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The Effect of Global Oil Price Shocks on China's Chemical Markets

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Abstract
This paper investigates the effects of global oil price shocks on China's chemical market and two typical markets: fuel oil and PTA. The ARJI-GARCH model is applied to extract the jump intensity of crude oil returns. Then, jump intensity and positive and negative oil price shocks are added to the ARMA-GARCH model to examine the spillover effects of the crude oil market on chemical markets. Our results indicate that global oil returns are characterized by time-varying jump behavior. In addition, the impacts of oil returns jumps on the chemical markets are different. The oil returns jumps only have significant effects on the whole market and the fuel oil market. Moreover, the oil price shocks have asymmetric effects on chemical markets, except for the fuel oil market. Specifically, negative oil price shocks have greater effects on these markets than do positive shocks.

Keywords: Oil price shocks, Chemical markets, ARJI-GARCH

Introduction
In conjunction with years of rapid economic growth, China has become the world's largest energy consumer, accounting for approximately 23% of global energy consumption in 2015. China's oil consumption in 2015 was 559.7 million tons, an increase of 6.3% (BP Statistical Review of World Energy 2016). Since China became a net oil importer in 1993, its crude oil importation has risen dramatically, reaching7.37 million barrels per day in 2015.According to the U.S. Energy Information Administration (EIA), in August 2011 China's dependency on imported oil was as high as 55.2%, making it the world's largest oil importer. Subsequently, China's dependence on foreign oil increased steadily and now exceeds 60%. Due to geopolitical risk, financial speculation, the US shale revolution, OPEC's monopoly on oil prices and other factors, international oil prices have changed dramatically and experienced several wild fluctuations since 2007. For example, oil prices rose from \$49.95 per barrel in early 2007 to \$147.25 per barrel in July 2008, surging by194.7% in one-and-a-half years. Oil prices then experienced an unprecedented decline, from \$100 per barrel in September 2014 to \$39 per barrel in December 2015 (EIA). Considering China's demand for and heavy dependence on crude oil imports, its economy will inevitably be affected by oil price fluctuations.

As a corner stone of economic development, oil has penetrated into all aspects of society [1]. International volatility in oil prices not only influences macroeconomic performance but also impacts market behaviors. A great deal of research has explored the spillover effect of oil price fluctuations. For example, studies by Hamilton (1983) and Cunado and Gracia (2004) examine the spillover effect of oil price fluctuations on macroeconomic performance. Other literature offers more detail on the spillover effects of oil prices on particular markets, such as agricultural markets, metal markets and energy markets [2-5]. However, most of this research is conducted in the context of developed countries. Only a few surveys investigate oil price spillover effects in China, and these are confined to agricultural markets and metal markets [6,7]. There are few studies of the impact of oil price fluctuations on China's chemical markets. The chemical market mainly refers to basic chemical materials and chemical energy, such as coke, PP (polypropylene), fuel oil, steam coal, PTA (Pure Terephthalic Acid) and so on. The chemical market is a downstream market for crude oil, and its production costs are directly affected by crude oil prices.

Meanwhile, China has become the largest manufacturing economy in the world, with a dominant share of manufacturing activity. The manufacturing industry is the key driver of China's economic growth and has developed rapidly, from a 17.6% share of GDP in 1952 to a 40.53% share in 2015. As the most important component of the manufacturing industry, China's chemical markets have a profound effect on its economy. China's internationalization makes its economy more susceptible to global market shocks, especially to oil price shocks. Therefore, it is of vital significance to study the spillover effects of oil prices on China's chemical markets.

This paper mainly studies the spillover effects of oil price fluctuations on China's chemical markets. In this paper, we apply the traditional GARCH model, incorporating autoregressive jump intensity (ARJI), to extract the jump behavior of oil prices. Then, the oil price shocks can be divided into positive fluctuations and their negative counterparts to investigate whether different oil price shocks can affect chemical markets a symmetrically. A side from analyzing the entire chemical market, we select two typical chemical markets to investigate the impacts of oil price shocks. First, we select PTA, which is a downstream product of crude oil and a raw material for manufacturing activity. Second, fuel oil is chosen because it derived from crude oil and is processed in oil refineries. These two products are good representatives of basic chemical materials and chemical energy, respectively.

Literature Review

The crude oil widely used in many areas of the economy is becoming more and more important, and oil price fluctuations are attracting more attention from firms and investors, as well as researchers. The comprehensive impacts of oil price shocks on economies have become a popular topic for research. Existing literatures are mainly focused on the characteristics of global crude oil price fluctuations and the impacts of oil price shocks on economies.

According to the traditional resource extraction model of Hotelling (1993), oil prices exhibit the most severe and striking volatility out of all exhaustible resources [8]. Early research on oil price fluctuations developed rapidly during the two oil crises of the 1970s. Subsequently, some literatures focused on the characteristics of oil price fluctuations to better understand the dynamics of the crude oil market. It is generally believed that global oil prices are characterized by volatility clustering and high jumps [9-11]. Volatility clustering is a phenomenon in which low (high) volatility is always followed by low (high) volatility in the next period, indicating that the volatility will persist for a period of time [12]. Moreover, jumps account for a large part of the total variance in oil prices [11]. After added jumps, models can describe oil returns and predict volatility more accurately [13]. In addition, the conditional variance of crude oil prices can be composed of "permanent variance" and "temporary variance", both influenced by structural changes in oil prices [14].

Existing research on the influence of oil price shocks has shifted from macro economic performance, such as economic activities and macro indicators, to specific markets, which mainly include agricultural markets, metal markets and energy markets [2,3,15-17].

