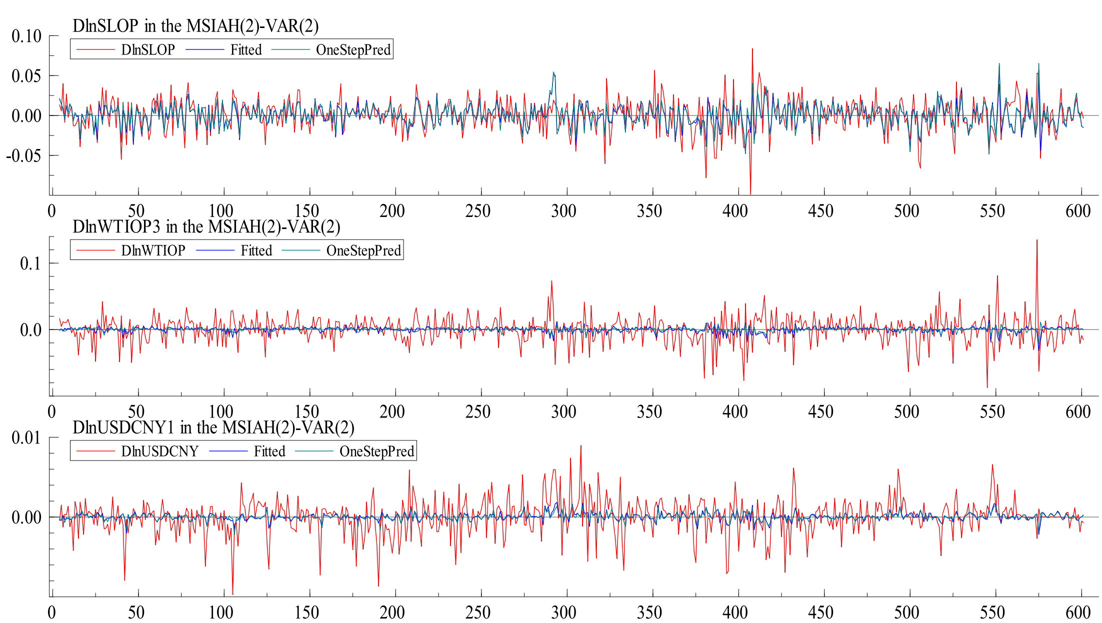

Fig. 4. The actual, one-step predicted, and smoothed values of the three variables.

4. Test of the empirical results

4.1. Validity test and robustness test of the MS-VAR model

To test the validity of the MS-VAR model, we first plot the actual, one-step predicted, and smoothed values of the three variables. As shown in Fig. 4, the model fits the changes in Shengli crude oil prices best, while the changes in WTI crude oil prices and USD/CNY exchange rate do not fit as well. This confirms the complexity of the factors affecting the exchange rate of the WTI crude oil price and USD/CNY exchange rate and demonstrates the effectiveness of the MS-VAR model.

Moreover, we introduce three variables to test the robustness of our conclusions considering that the relationship between crude oil price and the exchange rate is likely to be affected by economic growth, market and policy uncertainties. We first introduce China's month-over-month social financing scale growth rate (SF_rate) to measure economic growth. In China, the growth rate of the social financing scale, which is one of the economic leading indicators, is almost consistent with the growth rate of nominal GDP as a whole (The Central Government of China, 2019). Hence, the month-over-month growth rate of the social financing scale becomes a desirable proxy to measure the economic growth in a higher frequency, compared with the quarterly or annual data. Second, we introduce the broad money supply (M2) to measure the stance of monetary policy. The exchange rate of RMB against the US dollar may be affected by the central bank's monetary policy, while the money supply is one of the most direct manifestations of changes in monetary policies. Third, OPEC's crude oil supply (OS_OPEC) is introduced to control the possible impact of oil market uncertainty on crude oil prices, considering that OPEC determines the world's crude oil supply and the stability of the crude oil market to a large extent.

Regression results of the MS-VAR with the above three control variables[6] are listed in Table 8. It can be seen that the revised regression results are quite similar to the previous ones. This supports that our research results are robust and reliable. The complete coefficient regression results are provided in Appendix B (Table B.2).

4.2. Placebo test of the MS-VAR model based on the Brent and Oman crude oil markets

As shown above, after the launch of INE crude oil futures, the fluctuations in the US dollar against the RMB exchange rate have a significant positive impact on China's crude oil price. However, we are still not sure whether this is indeed related to the fact that INE crude oil futures are denominated in RMB. Theoretically, the impact of exchange rates on dollar-denominated crude oil futures and non-USD-denominated crude oil futures is vastly different. In the trading of non-USD-denominated crude oil futures, traders need to consider changes in the currency exchange value of the crude oil futures in addition to the traditional factors affecting crude oil prices. While in the trading of USD-denominated crude oil futures, the consistency of the futures denominated currency and spot denominated currency makes it unnecessary for traders to consider changes in the exchange rate to make an arbitrage space between futures prices and spot prices. Therefore, the relationship between the exchange rate and oil price may change after the launch of non-USD-denominated crude oil futures, but may not change after the launch of US dollar-denominated crude oil futures.

