The impacts of global oil price shocks on China's fundamental industries
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HIGHLIGHTS
- We investigate the impacts of oil price shocks on China's fundamental industries.
- Jump behavior does exist in the crude oil market.
- The impacts of oil price shocks are asymmetric.
- China's four commodity markets are affected by the jump behavior.

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ABSTRACT
This paper investigated the impacts of oil price shocks on China's fundamental industries. In order to analyze the reactions of different industries to oil price shocks, we focused on four fundamental industries: grains, metals, petrochemicals and oil fats. We separated the oil price shocks into two parts, positive and negative parts, to investigate how commodity markets react when oil prices go up and down. We further studied the extreme price movements, called jumps, existing in the oil markets and how jump behavior has affected China's commodity markets. Our results suggest that asymmetric effects of oil price shocks did exist in the four markets and the negative oil price shocks had stronger influences on the four markets in China. The petrochemicals market suffered most from the oil price shocks, and the grains market was least sensitive to the shocks. When jumps occurred in the crude oil market, the four commodity markets would be affected differently. The oil fats market and petrochemicals market tended to "overreact" to jumps.

1. Introduction

Crude oil, the most influential resource of raw materials and primary energies, has strategic impacts on economic development and social stability. With recent rapid economic growth, China's crude oil consumption has increased significantly. In 2003, China surpassed Japan as the world's second largest consumer of crude oil after the US. At the end of 2012, China's consumption of crude oil reached 476.13 million tons. However, due to the domestic production of crude oil failing to meet the huge demand, China is facing severe challenges from a long-term energy supply gap and is increasingly dependent on crude oil in the process of economic transitions. In 2012, China's domestic production of crude oil was only 207.48 million tons, but the supply gap was 268.65 million tons. China's dependence on imported crude oil increased to 56.42%. In September 2013, the Energy Information Administration (EIA) announced that China had already become the world's largest net importer of crude oil.

Moreover, due to fluctuations in the world's economy and various political events, the global crude oil price changes fiercely. In September 2008, West Texas Intermediate (WTI) crude oil price experienced a 16.41% increase in a single day. Since 2002, global crude oil price continued to increase and peaked at $147 per barrel in 2008. Later, the oil price suffered a sharp decline, but now it still remains above $100 per barrel. Crude oil, the lifeblood of the industrial economy, strongly relates to economic security. Because of oil price fluctuations and heavy dependence on imported oil, crude oil volatility will inevitably affect China's economy. Therefore, it is necessary to investigate the effects of oil price volatility and to hedge the risk of oil price fluctuations.

In addition, volatility in crude oil prices could be transmitted to the bulk commodity markets through various transmission mechanisms and affect relevant industries. The most affected sectors are the oil-related industries (oil exploration, production, refining, etc.), highly oil-sensitive transportation industries (airlines, trucking, railroads, etc.) and highly oil-intensive...
manufacturing industries (aluminum, steel, etc.) (Hammoudeh et al., 2004). Further, the reactions of different commodity markets to oil price shocks vary, resulting from different market efficiencies and correlations with crude oil. This research will help us achieve insight into the specific impacts of oil price shocks on the economy at an industry level, and this is now a new research trend (Baffes, 2007; Jiménez-Rodríguez, 2008). With increasing dependence on global crude oil, it is urgent to investigate the impacts of oil price fluctuations on China's economy at an industry level. Therefore, our research mainly focuses on the impacts of oil price shocks on China's fundamental industries.

In order to investigate the impacts of oil price shocks on China's economy at an industry level, we selected four fundamental industries: grains, metals, petrochemicals and oil fats, according to data availability. In addition, to better describe the crude oil market, extreme price movements, called jumps, are also taken into consideration. We applied the Autoregressive Conditional Jump Intensity model (ARJI) developed by Chan and Maheu (2002), incorporating with the GARCH process (Bollerslev, 1986), to describe the volatility process and jump behavior of WTI oil. We separated the oil price shocks into two parts, positive and negative parts, to investigate how commodity markets react when oil prices go up and down. Moreover, price jumps will lead to an increasing volatility in the oil market, so related industries would be affected. Jump behavior in crude oil prices was also taken into consideration in order to analyze its impacts on commodity markets. Through the ARJI–GARCH model, jump intensity series are extracted to further examine the impacts of jump behavior on China’s commodity markets. Our results suggest that asymmetric effects of oil price shocks did exist in the four markets and the negative oil price shocks had stronger influences on the four indices in China. Within the four markets, comparatively, the petrochemicals index suffered most from oil price shocks, contrary to the grains market, which proved less sensitive to oil price shocks. Ultimately, jump behavior of crude oil has different impacts on the four markets.