Regarding agricultural markets, Mitchel (2008) notes that an increase in oil prices is the critical factor in raising the prices of agricultural commodities [18]. There are two ways for oil prices to affect the prices of agricultural commodities. The direct way is that the rising oil prices increase input prices, thus driving the prices of agricultural products higher [19]. The indirect way is that oil prices influence the import and export prices of agricultural products through exchange rates and other factors [20]. Agricultural markets respond differently to oil price volatility in different countries due to differences in agricultural development levels. In the U.S., the spillover effects of oil price shocks on different agricultural products are not always significant. There was no obvious interaction between oil prices and six types of specific agricultural commodities during 2003-2005, but corn prices and soybean prices were co integrated with oil prices during 2006-2007 [21]. Volatility spillover among crude oil, corn and wheat markets only occurred after the fall of 2006 [22]. In Turkey, Nazlioglu and Soytas (2011) conclude that crude oil prices have a neutral effect on agricultural markets because oil price shocks cannot affect the prices of agricultural commodities in the short run and will not transfer to agricultural markets even in the long run [23]. In South Africa, there is no long-run relationship between oil prices and agricultural commodity prices [24]. In China, oil prices are not the major driving force behind the soaring prices of three typical agricultural products – corn, soybean and pork [25]. Although oil shocks had a minor influence on agricultural markets before the food crisis of 2006-2008, the effect became much higher after the crisis, when it was even greater than that of aggregate demand shocks [26].

In terms of metal markets, existing research focuses on precious metals and non-ferrous metals. There are co-movement effects between oil prices and precious metal prices [27-29]. In particular, the transmission of volatility between gold and oil returns is significant, and the oil market can be used to predict gold market prices and vice versa [27,28]. However, an opposite conclusion from Soytas, et al. (2009) is that oil prices have no predictive value for spot prices of precious metals in Turkey [30]. As for non-ferrous metals, oil price shocks have no calming effect on the copper market [8]. Meanwhile, Lescaroux (2009) finds the high correlation between oil prices and the prices of six non-ferrous metals to be mainly due to common shocks to inventory levels [31]. If the influences of supply and demand are removed, the links between these prices become fairly feeble. Zhang and Tu (2016) note that jumps in oil prices have significant effects on metal markets and that the impacts of oil price shocks in different directions are symmetric [7].

In regard to energy markets, some research focuses on the asymmetric impact of oil price shocks. The "Rockets and Feathers" Theory reveals the asymmetric effects of crude oil price shocks on gasoline prices; that is, gasoline prices rise immediately –like rockets – when the prices of crude oil go up, but they fall like feathers when crude oil prices decline [5]. This theory is also verified by Borenstein et al. (1997) [32]. Meanwhile, other research examines the dynamic correlation between crude oil and other energy. Radchenko (2005) examines the relationship between crude oil prices and gasoline prices and finds that both long-run and short-run shocks to oil prices influence gasoline prices [33]. However, gasoline prices only respond immediately to the long-run shocks, while it takes time for the short-run shocks to affect gasoline prices. Evidence from the American energy market shows that there is significant volatility transmission between crude oil and natural gas, but the price correlation is weaker because of oil and gas deregulation policy [34,35]. Lee and Zyren (2007) argue that a structural shift to higher crude oil prices leads to temporary rather than persistent impacts on the volatility of gasoline and heating oil prices [36]. Moreover, a study by Chou and Tseng (2016) has compared the spillover effects of oil price shocks and other factors, such as exchange rates, on gasoline prices [37].

Regarding the methodologies used to analyze oil price fluctuations and spillover effects, the main methods are the ARCH model by Engle (1982), Granger causality analysis, the VAR model (which prevailed during the 1990s), the ECM model by Davidson and Yeo (1978), the GARCH model by Bollerslev (2001), and so on [38-40].

GARCH models are widely used to study asset price volatility and can be further modified. Although univariate GARCH models are widely used at an early stage to depict the characteristics of oil price fluctuations and their unilateral effects on other markets, they still have an obvious drawback: they are usually applied to a single market and cannot address the volatility correlation among several markets [41,42]. Therefore, multivariate GARCH models, including the BEKK-GARCH model, the CCC-GARCH model, and the DCC-GARCH model, have been developed as improvements on previous models. The BEKK model is widely used in research on spillover effects, such as the impact of oil price fluctuations on the stock market, the corn and fuel ethanol markets and natural gas markets [34,43,44]. Unlike the CCC-GARCH model, which assumes a constant conditional correlation, the DCC-GARCH model allows the parameters of volatility to vary and to relate to previous volatility, such that this model can be used to explore the dynamic correlation between different markets. Studies by Filis et al. (2011) and Antonakakis and Filis (2013) have used DCC-GARCH models to examine the dynamic correlation between crude oil price fluctuations and stock markets [45,46]. Furthermore, because the traditional GARCH model cannot reflect asymmetric effects, the EGARCH model and TGARCH model were introduced to explain the leverage effects and a symmetry of volatility [47,48]. Because all these GARCH models can explain smooth volatility that depends on past information and fail to explain abnormal fluctuations caused by sudden events, Chan and Maheu (2002) introduce jumps into the GARCH model; they allow the conditional jump intensity to be time-varying and follow an autoregressive-moving average process, the so-called ARJI-GARCH model [49]. Later, Chang (2012) implemented this model to explore the time-varying and asymmetric dependence between global oil spot prices and futures prices [50]. Gronwald (2012) also combines the GARCH model with jumps to describe oil price behavior [11]. Furthermore, Zhang and Chen (2014) extend it to the ARJI-ht-EGARCH model to investigate the impacts of global oil prices on bulk commodities [51]. An ARJI model with structural changes, adopted by Chiou and Lee (2009), can examine the asymmetric effects of oil prices on stock returns and explore the importance of structural changes in this dependency relationship [52].