Based on the launches of the Brent and Oman crude oil futures, we use the MS-VAR model to construct a placebo test. There are two reasons for doing this. First, these futures reached a certain scale globally shortly after their launch, just like the INE crude oil futures. Second, they are denominated in US dollars rather than Britain or Oman's domestic currency. Therefore, we can compare the similarities and differences of the impacts of the launches of US dollar-denominated and non-USD-denominated crude oil. For effective comparison to our previous results, we similarly take the logarithmic differences in all data and again chose the MSIAH(2)-VAR(2) model. Brent crude oil futures were launched on 23 June 1988 and Oman crude oil futures were launched on 1 June 2005. We select the sample period that starts 1 year before the launch of crude oil futures, just as before, and the two samples' periods are also close to the previous one. The descriptive statistics and unit root tests of variables used for the placebo test are shown in Appendix C (Tables C.1 and C.2).

The coefficients of the Brent crude oil price equation and WTI crude oil price equation obtained from the placebo test are shown in Table 9. On the one hand, fluctuations in the WTI crude oil price have a significant positive impact on the Brent crude oil price in both regimes, as they do on China's crude oil price. On the other hand, it is worth noting that fluctuations in the USD/GBP exchange rate have no significant impact on Brent crude oil price or WTI crude oil price in either regime. Fig. 5 shows that the three-variable system does not exhibit obvious regional division and regional transfer characteristics before and after the launch of Brent crude oil futures. The relationships between the Brent crude oil price, the WTI crude oil price, and the USD/GBP exchange rate have no structural changes after the launch of the Brent crude oil futures.

The coefficient regression estimation results for Oman are shown in Table 10. The fluctuations in the WTI crude oil price have a significant positive impact on the Oman crude oil price in both regimes. Notably, fluctuations in the USD/OMR exchange rate have a significant positive impact on the Oman crude oil price in regime 1 but not in regime 2. The impact of the USD/OMR exchange rate on the Oman crude oil price seems to be weaker, which is different from the case of INE crude oil futures. As shown in Fig. 6, before and after the launch of Oman crude oil futures (1 June 2007), the three-variable system doesn't exhibit obvious regional division and regional transfer characteristics. Almost all the sample period stays in regime 1 while regime 2 only accounts a very short duration.

5. Conclusion and policy implications

The INE crude oil futures market has already become one of the world's top three crude oil futures markets. The launch of this RMB-denominated oil futures contract has far-reaching implications for China's crude oil market and currency. However, research on whether the relationships between China's exchange rate, domestic crude oil price, and international crude oil price exhibit structural change before and after the launch of INE crude oil futures is still scarce. According to our empirical research, although the fact that China's crude oil price is unidirectionally affected by the impact of international oil prices has not been changed after the launch of the futures, China's exchange rate and crude oil prices do exhibit a different relationship. This change may be due to the fact that the currency dominating INE crude oil futures is RMB.

By adopting the MS-VAR model, we have some interesting and meaningful findings:

(1) The dynamic relationships between China's crude oil prices, exchange rate, and international crude oil prices exhibited significant regime switching after the launch of the INE crude oil futures. On the one hand, China's crude oil market price is deeply influenced by the international crude oil market in both regimes, but not vice versa. This demonstrates that China has not yet lost its long-standing status as a price-taker in the international oil markets. On the other hand, fluctuations in the USD/CNY exchange rate have a significant positive impact on China's crude oil prices under the second regime, which is mainly appears after the launch of INE crude oil futures.

(2) The positive impact of the USD/RMB exchange rate on China's crude oil prices is accompanied by a higher trading volume of INE crude oil futures, indicating that the structural change between the relationship of China's crude oil prices and the USD/CNY exchange rates may be closely related to the trading volumes of INE crude oil futures.

(3) The placebo test results of the MS-VAR model based on the launch of Brent crude oil futures show that the relationships between British crude oil price, exchange rate, and international crude oil prices show no significant regime switching before and after the

[6] Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests show that time series data of SF_rate SF_rate and lnM2 lnM2 (logarithmic form of M2M2) are stationary while lnOS_OPEC lnOS_OPEC (logarithmic form of OS_OPEC OS_OPEC) contains a unit root and its first-order differences sequences are stable. Hence, we use SF_rate, lnM2, and DlnOS_OPEC SF_rate in the regression. All the control variables are monthly data.

Table 8
Coefficients of the Shengli crude oil price and WTI crude oil price equations in the MSIAH(2)-VAR(2) model (with control variables).