2. Literature review

The existing research is extensively concerned with the relationship between crude oil prices and macro-economy (Brown and Yücel, 2002; Darby, 1982; Hamilton, 1983; Mork, 1989), and the results suggested oil price increases had negative impacts on GDP growth and also contributed to higher inflation pressure in oil-importing countries (Jiménez-Rodríguez, 2008). Negative correlation was found between oil price changes and GNP in the US (Hamilton, 1983). The oil price shocks were important factors resulting in some of the US recessions prior to 1972. Based on examining the relationship between crude oil prices and macro-economy when oil prices decreased, Mork (1989) extended Hamilton's (1983) work and concluded that oil price changes had asymmetric impacts on the national economy. Applying the structured co-integrated VAR model in G7 countries, Cologni and Manera (2008) reported that oil prices could affect inflation rate, and the inflation rate shocks would be further transmitted to the real economy by increasing interest rates.

In order to identify the impacts of oil price shocks on different economic sectors, many subsequent researchers began to analyze the reactions of different industries and markets to oil price shocks. After examining the co-movements of various commodities, including wheat, cotton, copper, crude oil, etc., Pindyck and Rotemberg (1990) demonstrated that the cross-price elasticity of demand and supply was zero, suggesting these commodities have no impacts on each other. Further, Lee and Ni (2002) verified that all sectors were not equally affected by oil price shocks. The most affected sectors were oil-related industries, highly oil-sensitive industries and highly oil-intensive manufacturing industries (Hammoudeh et al., 2004). Cong et al. (2008) argued that when oil volatility increased, the speculations in mining index and petrochemicals index might increase which would raise the returns of related companies. Baffes (2007), using data from 1960 to 2005, examined oil price pass-through to 35 different commodity markets. The results, at a more disaggregated level, illustrated that the fertilizer index had the highest pass-through (0.33), followed by agriculture (0.17) and metals (0.11). Precious metals also exhibited a strong response to oil price shocks.

The agriculture market has long been the subject of a vast literature that investigated the relationship between oil and agricultural commodity markets (Baffes, 2007; Yu et al., 2006; Zhang and Reed, 2008). Some studies indicated that a higher oil price would raise the input-cost, and this cost-push effect may result in a higher price of agricultural products (Campiche et al., 2004). Based on the co-integration test and the Granger Causality test, Nazlioglu and Soytas (2012) analyzed the dynamic correlations between crude oil price and 24 agricultural commodities prices, and the results provided strong evidence that oil price changes had significant impacts on agricultural commodity markets. It is also found that increase in oil price volatility will lead to higher food prices. This phenomenon indicated the risk transmission mechanism did exist between these two markets (Alghalith, 2010).

Moreover, conclusions concerning the impacts of oil price shocks on agricultural markets appeared to be different, owing to the differences of time periods, data sets and methodologies. For examples, Alom et al. (2011) reported a positive relationship between food prices and crude oil prices in the selected Asian and Pacific countries; however, the results varied across countries and period. It is also found that volatility spillover effects and risk pass-through effects of crude oil on the agricultural markets in the pre-crisis differed with those in the post-crisis period (Nazlioglu and Soytas, 2012). In contrast, Nazlioglu and Soytas (2011) analyzed the data from 1994 to 2010 in Turkey, implying that the impacts of oil price shocks on the Turkish agricultural commodity market were neutral. Other research, conducted by Gilbert (2010), Lombardi et al. (2012), Lee et al. (2010), and Zhang and Reed (2008), also supported the neutrality hypothesis.

In terms of non-energy commodities, metal markets also attracted the attentions of researchers. Baffes (2007) provided evidence that precious metal prices had strong reactions to oil price volatility. According to Beahm (2008), the relationship between gold prices and crude oil prices was a key driver of precious metal prices. Lescaux (2009) found that the prices of crude oil and precious metals tended to move together. Hammoudeh and Yuan (2008) had drawn a similar conclusion after analyzing crude oil and precious metal markets in the US.