In summary, a number of studies describe the characteristics of oil price fluctuations: volatility clustering and high jumps. Current research on the impacts of oil price shocks has focused more on specific markets rather than on the macro economy. Some literatures have referred to agricultural markets, metal markets and energy markets, but few have addressed chemical markets, let alone specific chemical markets such as fuel oil and PTA. Because the chemical market is a crucial downstream market of crude oil and has an important impact on China's economy, it is essential to investigate the impact of global oil price shocks on China's chemical market. Furthermore, we select two typical markets – fuel oil and PTA – to analyze and compare the impacts of oil price shocks. In this paper, we adopt the modified GARCH model and incorporate the ARJI model to extract the jump intensity of oil prices; we also introduce external factors with regard to crude oil into GARCH models of chemical markets to examine the spillover effects of oil price shocks.

Methodology

The ARJI-GARCH model

Volatility clustering is a common feature of global oil returns series. The autoregressive moving average (ARMA) model is mainly used to solve the problem of heteroskedasticity and depict volatility clustering. Furthermore, the generalized auto regressive conditional heteroskedasticity (GARCH) model has been introduced, reflecting the long-memory feature of the returns series. The GARCH model is a good fit for time-varying volatility and smooth changes, but it is limited in its ability to explain large jumps that are discrete and in frequent [49]. Based on this defect, Press (1967) introduced the Poisson jump model– known as the compound events model – into the financial field [53]. Later research modified the model by allowing jumps to vary with time. In this paper, we adopt the ARJI-GARCH model proposed by Chan and Maheu (2002) to describe the volatility of crude oil prices [49]. The ARJI-GARCH model employs the autoregressive jump intensity of the traditional GARCH model, which can combine both jump behavior and observable past information. The model applied in our analysis is as follows:

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \psi_j \varepsilon_{t-j} + \sigma_t z_t + \sum_{k=1}^{n_t} \pi_{t,k} \quad (1)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{l} \alpha_j \varepsilon_t^2 + \sum_{i=1}^{k} \beta_i \sigma_{t-i}^2 \quad (2)$$

$$z_t \sim NID(0,1) \pi_{t,k} \sim N(\theta, \delta^2) \quad (3)$$

where r_t is the return of crude oil, $\mu$is the constant term, and Φ_i(i=1,2,…p) and ψ (j=1,2,…q) are the autocorrelation coefficients and moving average coefficients, respectively. σ^2_t re presents the conditional variance, which follows a GARCH (l,k) process as shown in the second formula. In the GARCH process, ε_t denotes the white noise sequence and σ^2_{t-i} represents the lag periods of conditional variance. α_j and β_i are the corresponding coefficients. z_t in the first formula follows an independent and identical normal distribution, and Π_{tk} , which denotes conditional jump size, follows a normal distribution with mean θ and variance δ^2.

Assume that the jump behavior of asset return follows a Poisson process given the past information set I_{t-1}, and let n_t denote the discrete counting process governing the number of jumps that arrive between t-1 and t. Then, given past information, the probability of $n_t = j$ is:

$$P(n_t = j|I_{t-1}) = \frac{\exp(-\lambda_t)\lambda_t^j}{j!} \quad j = 0, 1, 2 \ldots \quad (4)$$

Where, λ_t is the so-called conditional jump intensity, which determines the ex ante expectation of the number of jumps in period t based on the past information set I_{t-1}. As shown in formula (5), λ_t is allowed to follow an autoregressive process and can be modified by the expected deviation of the last period [49].

$$\lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \xi_{t-i} \quad (5)$$

ζ_{t-1} represents the expected deviation, which can be calculated as follows:

$$\xi_{t-1} = E[n_{t-1}|I_{t-1}] - \lambda_{t-1} = \sum_{j=0}^{\infty} jp(n_{t-1} = j|I_{t-1}) - \lambda_{t-1} \quad (6)$$

According to the Bayes rule, we can calculate the ex post probability of the occurrence of j jumps at time t. That is:

$$P(n_t = j|I_t) = \frac{f(r_t|n_t=j, I_{t-1})P(n_t=j|I_{t-1})}{P(r_t|I_{t-1})} \quad j = 0, 1, 2 \ldots \quad (7)$$

And the conditional density of oil returns can be calculated as follows:

$$P(r_t|I_{t-1}) = \sum_{j=0}^{\infty} f(r_t|n_t = j, I_{t-1})P(n_t = j|I_{t-1}) \quad j = 0, 1, 2 \ldots \quad (8)$$

Define $C_t = \sum_{k=1}^{n_t} \pi_{t,k}$ as the jump component. Given the number of jumps, the jump component follows a normal distribution with conditional mean and conditional variance as follows:

$$E[C_t|I_{t-1}] = \sum_{j=0}^{\infty} E[C_t|n_t = j, I_{t-1}] \times P(n_t = j|I_{t-1}) \quad (9)$$

$$Var(C_t|I_{t-1}) = (\delta^2 + \theta^2)\lambda_t \quad (10)$$

The conditional variance of asset returns contains two parts of volatility: normal volatility that follows a GARCH process and a jump component induced by sudden events. So, the conditional variance of returns can be described as the summation of these two parts:

$$Var(r_t|I_{t-1}) = \sigma_t^2 + (\delta^2 + \theta^2)\lambda_t \quad (11)$$

From (11), we know that the conditional variance of returns is an increasing function of the jump intensity. That is to say, jumps increase the volatility of returns [54].

We use the maximum likelihood method to estimate these unknown parameters. The log-likelihood function is as follows given sample size T:

$$L(\Psi) = \sum_{t=1}^{T} \ln[P(r_t|I_{t-1}, \Psi)] \quad (12)$$

Ψ is denoted as a set of all the parameters to be estimated.