	DlnSLOPt		DlnWTIOPt	
	Regime 1	Regime 2	Regime 1	Regime 2
Const	0.121427	−0.219562	0.036033	−0.171507
	(1.0466)	(−0.5323)	(0.0624)	(−0.2596)
DlnSLOPt-1	−0.455151***	−0.284201***	0.004040	−0.057430
	(−8.447)	(−3.359)	(0.063)	(−0.559)
DlnSLOPt-2	−0.108293***	−0.050398	−0.009216	−0.051534
	(−3.3829)	(−0.6533)	(−0.215)	(−0.5094)
DlnWTIOPt-1	0.860794***	0.529104***	0.055356	−0.237554***
	(18.3471)	(6.8322)	(1.0718)	(−2.7173)
DlnWTIOPt-2	0.314666***	0.406810***	−0.075581	0.096081
	(6.3311)	(4.679)	(−1.3324)	(0.8589)
DlnUSDCNYt-1	−0.216825	1.304636**	−0.521952	0.509743
	(−0.5669)	(2.0755)	(−0.9248)	(0.6091)
DlnUSDCNYt-2	0.053689	−0.064184	0.714273*	0.812690
	(0.1701)	(−0.0941)	(1.7615)	(0.9016)
SF_rate	−0.016855**	0.009294	−0.002731	−0.007979
	(−2.4476)	(0.7594)	(−0.3116)	(−0.5202)
SF_rate_1	0.019210**	−0.018886	0.033276***	0.003559
	(2.2617)	(−0.8721)	(3.0465)	(0.1201)
SF_rate_2	−0.004227	0.016230	−0.025903***	0.021254
	(−0.8263)	(0.874)	(−3.6851)	(0.8113)
lnM2	−0.24368	0.119044	0.013393	−0.514539
	(−0.7051)	(0.1627)	(0.03)	(−0.5584)
lnM2_1	−0.523979	−0.852429	−0.95678*	1.826096
	(−1.2525)	(−0.6221)	(−1.7463)	(1.0305)
lnM2_2	0.759412***	0.748211	0.94077**	−1.301084
	(2.8665)	(0.6282)	(2.4218)	(−0.8404)
DlnOS_OPEC	−0.250012**	0.263251	−0.144932	−0.790533
	(−2.5271)	(0.4634)	(−1.1228)	(−1.0924)
DlnOS_OPEC_1	0.326847**	−0.081993	0.468873**	1.469262
	(2.356)	(−0.1023)	(2.5512)	(1.3719)
DlnOS_OPEC_2	−0.08943	−0.219106	−0.236551*	−0.913803
	(−0.8797)	(−0.3818)	(−1.7499)	(−1.1452)
SE	0.009913	0.021197	0.013085	0.027625

Note: T-statistics are shown in parentheses. *, ** and *** denote 10%, 5% and 1% significance levels, respectively.

Table 9
Coefficients of the Brent crude oil price equation and WTI crude oil price equation in the placebo test based on the Brent crude oil market.

	DlnBROPt		DlnWTIOPt	
	Regime 1	Regime 2	Regime 1	Regime 2
Const	−0.000989	0.000831	−0.000880	0.001876
	(−1.2679)	(0.5267)	(−0.6802)	(1.2020)
DlnBROPt-1	−0.434935***	−0.132735	0.150165	−0.236758**
	(−7.2532)	(−1.4390)	(1.3802)	(−2.3726)
DlnBROPt-2	−0.201924***	0.066371	0.062399	−0.132088
	(−4.1701)	(0.7131)	(0.7171)	(−1.4326)
DlnWTIOPt-1	0.764359***	0.139211*	−0.122450	−0.020811
	(10.8922)	(1.8706)	(−1.3298)	(−0.3003)
DlnWTIOPt-2	0.168540***	0.160825*	−0.196473**	0.225256***
	(3.7991)	(1.8014)	(−2.4631)	(2.6382)
DlnUSDGBPt-1	0.071436	−0.144196	−0.178893	0.128224
	(0.6152)	(−0.6235)	(−0.9130)	(0.5638)
DlnUSDGBPt-2	0.036124	−0.028995	−0.074353	0.055395
	(0.3329)	(−0.1259)	(−0.3990)	(0.2401)
SE	0.011045	0.024294	0.021041	0.022529

Note: T-statistics are shown in parentheses. *, ** and *** denote 10%, 5% and 1% significance levels, respectively.

launch of US dollar-denominated crude oil futures. The placebo test based on the launch of Oman crude oil futures shows that the significant positive impact of the USD/OMR exchange rate on the price of Oman crude oil may be weaker after the launch of Oman crude oil futures. Both comparisons show that US dollar-denominated crude oil futures cannot become a signal and channel for the positive impact of the US dollar exchange rate on domestic crude oil prices, but the RMB-denominated INE crude oil futures can.

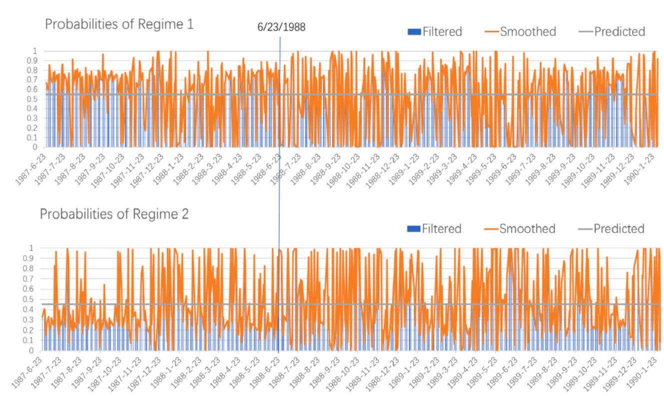

Fig. 5. Regime probabilities of the MSIAH(2)-VAR(2) model in the placebo test based on the Brent crude oil market.

The launch of INE crude oil futures has important policy implications. If INE crude oil futures can strengthen China's oil pricing power, they need to be an effective pricing benchmark to ensure that China's crude oil prices correctly reflect market supply and demand, rather than passively fluctuating with other market prices all of the time. Considering that fluctuations in the price of crude oil futures have an important impact on the macroeconomy (Gong and Lin, 2018), China needs to further improve the operation mechanism of the INE crude oil futures market to prevent fundamental market failures. Our findings have three policy implications.