A growing body of research has emerged on investigating the relationship between crude oil and biofuels. Due to high oil prices and growing demand for environmental protection, biofuels, as a substitute for fossil energies, are developing rapidly. Using the global computable general equilibrium (CGE) model, Timilsina et al. (2011) analyzed the impacts of oil price shocks on biofuel expansion. The result showed that an increase in the oil price would raise global biofuel penetration. Haixia and Shiping (2013) applied the EGARCH model and the BEKK–MVGARCH model to analyze the price volatility spillover among crude oil, corn and fuel ethanol markets. They provided strong evidence that unidirectional spillover effects from the crude oil market to the corn and fuel ethanol markets did exist.

In terms of methodologies and econometric models, many studies applied GARCH family models to capture the volatility clustering (Aloui and Jammazi, 2009; Arabi et al., 2012), but these...
models failed to explain the extreme, but discrete, movements found in asset returns. The news arriving into the market can be distinguished as normal news and abnormal news. According to Chan and Maheu (2002), abnormal news leads to extreme and discrete movements in returns that are considered as jumps. Mispricing would occur without taking the discrete jumps into consideration (Bates, 1996). Chan and Maheu (2002) and Maheu and McCurdy (2004) developed the Autoregressive Conditional Jump Intensity (ARJI) model to characterize the volatility clustering phenomenon and jump behavior in asset prices, and the model is a useful way to describe the extreme price movements (Gronwald, 2012). Recently, emerging literatures combined the GARCH method and the conditional jump model to describe the price behavior of crude oil (Gronwald, 2012; Lee et al., 2010; Wilmott and Mason, 2013).

In summary, most existing research concerning the relationship between the crude oil market and commodity markets mainly concentrated on Europe and US, while studies on China are rare. Since China has become the second largest crude oil consumption country and the largest net importer of crude oil, the relationship between the global crude oil market and China is much stronger. More attention should be given to China. What is more, in contrast to the studies mainly focusing on macro-economy, there is little empirical research to show how oil price shocks affect China’s commodity markets at an industry level. Further work is needed in this area.

Most important, extreme price movements called jumps do exist in the crude oil market (Gronwald, 2012; Lee et al., 2010). As price jumps occur, the oil market tends to be more volatile, and volatility risk of oil prices can be further transmitted into oil-related or oil-intensive markets. Previous studies verified the existence of oil price jumps (Gronwald, 2012; Lee et al., 2010); however, they paid little attention to how jump behavior in oil prices affected other markets. Zhang and Chen (2014) had investigated the impacts of oil price shocks on China’s bulk commodity market, but they mainly concentrated on the aggregate commodity market, and the analysis on the fundamental industries was brief. In addition, they did not consider the jump behavior in the crude oil market and its impacts on China’s fundamental industries. Our research further studied these issues.

This paper differs from the previous research mainly in three aspects. First, we investigated the impacts of oil price shocks on China’s economy at an industry level. Contrary to the existing studies concentrating on the whole macro-economy, we focused on four fundamental markets: grains, metals, petrochemicals and oil fats markets. Second, we analyzed whether oil price volatility had asymmetric impacts on China’s commodity markets. By separating the oil price shocks into positive and negative parts, we examined the impacts caused by opposite oil price movements. Third, we verified the existence of jump behavior in oil prices and further analyzed its impacts on the other markets. We described the jump behavior in oil markets applying the ARJI model, rather than the traditional VAR model and the impulse response function. Moreover, jump intensity of oil prices was further considered as an input factor, to examine how jumps in oil prices affected China’s commodity markets, in contrast to the existing research which paid little attention to this issue.

3. Methodology

3.1. The ARJI–GARCH model

The ARJI model developed by Chan and Maheu (2002) has proven to be a good way for capturing jump behavior in asset prices (Gronwald, 2012). The ARJI–GARCH model assumes that the jump intensity varies with time whilst also considers volatility clustering, which is approximate to the real market. The model allows us to study changes in the intensity of extreme price movements. In addition, this is also a trend in recent studies (Gronwald, 2012; Lee et al., 2010). Therefore, we applied the ARJI model, incorporating with the GARCH process, to describe the price behavior of crude oil. Further, we extracted the jump intensity series in order to examine how jump behavior in crude oil prices affects China’s commodity markets. The ARJI–GARCH model is applied to describe the volatility process and jump behavior in crude oil prices as follows:

\[ r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \psi_j \epsilon_{t-j} + \epsilon_t + \sum_{k=1}^{n_0} \lambda_{i,k} \]  \hspace{1cm} (1)

\[ \epsilon_t = \sigma z_t, \quad z_t \sim \text{NID}(0,1) \]  \hspace{1cm} (2)

\[ \lambda_t = \lambda_0 + \lambda_1 \epsilon_{t-1} + \sum_{i=1}^{n_{0}} \beta_i \epsilon_{t-i} \]  \hspace{1cm} (3)