The ARMA-GARCH model

To investigate how different types of oil price volatility affect the whole chemical market and typical chemical markets, a modified model containing the positive volatility and negative volatility of crude oil prices in the mean equation should be used. In addition, to examine the market's reaction to the jump behavior of crude oil returns, we introduce the jump intensity extracted above into the mean equation as well. The modified ARMA-GARCH model can be written as follows:

$$R_t = \mu + \sum_{i=1}^{p} \phi_i R_{t-i} + \sum_{j=1}^{q} \psi_j \varepsilon_{t-j} + k_1 P\_oil_t + k_2 N\_oil_t + \sum_{i=1}^{m} d_i \lambda_{t-i+1} + a_t \quad (13)$$

$$a_t = \sqrt{h_t} X_t \text{ , } X_t \sim NID(0,1) \quad (14)$$

$$h_t = \omega + \alpha a_{t-1}^2 + \beta h_{t-1} \quad (15)$$

Where, R_t represents the returns of the whole chemical market and two typical markets [16]. Positive crude oil returns can be derived by $P\_oil_t = Max(r_t, 0)$, and negative crude oil returns can be calculated by $N\_oil_t = Min(r_t, 0)$. λ_t denotes the jump intensity of crude oil returns at time t. Assume that the error term is the product of two parts: x_t, which follows an independent and identical normal distribution, and $\sqrt{h_t}$, which is the root of conditional heteroskedasticity. In this paper, we assume follows a GARCH process of order (1,1), as shown in (15).

Data and experimental results

In this paper, we select Brent crude oil spot prices derived from the U.S. Energy Information Administration to represent global crude oil prices. The chemical market indexes are derived from Choice Financial Terminal-bulk commodity database. Based on the availability of existing data, we choose daily observations from January 2007 to September 2015. We define returns as follows:

$$R_t = 100 * \ln\left(P_t / P_{t-1}\right) \quad (16)$$

Where P_t is the closing price/ index. After deleting data that do not appearon the same day, we obtain 2101 observations.

Descriptive statistics

As shown in Table 1, the standard deviation of the crude oil returns is larger than other standard deviations, suggesting that the fluctuations of the global oil market are the most violent. In contrast, the whole chemical market behaves relatively smoothly in relation to the lowest standard deviation, as can be verified in Figure 1 and Figure 2. Both crude oil prices and returns series tend to fluctuate severely, especially in late 2008 and early 2009. Additionally, it can be seen that the volatility-clustering phenomenon among crude oil prices, the chemical market index, the PTA index and the fuel oil index is obvious. All of these returns have negative skewness, indicating that large losses have a low probability of occurring in China's chemical markets, which is consistent with the global crude oil market. With regard to kurtosis, crude oil returns and fuel oil returns, whose kurtoses are greater than 3, have high peaks and heavy tails. Further evidence for the null hypothesis that the return series follows a normal distribution is given by the JB test. According to the JB statistics, we must reject the null hypothesis and conclude that the time series of returns for the crude oil market, the whole chemical market, PTA and fuel oil seem not to follow a normal distribution. Moreover, the results of the L jung-Box Q and Q2 tests suggest that all these time series behave in an auto-correlated manner and exhibit the ARCH effect. Thus, it is reasonable to adopt the GARCH model.

Table 1: Summary statistics (2007-2015)

Variable	Mean	Standard Deviation	Skewness	Kurtosis	JB Statistic	Q(15)	Q^2(15)
Crude oil	-0.0178	0.9042	-0.2272	4.9457	2166***	44.077***	737.52***
Chemical market	-0.0118	0.5602	-0.3105	1.7134	292.16***	35.122***	926.32***
PTA	-0.0153	0.5938	-0.1822	2.2581	459.98***	28.584**	691.37***
Fuel oil	-0.0134	0.7047	-0.3472	4.9470	2191.3***	41.44***	865.76***

Notes: (1)The JB statistic is used as a normality test. JB=T[S^2+$(K-3)^2$/4]/6, where S represents skewness, K represents kurtosis and T is the number of samples. (2) The Ljung-Box Q test can be used to test the autocorrelation of the time series. $Q(q) = T(T+2)\sum_{i=1}^{q} \frac{\rho_i^2}{T-i}$, where q is the lags, andρ_i is the coefficient of autocorrelation between the current and the ith lag period.The Q^2 test is used to test for the ARCH effect by replacing the time series with squared returns. (3)***,**,* indicate statistical significance at the 1%, 5%, and 10% levels of significance, respectively.