First, China should establish an effective crude oil pricing mechanism that can cope with the abnormal impact of the exchange rate on the futures and spot markets. INE crude oil futures have become a new

Table 10
Coefficients of the Oman crude oil price equation and WTI crude oil price equation in the placebo test based on the Oman crude oil market.

	DlnOMOPt		DlnWTIOPt	
	Regime 1	Regime 2	Regime 1	Regime 2
Const	−0.000826	0.000211	−0.000564	−0.000220
	(−0.9625)	(0.2030)	(−0.4096)	(−0.0921)
DlnOMOPt-1	−0.284214***	−0.329403***	0.005637	0.020662
	(−5.9465)	(−4.8801)	(0.0731)	(0.1301)
DlnOMOPt-2	0.056143	−0.070681	−0.085311	0.169261
	(1.5132)	(−1.5411)	(−1.4151)	(1.6031)
DlnWTIOPt-1	0.529657***	0.702749***	−0.030614	0.071245
	(17.6430)	(17.6575)	(−0.6428)	(0.7827)
DlnWTIOPt-2	0.100800***	0.130865**	0.149752**	−0.483327***
	(2.6226)	(2.1290)	(2.4225)	(−3.3323)
DlnUSDOMRt-1	13.039832***	−0.259865	5.782470***	−3.439040
	(193.0833)	(−0.1625)	(408.3910)	(−1.6225)
DlnUSDOMRt-2	13.087525***	−1.892151	−4.965232***	−1.508044
	(154.9456)	(−1.1135)	(−188.9317)	(−0.8219)
SE	0.018353	0.011536	0.018875	0.025850

Note: T-statistics are shown in parentheses. *, ** and *** denote 10%, 5% and 1% significance levels, respectively.

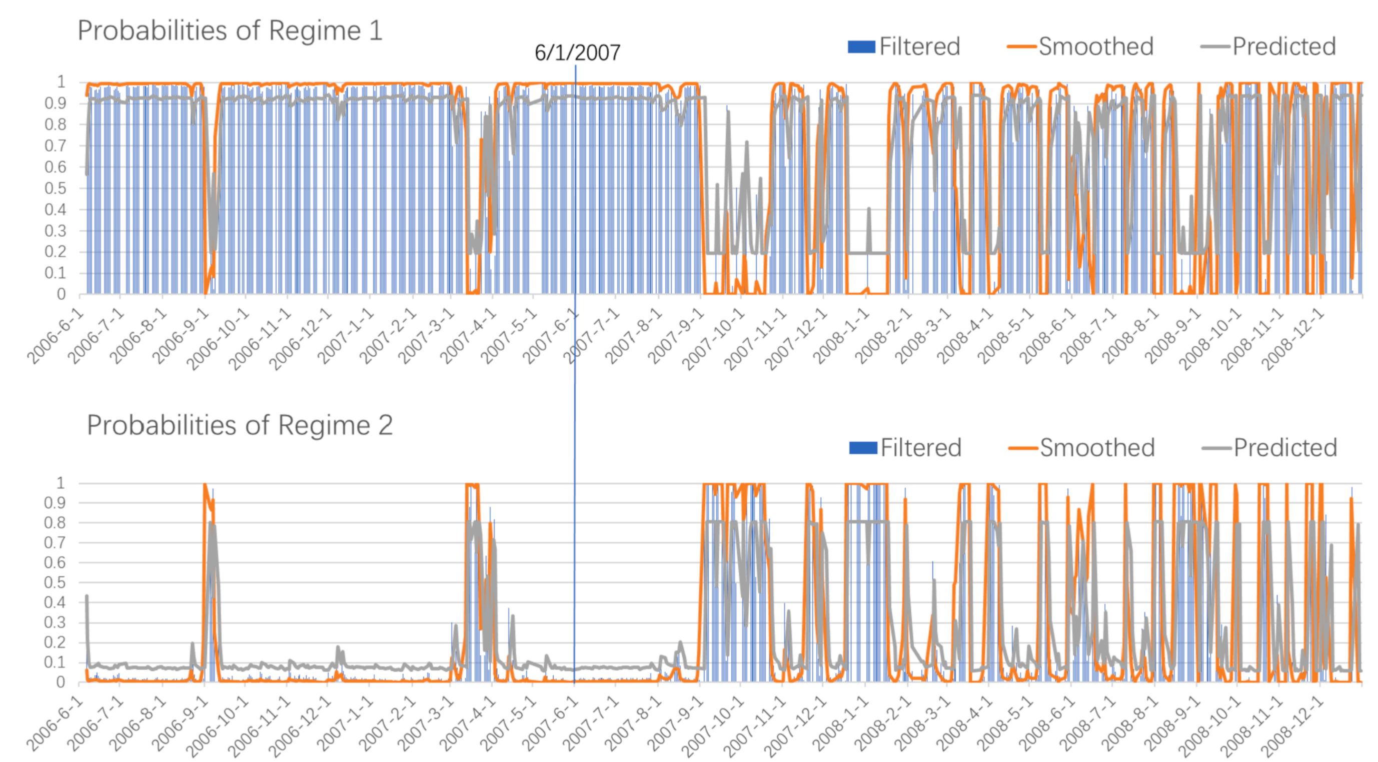

Fig. 6. Regime probabilities of the MSIAH(2)-VAR(2) model in the placebo test based on the Oman crude oil market.