The conditional jump size \( \epsilon_{t-1} \) is assumed to be normally distributed with mean \( \theta \) and variance \( \delta^2 \), when the history observation \( l_{1-1} = (r_{1-1}, r_{2-1}, r_{3-1}, \ldots r_{T}) \) is given. \( n_0 \) is on behalf of the number of jumps arriving at the time between \( t-1 \) and \( t \), and follows a Poisson distribution with \( \lambda_t > 0 \).

\[ P(n_t = j|l_{t-1}) = \exp(-\lambda_t) \lambda_t^j / j! \quad j = 0, 1, 2, \ldots \]  \hspace{1cm} (4)

where \( \lambda_t \) is called the jump intensity, which means the conditional expected value of the counting process under the \( l_{1-1} \). And the conditional jump intensity \( \lambda_t \) is assumed to follow an ARMA (1, 1) process (Chan and Maheu, 2002).

\[ \lambda_t = \lambda_0 + \rho \lambda_{t-1} + \gamma \epsilon_{t-1} \]  \hspace{1cm} (5)

where \( \lambda_{t-1} > 0, \rho > 0, \gamma > 0 \). And \( \epsilon_{t-1} \) is the jump intensity residual, and it is calculated as

\[ \epsilon_{t-1} = E[n_t - 1|l_{t-1}] - \lambda_{t-1} = \sum_{j=0}^{\infty} j P(n_t = j|l_{t-1}) - \lambda_{t-1} \]  \hspace{1cm} (6)

According to Maheu and McCurdy (2004), the conditional variance can be decomposed into two separate parts: the diffusion-induced component and the jump-induced component (Gronwald, 2012). The conditional variance takes the following form:

\[ \text{Var}(r_t|l_{t-1}) = \sigma_t^2 + (\delta^2 + \theta^2) \lambda_t \]  \hspace{1cm} (7)

Having observed \( r_t \) and using Bayes’ rule, we can infer ex-post probability of the occurrence of \( j \) jumps at time \( t \), which is defined as

\[ P(n_t = j|l_{t-1}) = \frac{f(r_t|n_t = j, l_{t-1}) P(n_t = j|l_{t-1})}{P(r_t|l_{t-1})} \quad j = 0, 1, 2, \ldots \]  \hspace{1cm} (8)

Given the sample size \( T \), the log likelihood function of the ARJI–GARCH model can be written as

\[ L(\theta) = \sum_{t=1}^{T} \log [P(r_t|l_{t-1}, \theta)] \]  \hspace{1cm} (9)

\[ P(r_t|l_{t-1}) = \sum_{j=0}^{\infty} f(r_t|n_t = j, l_{t-1}) P(n_t = j|l_{t-1}) \quad j = 0, 1, 2, \ldots \]  \hspace{1cm} (10)

where \( \theta \) represents all the parameters to be estimated.

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4.1. Descriptive statistics

As shown in Table 1, compared to the four commodity indices, the standard deviation of WTI oil returns is much greater, suggesting that the oil market has more dramatic fluctuations. Except the metals index whose skewness coefficient is positive, the other four series all have negative skewness coefficients. In terms of kurtosis, high degrees of kurtosis reveal a fat-tail distribution of all the five series. Along with the Jarque–Bera test, the skewness and kurtosis statistics, all the five series rejected the normality hypothesis at the 1% level. Ljung–Box Q and Q² statistics, significant at 1% level, provide strong evidence of autocorrelations and conditional heteroskedasticity for the five markets, indicating that the GARCH effect is apparently present in these five markets. Therefore the GARCH model is appropriate.

According to Fig. 1, the WTI spot prices have continued to increase since 2001, and now remain at a high level above $100 per barrel. From Figs. 1 and 2, we can find that price jumps are present and the volatility of oil prices changes largely when jumps occur. From Fig. 3, volatility clustering is apparent, and high (low) volatility tends to persist for a period of time, indicating that GARCH effects exist in the four markets.

We applied the conventional Augmented Dickey–Fuller (ADF) and Phillips and Perron (PP) statistics to examine the unit-root of prices and the first-order differences regarding WTI prices, metals index, grains index, oil fats index and petrochemicals index. Besides the traditional methods of unit-root test, we also used the KPSS stationary test (Kwiatkowski et al., 1992) under the null hypothesis that the series is trend stationary. Thus, if null hypothesis of KPSS is rejected, the series is non-stationary. According to Table 2, WTI prices, metals index, grains index, oil fats index and petrochemicals index are stationary in first-order difference.