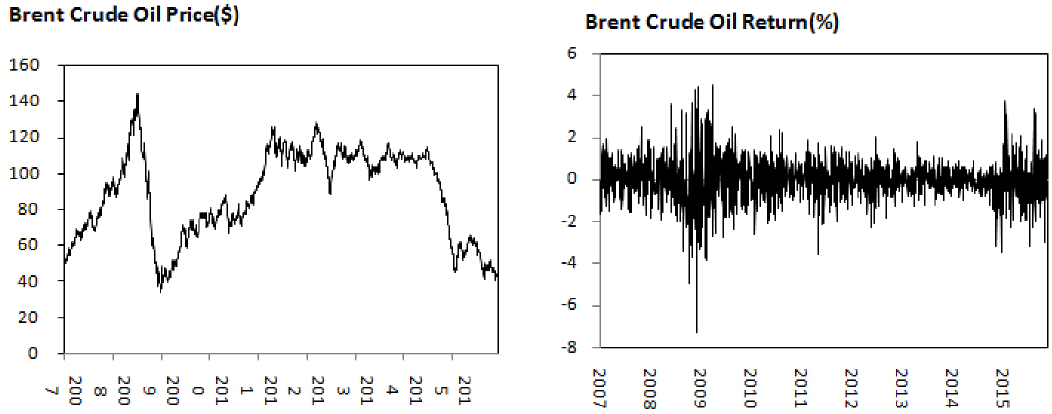

Figure 1: Time series plots of Crude oil

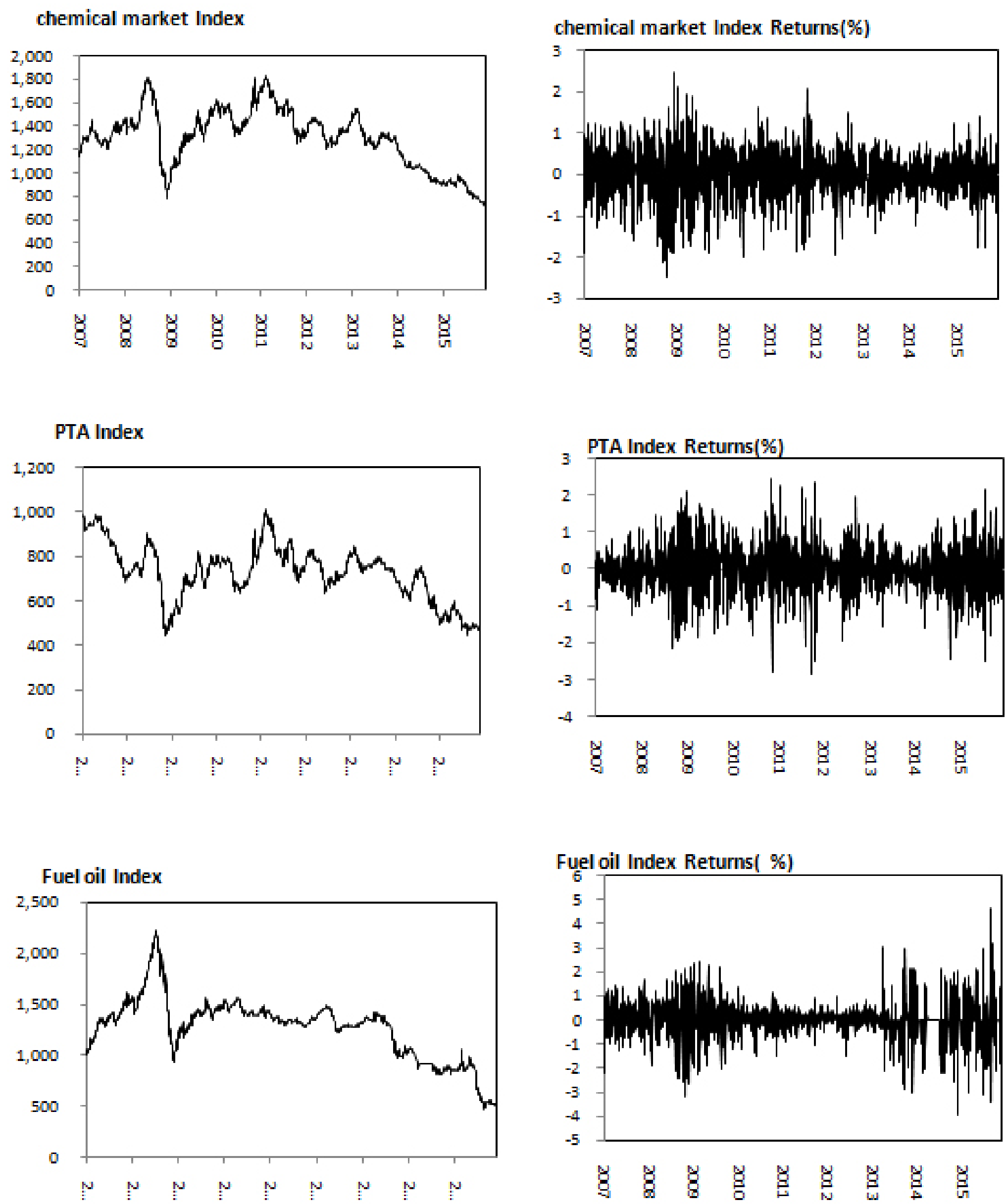

Figure 2: Time series plots of the chemical market and two typical markets

The presence of a unit root is very common in time series. The series will not be stationary if there is a unit root. To examine the stationarity of prices and the first order differences series regarding crude oil, the whole chemical market, PTA and fuel oil, we apply the traditional Augmented Dickey-Fuller (ADF) test, the Phillips and Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [55-57]. These tests are implemented after considering the intercept and removing the trend term of the original time series. The ADF and PP tests are for the null hypothesis that the time series has a unit root, while the null hypothesis of the KPSS test is that the time series does not have a unit root. Therefore, only when the ADF test and PP test cannot reject the null hypothesis and the KPSS test rejects the null hypothesis at the same time can we infer that the time series is non stationary.

The results in Table 2 suggest that all of the prices and index series are not stationary. However, the first difference of the original series are all stable and have no unit root because both the ADF tests and the PP tests can reject the null hypothesis while the KPSS tests have opposite results. Therefore, we can use the stationary returns series in the following analysis.

Table 2: Unit root and stationarity tests (2007-2015)

variable	Level			First difference		
	ADF Test	PP Test	KPSS Test	ADF Test	PP Test	KPSS Test
Crude oil	-1.264	-1.147	1.903***	-11.895***	-44.407 ***	0.108
Chemical market	-3.447**	-5.944***	0.935***	-10.692***	-46.330***	0.036
PTA	-3.982***	-5.344***	1.539***	-10.932***	-45.143 ***	0.073
Fuel oil	-3.136*	-3.694**	1.159***	-11.347***	-48.859 ***	0.047

Notes: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels of significance, respectively.