bridge linking the foreign exchange market to the crude oil market. At present, the Shanghai International Energy Exchange sets both RMB and US dollar as the futures margin payment currency to alleviate transaction exchange problems for some foreign traders. However, this does not fundamentally release the exchange rate risk caused by the difference between the futures' valuation currency and the subject matter's valuation currency. At the same time, for China, the increasing dependence on foreign countries and continuous development of INE crude oil futures means that it is increasingly necessary to pay attention to the influence of exchange rate fluctuations on crude oil market prices. Therefore, in the short run, the government should reduce the intervention to ensure the market liquidity (Qin et al., 2020), such as reducing exchange rate intervention and providing a relatively stable and market-oriented foreign exchange trading environment. In the long run, the government ought to gradually promote the underlying spot crude oil of INE crude oil futures to be denominated in RMB, and realize the integration of futures and spot pricing systems.

Second, INE crude oil futures may have an important effect on oil prices in China's crude oil market, but the price discovery capability of the market needs to be further enhanced. Certainly, it is necessary to strengthen the participation of relevant industries and institutions to promote the link between the prices of oil products and those of crude oil futures. Furthermore, restrictions on price limit policy in the INE crude oil futures market should gradually be released within the controllable range of market risks. Price limit policy plays an important role in preventing excessive fluctuations (Yang et al., 2021; Du et al., 2021), but may also become an obstacle to equilibrium price formation.[7] In 2018

[7] Brent crude oil futures market and Oman crude oil futures market do not have price limit policies, and that of the WTI crude oil futures market is much more flexible and mature than that of the INE crude oil futures market.

and 2019, the Shanghai International Energy Exchange raised the range of price limits policies for its crude oil futures contracts by a factor of 25 to cope with large fluctuations in crude oil prices. However, most of these adjustments are only for nearby delivery contracts, and they are in the form of instant notification, with no definite written adjustment regulation. A more reasonable and lenient price limit policy is important to realize price discovery in the INE crude oil futures market. The markets should develop in the direction of marketization, and the manager should reduce administrative intervention so that the price of INE crude oil futures can more promptly and accurately reflect the market supply and demand in China and the Asia-Pacific region.

Third, fundamentally, a more robust and flexible market system is the key to INE crude oil futures gaining wider international recognition. Both the establishment of "petroleum RMB" and the promotion of RMB internationalization are long-term goals, which require the establishment of a sufficient market scale for INE crude oil futures. China should eliminate the simplification of crude oil derivatives as soon as possible. The diversified derivatives category allows traders to invest and trade more flexibly on the NYMEX and ICE. As for China, a contract for difference (CDF) can be launched in due course to increase the liquidity of INE crude oil futures market transactions in the short term. China should also improve the legal system of the futures market as soon as possible. The legal construction of China's futures market lags behind the market development. Therefore, it is very important for China to enact the Futures Law quickly to protect the rights and interests of the traders and eliminate unnecessary concerns.

Credit author statement

Chuanwang Sun and Weiyi Cai conceived the conceptualization. Yiqi Peng and Weiyi Cai provided the Writing - original draft and Yanhong Zhan provided the data curation. Chuanwang Sun, Yiqi Peng and Yanhong Zhan provided the writing - review & editing. All authors read and approved the manuscript.

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Appendix A. Different representations of the Markov-switching vector autoregressive models

Markov-switching vector autoregressions can be considered as generalizations of the basic finite order VAR model of order p. Consider the p-th order autoregression for the N-dimensional time series vector:

$$y_t = \nu + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + e_t$$

$$e_t \sim NID(0, \Sigma) \tag{A.1}$$

The above intercept-adjust form can be reparametrized as the mean adjusted from:

$$y_t - \mu = \beta_1(y_{t-1} - \mu) + \ldots + \beta_p\left(y_{t-p} - \mu\right) + e_t$$

$$e_t \sim NID(0, \Sigma) \tag{A.2}$$

Where $\mu = \left(I_N - \sum_{j=1}^{p}\beta_j\right)^{-1}\nu$ is the $(N \times 1)$ dimensional mean of y_t. These two forms are equivalent in the linear VAR model.

While in the MS-VAR model where time series are subject to shifts in the regime, eqs. (A.1) and (A.2) turn out to be the following eqs. (A.3) and (A.4), respectively. Now the two forms with the regime variable s_t imply different dynamic adjustments of the observed variables after a change in regime in MS-VAR. In the intercept-adjusted form, the dynamic response to a once-and-for-all regime shift in the intercept term $\nu(s_t)$ is identical to an equivalent shock in the white noise series e_t, while in the mean-adjusted form, a permanent regime shift in the mean $\mu(s_t)$ causes an immediate jump of the observed time series vector onto its new level (Krolzig, 2013).

$$y_t = \nu(s_t) + \beta_1(s_t)y_{t-1} + \ldots + \beta_p(s_t)y_{t-p} + e_t$$

$$e_t \sim NID\left(0, \sum(s_t)\right) \tag{A.3}$$

$$y_t - \mu(s_t) = \beta_1(s_t)[y_{t-1} - \mu(s_{t-1})] + \ldots + \beta_p(s_t)\left[y_{t-p} - \mu\left(s_{t-p}\right)\right] + e_t$$

$$e_t \sim NID\left(0, \sum(s_t)\right) \tag{A.4}$$

Based on the above two forms, the MS-VAR model has different settings, which is shown in Table A.1.