In line with previous studies (Chen and Meheu, 2002; Maheu and McCurdy, 2004; Gronwald, 2012), we also applied GARCH (1, 1) model. Comparing the likelihood values and the significance of squared standardized residual series, we selected optimal model. As shown in Table 3, all the coefficients of ARMA (1, 1) model (μ, φ₁, and ψ₁) and GARCH (1, 1) model (ω, α, and β) of WTI oil returns are significant at 1% level, indicating that the WTI oil returns have strong ARCH and GARCH effects. According to Fig. 2, in 2009, the volatility of WTI crude oil market maintained at a very high level for almost one year. However, the volatility of oil prices was at a relatively low level during 2004–2007. It can be concluded that the oil returns exhibit a strong level of volatility clustering that GARCH family models should be applied to describe such phenomenon. In terms of jump behavior in oil returns, the significant mean (θ) and variance (δ²) of jump size demonstrate that instantaneous extreme movements certainly occur when abnormal news flows into the global oil market. The coefficients of jump intensity (δθ), ρ and r are significant, suggesting that...
the ARJI model is appropriate to describe the jump behavior in WTI oil returns. The positive $\rho$ (0.654720) and $\gamma$ (0.847101) indicate that the current jump intensity ($\lambda_t$) will be affected by the most recent jump intensity ($\lambda_{t-1}$) and intensity residuals ($\epsilon_{t-1}$), implying a high degree of persistence in jump intensity. Fig. 4 describes the jump intensity, most of which are between 0 and 1; however, when some abnormal events occurred, the jump intensity increased remarkably. For example, in 2003, the jump intensity peaked at 2.0, due to the uncertainty of global oil supply caused by the Iraq war. In consequence, jump behavior in crude oil prices varies with time. The modified Ljung–Box $Q^2$ statistics with 10 lags does not reject the null hypothesis that no serial correlation exists, indicating that ARJI–GARCH model is suitable for describing the volatility process and jump behavior existing in the crude oil market.


Table 4 presents the results of the application of the AR–GARCH model to the four commodity indices returns, incorporating with positive ($P_{oil}$), negative ($N_{oil}$) oil price shocks and jump intensity ($\lambda_t$) of crude oil. According to the Ljung–Box statistics, the squared standardized residuals with 15 lags of the four commodity indices returns are not significant at 10%, indicating that there is no serial autocorrelation. Therefore, our model is efficient and appropriate.

According to Table 4, the coefficients of the GARCH (1, 1) model ($\omega$, $\alpha$, and $\beta$) are significant at 1% level, verifying that the four commodity markets in China all exhibit strong GARCH effects. The statistical significances of the four $k_1$ values (0.02759, 0.05562, 0.07216 and 0.04229) demonstrate that the four commodity markets are affected by the positive oil price shocks. In terms of the negative oil price shocks, except metals index returns, the other three indices return all strongly respond to such negative shocks, verified by the significant $k_2$ values. Especially, we can find that the petrochemicals index is most sensitive to both positive and negative oil price shocks, contrary to the grains index that has the weakest reactions among the four indices. Furthermore, comparing the values of $k_1$ and $k_2$ of each market, except metals market that has no response to the negative oil price shocks, grains index, oil fats index and petrochemicals index are more sensitive to the negative oil price shocks than the positive ones. Thus, it can be concluded that the impacts of oil price shocks are asymmetric. Decreases in oil prices have much stronger impacts on China’s commodity markets than increases in oil prices.

As regards to the jump behavior in crude oil prices, all the four commodity markets have different responses to these extreme price movements. The significantly negative $d_1$ values ($-0.23236$, $-0.55411$, $-0.93759$, and $-0.39742$) of the four indices suggest that the current jump intensity ($\lambda_t$) of crude oil will negatively affect all the four commodity markets. When the jump intensity in crude oil market is higher, the four commodity markets returns tend to decrease. Especially, we can also find that the grains index has the weakest reactions, in contrast to the petrochemicals index high sensitivity to the jump intensity among the four indices. The coefficient $d_2$, measuring the responses to the most recent jump intensity ($\lambda_{t-1}$), is only significant in the petrochemicals market and oil fats market. The positive values of $d_2$ ($0.44718$ and $0.42447$) indicate that after overreacting to the current jump behavior in oil prices, petrochemicals index and oil fats index returns tend to adjust back to a reasonable level in the next period.