Empirical Results

Application of ARJI-GARCH model to crude oil returns

We estimate the coefficients of the ARJI-GARCH model on crude oil returns, and the results are shown in Table 3. The mean equation follows an ARMA (2,2) process, with all the parameters (μ 、ϕ_1 、ϕ_2 ·Ψ_1 ·Ψ_2) significant at least at the 10% level. The coefficients of the GARCH (1,1) model (ω、α 、β)、are significant at the 1% level, indicating that the crude oil returns have a GARCH effect. This is supported by figure 1, which describes the trends in global oil prices and returns during 2007 and 2015. There are severe price fluctuations in global crude oil, especially during the financial crisis of 2008. According to the right graph, it is easy to see that volatility in crude oil returns remained at a high level during many periods, particularly in late 2008 and early 2009, while it remained relatively low in other periods. This is the so-called volatility clustering, and the GARCH model is appropriate to describe this phenomenon. Meanwhile, an assumption of the ARJI-GARCH model is that jumps in crude oil prices follow a normal distribution-- N(θ, δ^2). The results in Table 3 show that the variance (δ^2) of normal distribution is significant at the 1% level, while the mean (θ) is not significant at all. The non-significance of the mean does not have great impact on the establishment of the model. We only focus on the variance of jumps--δ^2. The significant coefficient of δ^2 depicts the jump behavior of the crude oil returns, suggesting that crude oil prices will respond directly to some abnormal information and even exhibit extreme movements, such as jumps. Moreover, the coefficients of jump intensity (p, γ) are significantly positive at the 1% level, indicating that the jumps in oil returns follow a first-order autoregressive process and that it is reasonable to use this ARJI model. The estimation of p is very close to 1, implying a high degree of persistence in jump intensity because the current jump inoil returns is greatly affected by previous jump intensity.

Table 3: ARJI-GARCH model on crude oil returns (2007-2015)

Parameter	Coefficients	Standard error	T-statistics	Significance
μ	0.0784*	0.0468	1.6749	0.0939
ϕ_1	-0.9196***	0.0550	-16.7069	0.0000
ϕ_2	-0.9048***	0.0448	-20.2156	0.0000
ψ_1	0.9302***	0.0460	20.2092	0.0000
ψ_2	0.9317***	0.0385	24.2198	0.0000
ω	0.0062***	0.0023	2.6866	0.0072
α	0.0287***	0.0087	3.3135	0.0009
β	0.9329***	0.0131	71.2071	0.0000
δ^2	0.7819***	0.1415	5.5276	0.0000
θ	-0.0960	0.0645	-1.4878	0.1368
λ_0	0.0026	0.0018	1.4371	0.1507
p	0.9955***	0.0029	338.2788	0.0000
γ	0.1788***	0.0638	2.8034	0.0051

Notes: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels of significance, respectively.

Application of ARMA-GARCH model to the whole chemical market

As shown in Table 4, ϕ_1 and ψ_1 are significant at the 1% level, indicating that the current returns of the chemical market are significantly affected by the one-period lag returns and white noise. In addition, the current jump intensity (λ_t) of crude oil returns has a negative impact on chemical market returns, while the past jump intensity (λ_{t-1}) has an opposite effect according to the significance of d_1 and d_2 at the 5% level. This clearly shows that both current and previous jump intensities can affect chemical market returns. Although the current jumps may reduce the returns of the chemical market, they can adjust back to a higher level than before in the next period. Moreover, there is straightforward evidence (k_1=0.1413,k_2 = 0.2168) to suggest that chemical market returns respond differently to positive and negative oil price volatility. To examine whether the positive and negative effects of oil price shocks on chemical market returns are significantly unequal, that is the so-called asymmetry effect, we employ the Log Likelihood Ratio Test (LR test). The basic idea of the LR test is that once the null hypothesis (k_1=k_2) is correct, the maximum likelihood estimates of the constrained model and the unconstrained model are approximate. The LR statistics can be defined as follows: LR=-2 $\{L(\tilde{\psi}) - L(\hat{\psi})\} \sim \chi^2(m)$. Where $L(\tilde{\psi})$ and $L(\hat{\psi})$ are the maximum likelihood estimates of the constrained model and the unconstrained model, respectively, and m is the number of constraint conditions. The LR test statistic is distributed as a Chi-square distribution with m degrees of freedom. If LR> $\chi^2(m)$, it is reasonable to reject the null hypothesis and accept the alternative that there is an asymmetry effect of positive and negative oil price volatility on chemical market returns. In contrast, if LR≤ x^2(m), the null hypothesis cannot be rejected. According to the result of the LR Test, the LR test statistic is 3.88 and significant at the 5% level. Hence, we can strongly reject k1=k2, so that the positive and negative impacts of crude oil price shocks are asymmetric.

Table 4: ARMA-GARCH model on whole chemical market (2007-2015)

Parameter	Coefficients	Standard error	T-statistics	Significance
μ	-0.0007	0.0102	-0.0642	0.9488
ϕ_1	0.3719***	0.0494	7.5202	0.0000
ψ_1	-0.4246***	0.0483	-8.7866	0.0000
d_1	-0.5885**	0.2542	-2.3151	0.0206
d_2	0.6263**	0.2504	2.5010	0.0124
k_1	0.1413***	0.0235	6.0187	0.0000
k_2	0.2168***	0.0228	9.5030	0.0000
ω	0.0032*	0.0013	2.5956	0.0094
α	0.0544***	0.0089	6.0997	0.0000
β	0.9331***	0.0120	77.5124	0.0000
$L(\hat{\psi})$	-1450.34			
$L(\tilde{\psi})$	-1452.28			
LR statistics	3.88**			

Notes:***, **, * indicate statistical significance at the 1%, 5%, and 10% levels of significance, respectively.