Usually, it is more plausible to assume that the mean smoothly approaches a new level after the transition from one state to another. To verify this, we also use the information criteria to choose the suitable models for our study. Table A.2 provides the results and supports that Markov-switching intercept autoregressive and heteroskedasticity VAR model with 2 regimes and 2 lags, i.e. MSIAH(2)-VAR(2) is the most suitable setting in this study.

Table A.1
Shorthand and the full name of Markov-Switching vector autoregressive models.

Model shorthand	Full name of the model
MSM-VAR model	Markov-switching mean VAR model
MSMA-VAR model	Markov-switching mean and autoregression VAR model
MSMAH-VAR model	Markov-switching mean autoregressive and heteroskedasticity VAR model
MSI-VAR model	Markov-switching intercept VAR model
MSIA-VAR model	Markov-switching intercept and autoregression VAR model
MSIAH-VAR model	Markov-switching intercept autoregressive and heteroskedasticity VAR model

Note: We specify with the general MS term the regime-dependent parameters: M: Markov-switching mean, I: Markov-switching intercept term, A: Markov-switching autoregressive parameters, H: Markov-switching heteroskedasticity.

Table A.2
AIC, HQ, and SC information criteria in the MS-VAR analysis process.

	AIC	HQ	SC
MSM(2)-VAR(2)	−19.8624	−19.7708	−19.6273
MSMA(2)-VAR(2)	−18.8898	−18.7468	−18.5224
MSMAH(2)-VAR(2)	−18.8697	−18.7095	−18.4583
MSI(2)-VAR(2)	−19.8309	−19.7394	−19.5958
MSIA(2)-VAR(2)	−19.9677	−19.8246	−19.6003
MSIAH(2)-VAR(2)	−20.1782	−20.0181*	−19.7668*
MSM(3)-VAR(2)	−19.9655	−19.8540	−19.6790
MSMA(3)-VAR(2)	−18.9845	−18.7700	−18.4335
MSMAH(3)-VAR(2)	−18.9444	−18.6955	−18.3052
MSI(3)-VAR(2)	−19.9717	−19.8602	−19.6852
MSIA(3)-VAR(2)	−20.0655	−19.8510	−19.5145
MSIAH(3)-VAR(2)	−20.2141*	−19.9652	−19.5749

Note: * indicates the optimal setting of MS-VAR under the information criteria.

Appendix B. Complete coefficient regression results of the MSIAH(2)-VAR(2) model

Table B.1
Regression results of the MSIAH(2)-VAR(2) model.

	Regime 1			Regime 2		
	DlnSLOPt	DlnWTIOPt	DlnUSDCNYt	DlnSLOPt	DlnWTIOPt	DlnUSDCNYt
Const	0.000895	0.002258**	0.000064	0.000346	−0.003901*	−0.000017
	(1.4950)	(2.7008)	(0.6399)	(0.2222)	(−1.8059)	(−0.0754)
DlnSLOPt-1	−0.433326***	−0.037269	0.000822	−0.283768***	0.003257	−0.017245
	(−7.5934)	(−0.5246)	(0.0968)	(−3.8098)	(0.0335)	(−1.6312)
DlnSLOPt-2	−0.120981***	−0.041535	−0.004310	−0.052085	0.007195	0.005363
	(−3.4087)	(−0.8872)	(−0.8185)	(−0.7904)	(0.0825)	(0.5781)
DlnWTIOPt-1	0.858739***	0.071954	−0.009629	0.573871***	−0.201288**	−0.003460
	(20.0690)	(1.3015)	(−1.4882)	(9.3130)	(−2.5591)	(−0.4010)
DlnWTIOPt-2	0.286305***	−0.031128	−0.011236	0.455403***	0.078262	0.007860
	(5.2158)	(−0.4766)	(−1.4082)	(5.7412)	(0.7617)	(−0.6945)
DlnUSDCNYt-1	−0.231532	−0.626081	0.026770	1.227560**	0.012727	0.217583**
	(−0.6563)	(−1.3753)	(0.4861)	(2.1372)	(0.0168)	(2.5783)
DlnUSDCNYt-2	0.234845	0.455128	−0.073883	−0.345722	0.503800	0.051166
	(0.6759)	(1.1053)	(−1.3674)	(−0.5490)	(0.6271)	(0.5532)
SE	0.009942	0.013600	0.001590	0.021090	0.028004	0.002999

Note: T-statistics are shown in parentheses. *, **and *** indicate 10%, 5% and 1% significance levels, respectively.

Table B.2
Regression results of the MSIAH(2)-VAR(2) model with control variables.