5. Discussion

From our empirical results, we find some interesting phenomena worthy of further discussion.

First, global crude oil prices have a feature of volatility clustering. A low (high) volatility is followed by a low (high) volatility in the next period, indicating that the volatility tends to persist for a period of time. Some studies based on the GARCH model also found the effects in the crude oil markets (Aloui and Jammazi, 2009; Arouri et al., 2012; Gronwald, 2012). In our opinion, investors with heterogeneous beliefs seem to respond differently when oil prices change. Some industries (such as oil production and oil refining industries) highly sensitive to crude oil prices are apt to adjust their oil inventory more rapidly, contrary to other sectors less dependent on crude oil. Thus, the selections in time and amounts, when heterogeneous investors adjust their inventory of crude oil, tend to be different, which makes the oil price volatility persist for a period of time, called volatility clustering.

Second, jump behavior actually exists in the crude oil market. As regards to the mean and variance ($\theta$ and $\sigma^2$) of the jumps, the significant values demonstrate that jumps certainly occur after abnormal information flows into the market. Unexpected events will result in discrete jumps. In line with the previous findings of Chiu and Lee (2009) and Gronwald (2012), we find that the jump intensity ($\lambda_t$) of crude oil varies with time (described in Fig. 4),

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rather than remaining constant. Because crude oil price is highly susceptible to global political and economic environments, as crude oil market is subject to different political and economic events, the reactions of crude oil prices certainly tend to vary. For example, in 2003, jump intensities of crude oil prices changed from 0.1 to 2.0 due to the Iraq War; in 2008, shocked by the financial crisis, jump intensities of crude oil prices increased fiercely and peaked at 1.8 per day. Intensities of above 0.5 occurred...
respectively. (5) Agricultural machines. However, China's agriculture is mainly transportation costs, chemical fertilizer and fuel consumption of markets. The differences can be attributed to two factors: (1) The four commodity markets. Compared to the four indices, the petrochemical products, and petrochemical industries are most highest pass-through. Crude oil is the principal raw material of market development of agriculture and metal futures, volatility risk can be partly hedged, so that the reactions to the past jump behavior of jump size, and the variance of jump size, respectively. (3) \( \omega \), \( \alpha \) and \( \beta \) are the parameters of the GARCH model, defined in Eq. (3). (4) \( \theta \) and \( \delta \) are the mean and the variance of jump size, respectively. (5) \( \omega \), \( \rho \) and \( \gamma \) are the parameters of jump intensity \( ( \lambda ) \), defined in Eq. (3).

Third, oil price shocks have different impacts on the four commodity markets. Compared to the four indices, the petrochemicals index is most susceptible to oil price shocks, in contrast to the grains index having the weakest response to such shocks. The differences can be attributed to two factors: (1) The four markets have different correlations with the crude oil market. (2) The cost-push effects of crude oil are different in the four markets.

As for the petrochemicals index, China's petrochemicals market suffers most from oil price shocks, due to the highest correlation with crude oil and the lack of hedging tools. Baffes (2007) studied 35 markets and suggested that petrochemical products had the highest pass-through. Crude oil is the principal raw material of petrochemical products, and petrochemical industries are most highly related to the crude oil market. In China, since the dependence on imported oil had reached about 57% at the end of 2012, it is inevitable that China's petrochemicals market will suffer serious shocks when oil prices change. Cong et al. (2008) suggested that increases in oil volatility might raise speculations in labor-intensive and the degree of mechanization is lower than that of America and Europe, which results in a relatively low dependence on oil.

As to the metals and oil fats index, they are also affected by oil price volatility, due to the use of oil in processing and manufacturing the products, as well as the import expense of raw materials affected by fuel cost. Most metallic minerals and oil crops utilized in China's metal and oil fat industries are imported. More than 60% of the iron ores and soybeans are imported from overseas. An increase in fuel cost will lead to a higher import expense, and the metal and oil fats market will suffer from the cost-push effect. However, the impacts of oil price shocks on these two markets are weaker than those on the petrochemicals market, resulting from their lower dependence on the global oil market.