Application of the ARMA-GARCH model to two typical chemical markets

According to Table 5, ϕ_1 and ψ_1 are significant at the 1% level in all these markets, demonstrating the presence of auto correlation and moving average. Meanwhile, ω,α,β are also significant in every market, suggesting that the volatility clustering of these return series can be captured by the GARCH model. So, it is reasonable to employ this first-order ARMA-GARCH model to the PTA and fuel oil markets. The current jump intensity (λ_t) and the last jump intensity (λ_{t-1}) have significant impacts on the returns of fuel oil, while they are not significant in the PTA market. Additionally, the direction of influence is the same as that in the whole chemical market. That is, the current jump intensity (d_1) has a negative impact on these returns, while the impacts of the last jump intensity (d_2) are positive, indicating that returns of fuel oil decrease along with the current jumps and increase in the next period. In addition, the crude oil price shocks, both positive and negative, have significant, positive impacts on PTA and fuel oil (see k_1 and k_2 in table 5). To examine the asymmetric effects of positive and negative oil price shocks on these returns, the LR Test is applied as before. The LR statistics are 8.34 and 0.42, respectively, showing that the null hypothesis (k_1=k_2) can be rejected only in the PTA market. So, we can conclude that the asymmetric effects are obvious in the PTA market, while there is little evidence of asymmetric effects in the fuel market.

Table 5: ARMA-GARCH model on specific chemical commodities

Parameter	PTA	Fuel oil
μ	0.0023	0.0018
	(0.0095)	(0.0103)
ϕ_1	0.5409 ***	0.4136***
	(0.0540)	(0.0474)
ψ_1	-0.5322***	-0.5621***
	(0.0564)	(0.0443)
d_1	-0.0193	-0.6000**
	(0.2646)	(0.2369)
d_2	0.0648	0.5875 **
	(0.2613)	(0.2312)
k_1	0.0894***	0.1751***
	(0.0247)	(0.0226)
k_2	0.1942***	0.1501***
	(0.0249)	(0.0230)
ω	0.0035 ***	0.0052 ***
	(0.0011)	(0.0011)
α	0.0837 ***	0.0846 ***
	(0.0112)	(0.0110)
β	0.9085***	0.9050 ***
	(0.0119)	(0.0110)
$L(\hat{\psi})$	-1580.44	-1688.44
$L(\hat{\psi})$	-1584.61	-1688.65
LR statistics	8.34***	0.42

Discussion

Global oil returns are characterized by time-varying jump behavior

Except for volatility clustering, another characteristic of the global oil return series is its high jumps. In fact, the jump intensity not only varies over time but also follows an autoregressive moving average process in terms of our empirical results. This result is consistent with those of Chan and Maheu (2002) and Gronwald (2012) [11,49]. Furthermore, Wang and Zhang (2014) argue that oil prices are highly susceptible to global political and economic environments, so the reactions of crude oil prices tend to vary with different political and economic events [12]. According to figure 3, the jump intensity of global oil prices exceeded 1 from late September 2008 through the first three quarters of 2009, and another great jump occurred at the beginning of 2015. This shows that the crude oil market experienced drastic rises and falls during these two periods, mainly due to sudden events.

From late September 2008 through the first three quarters of 2009, great jumps in the crude oil market were triggered by the failure of Lehman Brothers on September 15, 2008. Then, the financial crisis erupted and led to a global economic slowdown, increasing the uncertainty of the crude oil market. Meanwhile, a series of policies led to changes in market expectations and allowed jump intensity to reach its highest level: for example, U.S. President Barack Obama signed the $787 billion economic stimulus package into law on February 17th, and the Federal Reserve began "quantitative easing", an expansionary monetary policy that expanded the money supply by purchasing government bonds, on March 18th..

The jump behavior of crude oil returns in 2015 was mainly supply-driven. Due to the development of new technologies such as horizontal drilling and hydraulic fracturing, the U.S. Shale Revolution made tremendous progress, enabling the U.S. to significantly increase its production of oil and natural gas. In addition, OPEC members resisted reductions in oil production, aggravating the oversupply of crude oil. Moreover, as global crude oil is mainly priced in US dollars, the changes in the value of the dollar also had immediate shocks on the crude oil market.

The impacts of oil return jumps on the chemical markets are different

The impact of oil returns jumps on the whole chemical market is severe and remarkable. The current jumps in crude oil returns have a negative influence; however, the latest jumps have the opposite effect on the price volatility of the chemical market. This demonstrates that market returns can over react to current jumps in oil prices and adjust inversely in the next period [12]. The significant effect of jumps in the crude oil market on the chemical market can be mainly attributed to cost effects. Because crude oil is an important raw material for chemical products, jumps in crude oil prices can affect the costs of these products and lead to changes in their prices. In addition, oil price jumps will also influence operating rates and inventories, leading to fluctuations in the prices of chemical materials.