	Regime 1			Regime 2		
	DlnSLOPt	DlnWTIOPt	DlnUSDCNYt	DlnSLOPt	DlnWTIOPt	DlnUSDCNYt
Const	0.121427	0.036033	−0.005489***	−0.219562	−0.171507	−0.207853***
	(1.0466)	(0.0624)	(−12.6996)	(−0.5323)	(−0.2596)	(−7.7705)
DlnSLOPt-1	−0.455151***	0.004040	0.001536	−0.284201***	−0.057430	−0.015346
	(−8.447)	(0.063)	(0.1958)	(−3.359)	(−0.559)	(−1.506)
DlnSLOPt-2	−0.108293***	−0.009216	−0.005119	−0.050398	−0.051534	0.007503
	(−3.3829)	(−0.215)	(−0.8948)	(−0.6533)	(−0.5094)	(0.751)
DlnWTIOPt-1	0.860794***	0.055356	−0.007920	0.529104***	−0.237554***	−0.001383
	(18.3471)	(1.0718)	(−1.1273)	(6.8322)	(−2.7173)	(−0.151)
DlnWTIOPt-2	0.314666***	−0.075581	−0.010801	0.406810***	0.096081	0.011563
	(6.3311)	(−1.3324)	(−1.4581)	(4.679)	(0.8589)	(0.8461)
DlnUSDCNYt-1	−0.216825	−0.521952	0.029861	1.304636**	0.509743	0.127661
	(−0.5669)	(−0.9248)	(0.538)	(2.0755)	(0.6091)	(1.0924)
DlnUSDCNYt-2	0.053689	0.714273*	−0.095537*	−0.064184	0.812690	−0.011665
	(0.1701)	(1.7615)	(−1.8452)	(−0.0941)	(0.9016)	(−0.0921)
SF_rate	−0.016855**	−0.002731	0.002057	0.009294	−0.007979	−0.003942**
	(−2.4476)	(−0.3116)	(1.385)	(0.7594)	(−0.5202)	(−2.4792)
SF_rate_1	0.019210**	0.033276***	−0.003798**	−0.018886	0.003559	0.004033
	(2.2617)	(3.0465)	(−2.1872)	(−0.8721)	(0.1201)	(1.2401)
SF_rate_2	−0.004227	−0.025903***	0.002007**	0.016230	0.021254	−0.002956
	(−0.8263)	(−3.6851)	(2.0969)	(0.874)	(0.8113)	(−1.118)
lnM2	−0.24368	0.013393	−0.16982	0.119044	−0.514539	−0.056380

(*continued on next page*)

Table B.2 (*continued*)

	Regime 1			Regime 2		
	DlnSLOPt	DlnWTIOPt	DlnUSDCNYt	DlnSLOPt	DlnWTIOPt	DlnUSDCNYt
	(−0.7051)	(0.03)	(−1.6645)	(0.1627)	(−0.5584)	(−0.454)
lnM2_1	−0.523979	−0.95678*	0.217773**	−0.852429	1.826096	−0.508158***
	(−1.2525)	(−1.7463)	(2.0423)	(−0.6221)	(1.0305)	(−2.8466)
lnM2_2	0.759412***	0.94077**	−0.047583	0.748211	−1.301084	0.579181***
	(2.8665)	(2.4218)	(−1.0016)	(0.6282)	(−0.8404)	(3.1659)
DlnOS_OPEC	−0.250012**	−0.144932	0.004397	0.263251	−0.790533	−0.030179
	(−2.5271)	(−1.1228)	(0.2632)	(0.4634)	(−1.0924)	(−0.4156)
DlnOS_OPEC_1	0.326847**	0.468873**	−0.023229	−0.081993	1.469262	0.144955
	(2.356)	(2.5512)	(−0.9802)	(−0.1023)	(1.3719)	(1.2601)
DlnOS_OPEC_2	−0.08943	−0.236551*	0.015053	−0.219106	−0.913803	−0.065498
	(−0.8797)	(−1.7499)	(0.871)	(−0.3818)	(−1.1452)	(−0.68)
SE	0.009913	0.013085	0.001586	0.021197	0.027625	0.002664

Note: T-statistics are shown in parentheses. *,**and *** indicate 10%, 5% and 1% significance levels, respectively.

Appendix C. Detailed empirical results of the placebo test

Table C.1
Descriptive statistics of the variables in the placebo test.

Variable	Obs	Mean	Std. dev.	Min	Max	Sample period
lnBROP	668	2.8310	0.1350	2.4159	3.1411	6/23/1987–1/31/1990
lnWTIOP	672	2.9000	0.1310	2.5321	3.2036	6/23/1987–1/31/1990
lnUSDGBP	656	−0.5302	0.0576	−0.6444	−0.4151	6/23/1987–1/31/1990
lnOMOP	636	4.3092	0.2897	3.6055	4.9509	6/1/2006–12/31/2008
lnWTIOP	651	4.3577	0.2946	3.4105	4.9789	6/1/2006–12/31/2008
lnUSDOMR	677	−0.9547	0.0005	−0.9571	−0.9519	6/1/2006–12/31/2008

Note: In the placebo test, the daily dataset includes Brent crude oil price (BROP), Oman crude oil price (OMOP), USD/GBP exchange rate (USDGBP), USD/OMR exchange rate (USDOMR) and WTI crude oil price (WTIOP). Brent crude oil price, Oman crude oil price, USD/GBP exchange rate, USD/OMR exchange rate are all from the *Wind* database and WTI crude comes from US Energy Information Administration (EIA). Due to the difference in the number of closed days in each market within those sample intervals, the missing values of each sample are different. However, the absence is not serious, and does not affect the reliability of the placebo test results.

Table C.2
Unit root tests in the placebo test.