The fourth finding indicates that oil price shocks on China's commodity markets are asymmetric. Compared the coefficients of positive \(( h_1 \) shocks and negative \(( h_2 \) shocks to each commodity market, the impacts of prices decreasing on the commodity returns are much greater than when prices go up, described as the asymmetric effect of oil price shocks. Chiou and Lee (2009) also suggested that oil price volatility has asymmetric effects on the S&P 500 stocks returns. In our opinion, a certainty effect and a reflection effect (Kahneman and Tversky, 1979) exist in China's markets. On one hand, the direct effect of oil price shocks include input-cost effects (Chiou and Lee, 2009), indicating that crude oil prices and commodity indices tend to move together. On the other hand, Zhang and Chen (2011) demonstrated that China's market is mainly composed of individual investors who are highly susceptible to the volatility in oil prices, so that they are more likely to be irrational when making investment decisions. Speculation is more common than rational investment. Therefore, due to the cost-push effect, positive shocks of crude oil will raise the commodity prices in a short term. Irrational investors tend to stop their trading to obtain the certain gains. In contrary, when negative oil price shocks decrease the commodity returns, investors prefer to undertake more risk to redeem their loss rather than stop, inevitably increasing the volatility risk of commodity markets. Owing to irrational decisions, the impacts of oil price shocks are asymmetric.

The last finding is that jump intensity of oil prices has different impacts on the four commodity markets. Current jump intensity \(( \lambda_1 \) of crude oil has significantly negative impacts on the returns of the four commodity indices. As to the first-order lag jump intensity \(( \lambda_{t-1} \) of crude oil, it had no obvious impact on the grains index and metals index, but remaining positive influences on the other two markets. When jump intensity increases, the oil market will become more volatile so that all the four indices are negatively affected due to irrational decision-making. In addition, as to grains market and metals market, owing to mature development of agriculture and metal futures, volatility risk can be partly hedged, so that the reactions to the past jumps \(( \lambda_{t-1} \) become weaker. However, it is opposite in the case of the petrochemicals and oil fats markets. In terms of the petrochemicals market, there are no crude oil futures to hedge oil price risk.

Table 2
Unit root and stationary tests.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Level ADF</th>
<th>Level PP</th>
<th>KPSS</th>
<th>First Difference ADF</th>
<th>First Difference PP</th>
<th>First Difference KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTI</td>
<td>–2.2426</td>
<td>–10.916</td>
<td>12.793†</td>
<td>–12.265‡</td>
<td>–2321.134‡</td>
<td>0.1062†</td>
</tr>
<tr>
<td>Metals</td>
<td>–2.6362</td>
<td>–10.666</td>
<td>15.549‡</td>
<td>–12.199‡</td>
<td>–2616.972‡</td>
<td>0.1678</td>
</tr>
<tr>
<td>Oil fats</td>
<td>–2.3617</td>
<td>–9.882</td>
<td>12.499‡</td>
<td>–11.604‡</td>
<td>–2592.852‡</td>
<td>0.0805‡</td>
</tr>
<tr>
<td>Grains</td>
<td>–1.7712</td>
<td>–5.643</td>
<td>8.3056‡</td>
<td>–12.114‡</td>
<td>–2716.085‡</td>
<td>0.0445‡</td>
</tr>
<tr>
<td>PetroChem.</td>
<td>–2.9146</td>
<td>–10.338</td>
<td>10.373‡</td>
<td>–10.170‡</td>
<td>–2662.966‡</td>
<td>0.1636†</td>
</tr>
</tbody>
</table>

Notes: (1) \( Q^2(10) \) is the Ljung–Box test statistics for serial correlation in the squared standardized residuals with 10 lags. (2) The value in the square bracket indicates the significance level. (3) \( \omega \), \( \alpha \) and \( \beta \) are the parameters of the GARCH model, defined in Eq. (3). (4) \( \theta \) and \( \delta \) are the mean and the variance of jump size, respectively. (5) \( \omega \), \( \rho \) and \( \gamma \) are the parameters of jump intensity \( ( \lambda ) \), defined in Eq. (3).