We also find that the jumps have different effects on the two typical markets. In contrast to the PTA market, the fuel oil market can respond significantly to jumps in crude oil returns. There are two reasons for this. First, the fuel oil market has a closer relationship than the PTA market with the global oil market. The fuel oil market is highly correlated with the crude oil market because fuel oil is produced from the processing of crude oil. PTA, however, is synthesized by paraxylene (PX), a byproduct of oil refining. Meanwhile, PTA is the main raw material used in the manufacture of polyester fiber, resin, and film, and it is also widely used in clothing, furniture, upholstery, containers and other products. So, the price of PTA is not only associated with the price of crude oil but also influenced by downstream industries. Second, the fuel oil futures market is more developed than the PTA futures market. Fuel oil futures are large contracts, and minority investors are restricted from trading in them. The transaction volumes of fuel oil futures are extremely low, and zero turnovers are very common. So, the fuel oil market is far from well-developed and has a weak ability to prevent international market risks. In contrast, the PTA futures market, with a large number of warehouse receipts, is well developed and has a strong ability to resist external risks. The combined effect of these reasons leads to different responses of the PTA and fuel oil markets to jumps in the global oil market.

Oil price shocks have asymmetric effects on chemical markets, except for the fuel oil market

In light of the results of the LR tests in sections 4.2.2 and 4.2.3, the positive and negative volatility of global oil prices have different effects on the whole chemical market as well as the PTA market. That is, compared with rising oil prices, falling oil prices have a greater influence on these markets. In contrast, the asymmetric effects of oil price shocks are not significant in the fuel oil market. Existing research also finds these asymmetric effects in different markets.

For example, Peltzman (1998) examines 242 types of commodities markets and finds that the price movements of finished products are not symmetrical with respect to the input price shocks. Among all these products, 160 types of finished products responded more sharply to the rising input prices than to falling prices [58]. Chiou and Lee (2009) also suggest that oil price volatility has asymmetric effects on S&P 500 returns. The reasons for these asymmetric effects of oil shocks on economic activities have been attributed to reallocation effects and adjustment costs [52]. On the one hand, oil price increases lead to a contraction in supply due to higher input costs. Combined with sect oral reallocation of resources from energy-intensive to energy-efficient sectors, the effect of rising oil prices is slowing output growth. On the other hand, lower oil prices stimulate production and consumption, and sect oral reallocation of resources is in the opposite direction. However, the labor market has downward rigidity of nominal wages, such that production costs are still high. Hence, falling oil prices do notlead to increased output [59]. Moreover, Balke, et al. (2002) investigate the origins of the asymmetric effectsof oil price shocks on the U.S. economy and argue that monetary policy alone cannot explain the asymmetry [60].

In China's chemical markets, overcapacity is a common problem. Most firms have weak pricing power in the face of cost changes. When the price of crude oil rises, these firms donot increase their prices much because they prefer to bear the rising cost toretaintheir market shares. However, if the price of crude oil falls, firms will decrease the prices of their products immediately to reduce inventories. Hence, chemical markets respond much more to decreases in oil prices than to increases. Moreover, from the perspective of investor behavior, most chemical commodity futures marketsare mainly composed of individual investors who, compared with institutional investors, are irrational and susceptible to market movements.When apositiveoil price shockoccurs, the prices of chemical commodities will rise accordingly due to cost pass-through. According to the Prospect Theory demonstrated by Kahneman and Tversky (1979), people value gains and losses differently [61]. Irrational investors are risk-aversewhen faced withgains and feel the pain of loss more acutely than the pleasure of gain. To retain certain benefits, they promptly sell assets, whose prices have increased, leading to a smallerrise inthese prices. In contrast, falling crude oil prices are followed bylower chemical prices. Invest or stend to exit the market. Panic selling will further aggravate the falling prices of chemical commodities. Consequently, the negative price shocks have a greater impact onchemicalmarkets.

As for the fuel oil market, the asymmetric effect of crude oil price volatility is not significant.The main reasons are as follows. First, the fuel oil futures market is mainly composed of institutional investorswho are morerational than individual investors. Second, there is the high correlation between the fuel oil and crude oil markets. Fuel oil is one of the "left-over" products of crude refining, so its pricechanges synchronously with crude oil price shocks. The fuel oil market has a relatively high degree of marketization. China opened up the pricing system of the fuel oil market in 2001, and the import and export quotas of fuel oil havebeen replaced by automatic import licensessince 2004. Therefore, an asymmetric effect of oil price shocks on the fuel oil market is not apparent.

Conclusions and policy implications

This paper investigates the impacts of global oil price shocks on the chemical market and two typicalmarkets in China. The ARJI-GARCH model is applied to extract the jump intensity of crude oil returns.Then, we add jump intensity and positive and negative oil price shocks to theARMA-GARCH model to examine the spillover effects of the crude oil market on chemical markets. The main conclusions are summarized as follows.

First, global oil returnsare characterized by time-varying jump behavior caused by sudden political and economic events. Great jump intensity reflects violent fluctuations in the crude oil market. Second, the impacts of oil returns jumps on the chemical markets are different. The oil returnsjumpsonly have significant effects on the whole market and the fuel oil market. Finally, the oil price shocks have asymmetric effects on chemical markets, except for the fuel oil market. Compared to positive shocks, negative oil price shocks have greater effects on these markets.

Based on our results, we propose several policy implications. First, the restart of the crude oil futures market should be accelerated to somehow hedge oil price risks. In this way, firmsthat usecrude oil or its derivatives as their raw materials can control and stabilize their costs to realize their expected profits. It has been nearly four years since China announced its restart of oil futures in 2013. However, there are many preliminary tasks to be completed, such as improving the relevant legal frame works and the regulatory system. Second, it is necessary to promote upgrades to the chemical industry chain. Chemical firms should use new technology to improve their energy efficiency and reduce costs. Meanwhile, advanced chemical materials should be exploited to encouragethe chemical industry to upgrade. Finally, the chemical commodity futures markets should be improved.A well-developed chemical commodity futures market can not only help to establish a market-oriented pricing mechanism to correct irrational expectations, thus reducing speculation and overreaction, it can also help resist external risks from the global oil market.

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