	Original series		First-order difference series	
	ADF	PP	ADF	PP
lnBROP	−1.800	−1.828	−15.542*	−24.039*
	(0.3806)	(0.3667)	(0.0000)	(0.0000)
lnWTIOP	−1.661	−1.758	−16.584*	−27.674*
	(0.4515)	(0.4015)	(0.0000)	(0.0000)
lnUSDGBP	−1.741	−1.757	−15.413*	−23.885*
	(0.4099)	(0.4019)	(0.0000)	(0.0000)
lnOMOP	−0.325	0.457	−9.833*	−28.558*
	(0.9785)	(0.9835)	(0.0000)	(0.0000)
lnWTIOP	−0.876	−0.614	−11.502*	−24.905*
	(0.7959)	(0.8679)	(0.0000)	(0.0000)
lnUSDOMR	−4.320*	−9.767*	−15.585*	−47.454*
	(0.0004)	(0.0000)	(0.0000)	(0.0000)

Note: The original hypothesis of the ADF and PP tests is "the sequence is non-stationary." Corresponding p-values of the Statistics are provided in parentheses; * rejects the null hypothesis at 1% significance level.

Table C.3
Complete regression coefficients of MSIAH(2)-VAR(2) in the placebo test based on the Brent crude oil market.

	Regime 1			Regime 2		
	DlnBROPt	DlnWTIOPt	DlnUSDGBPt	DlnBROPt	DlnWTIOPt	DlnUSDGBPt
Const	−0.000989	−0.000880	−0.000380	0.000831	0.001876	0.000225
	(−1.2679)	(−0.6802)	(−1.087)	(0.5267)	(1.2020)	(0.3823)
DlnBROPt-1	−0.434935***	0.150165	−0.057102**	−0.132735	−0.236758**	0.032562
	(−7.2532)	(1.3802)	(−2.1551)	(−1.4390)	(−2.3726)	(0.9860)
DlnBROPt-2	−0.201924***	0.062399	−0.023118	0.066371	−0.132088	−0.046838
	(−4.1701)	(0.7171)	(−1.0341)	(0.7131)	(−1.4326)	(−1.4320)
DlnWTIOPt-1	0.764359***	−0.122450	0.040140*	0.139211*	−0.020811	0.013215
	(10.8922)	(−1.3298)	(1.7990)	(1.8706)	(−0.3003)	(0.5070)
DlnWTIOPt-2	0.168540***	−0.196473**	0.040029*	0.160825*	0.225256***	0.017009
	(3.7991)	(−2.4631)	(1.8108)	(1.8014)	(2.6382)	(0.5184)
DlnUSDGBPt-1	0.071436	−0.178893	0.027951	−0.144196	0.128224	0.123009

(*continued on next page*)

Table C.3 (*continued*)

	Regime 1			Regime 2		
	DlnBROPt	DlnWTIOPt	DlnUSDGBPt	DlnBROPt	DlnWTIOPt	DlnUSDGBPt
	(0.6152)	(−0.9130)	(0.4911)	(−0.6235)	(0.5638)	(1.2794)
DlnUSDGBPt-2	0.036124	−0.074353	0.094244*	−0.028995	0.055395	−0.146399
	(0.3329)	(−0.3990)	(1.839)	(−0.1259)	(0.2401)	(−1.6516)
SE	0.011045	0.021041	0.004497	0.024294	0.022529	0.008656

Note: T-statistics are shown in parentheses. *, ** and *** reject the null hypothesis at 10%, 5%, and 1% significance levels, respectively.

Table C.4
Complete regression coefficients of MSIAH(2)-VAR(2) in the placebo test based on Oman crude oil market.

	Regime 1			Regime 2		
	DlnOMOPt	DlnWTIOPt	DlnUSDOMRt	DlnOMOPt	DlnWTIOPt	DlnUSDOMRt
Const	−0.000826	−0.000564	0.000000	0.000211	−0.000220	−0.000001
	(−0.9625)	(−0.4096)	(0.0666)	(0.2030)	(−0.0921)	(−0.0287)
DlnOMOPt-1	−0.284214***	0.005637	−0.000205	−0.329403***	0.020662	−0.007551**
	(−5.9465)	(0.0731)	(0.8420)	(−4.8801)	(0.1301)	(−2.2281)
DlnOMOPt-2	0.056143	−0.085311	−0.000391**	−0.070681	0.169261	−0.000140
	(1.5132)	(−1.4151)	(−2.0977)	(−1.5411)	(1.6031)	(−0.0654)
DlnWTIOPt-1	0.529657***	−0.030614	0.000543***	0.702749***	0.071245	0.002636
	(17.6430)	(−0.6428)	(4.0852)	(17.6575)	(0.7827)	(1.3862)
DlnWTIOPt-2	0.100800***	0.149752**	0.000104	0.130865**	−0.483327***	0.007958***
	(2.6226)	(2.4225)	(0.5332)	(2.1290)	(−3.3323)	(2.6083)
DlnUSDOMRt-1	13.039832***	5.782470***	−0.544554***	−0.259865	−3.439040	−0.522746***
	(193.0833)	(408.3910)	(−16.6526)	(−0.1625)	(−1.6225)	(−6.2270)
DlnUSDOMRt-2	13.087525***	−4.965232***	−0.245283***	−1.892151	−1.508044	−0.105138
	(154.9456)	(−188.9317)	(−10.4110)	(−1.1135)	(−0.8219)	(−1.1805)
SE	0.018353	0.018875	0.000090	0.011536	0.025850	0.000599

Note: T-statistics are shown in parentheses. *, ** and *** reject the null hypothesis at 10%, 5%, and 1% significance levels, respectively.

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