Table 3

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coeff.</th>
<th>Std. error</th>
<th>T-stat.</th>
<th>Signif.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu )</td>
<td>0.252687†</td>
<td>0.080258</td>
<td>3.14839</td>
<td>0.001642</td>
</tr>
<tr>
<td>( \phi_1 )</td>
<td>–0.710990‡</td>
<td>0.064151</td>
<td>11.08294</td>
<td>0.000000</td>
</tr>
<tr>
<td>( \psi_1 )</td>
<td>0.666708†</td>
<td>0.053013</td>
<td>12.57629</td>
<td>0.000000</td>
</tr>
<tr>
<td>( \omega )</td>
<td>0.066378‡</td>
<td>0.021293</td>
<td>3.17726</td>
<td>0.001825</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.265498‡</td>
<td>0.003636</td>
<td>4.34705</td>
<td>0.000034</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.950463†</td>
<td>0.009867</td>
<td>9.61231</td>
<td>0.000000</td>
</tr>
<tr>
<td>( \delta )</td>
<td>4.117940‡</td>
<td>0.556028</td>
<td>7.40599</td>
<td>0.000000</td>
</tr>
<tr>
<td>( \theta )</td>
<td>–0.798164‡</td>
<td>0.420411</td>
<td>–1.89853</td>
<td>0.057626</td>
</tr>
<tr>
<td>( \lambda_0 )</td>
<td>0.034003</td>
<td>0.013848</td>
<td>2.45539</td>
<td>0.014073</td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.654726‡</td>
<td>0.119306</td>
<td>5.48770</td>
<td>0.000000</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.847101‡</td>
<td>0.235848</td>
<td>2.95968</td>
<td>0.000331</td>
</tr>
<tr>
<td>( Q^2(10) )</td>
<td>11.9373</td>
<td>(Statistic)</td>
<td>[0.2893]</td>
<td></td>
</tr>
</tbody>
</table>

Notes: (1) \( Q^2(10) \) is the Ljung–Box test statistics for serial correlation in the squared standardized residuals with 10 lags. (2) The value in the square bracket indicates the significance level. (3) \( \omega \), \( \alpha \) and \( \beta \) are the parameters of the GARCH model, defined in Eq. (3). (4) \( \delta \) are the mean and the variance of jump size, respectively. (5) \( \omega \), \( \rho \) and \( \gamma \) are the parameters of jump intensity \( ( \lambda ) \), defined in Eq. (3). (6) \( \lambda_0 \) and \( \delta \) are the mean and the variance of jump size, respectively. (7) \( Q^2(10) \) is the Ljung–Box test statistics for serial correlation in the squared standardized residuals with 10 lags.
when it comes to oil fats markets, although the oil fats futures exhibit high trading volume, only a few enterprises use them to avoid volatility risk, indicating that the risk management function has not been used to best advantage. Consequently, these two markets tend to “overreact” to the jump behavior in oil price in current period. Then, the price will adjust back to a reasonable level in the next period of time. In sum, the jump behavior of crude oil will undoubtedly increase the risk in the four commodity markets. Therefore, it is imperative to develop crude oil futures market in China.

6. Conclusion

In this paper, we investigated the impacts of oil price volatility on China’s different commodity markets. We applied the autoregressive conditional jump intensity (ARJ) model, combining with the generalized conditional heteroscedasticity (GRACH) method, to describe the volatility process and jump behavior in the crude oil market. In addition, we further separated the oil price shocks into two parts, positive and negative parts, to identify how the oil price changes influence returns in different China’s commodity markets. We also considered the jump behavior in oil prices as an input factor to investigate how the commodity markets in China are affected when jumps occur in the global oil market. The main conclusions are summarized as follows.

First, the global oil market has a feature of volatility clustering. Due to heterogeneous beliefs, the selections in time and amounts, when heterogeneous investors adjust their inventory of crude oil, tend to be different, leading the volatility of oil prices to persist for a period of time. Second, jump behavior does exist in the crude oil market. When abnormal information flows in to the oil market, extreme price movements will occur. Price jumps have the characteristic of dynamic changes, and the jump intensity varies over time. Third, the impacts of oil price shocks are asymmetric. Both positive shocks and negative shocks of crude oil prices have significant influences on China’s commodity markets. However, these impacts are asymmetric. The negative shocks have stronger influences on each market. The petrochemicals market suffers most, and the grains market is least susceptible to oil price shocks among the four examined markets. Forth, four commodity markets are strongly affected by the jump behavior in the crude oil market. Contrary to grains and metals indices, because of inefficient use of futures to manage the risk, the petrochemicals and oil fats indices tend to “overreact” to the current jump behavior in oil prices, and then will adjust back to a reasonable level in the next period of time.

These conclusions have important policy implications. First, it is critical to improve the strategic oil reserve system in China. Owing to the huge demand of crude oil and high dependence on imported oil, China’s economy is susceptible to the price volatility of global crude oil. The oil reserve system is a good way to reduce the impacts of oil supply shocks and stabilize the domestic oil prices. In this paper, we applied the AR–GARCH to commodity markets (2001–2011).

Table 4

<table>
<thead>
<tr>
<th>Variable</th>
<th>Grains</th>
<th>Metals</th>
<th>Petrochemicals</th>
<th>Oil fats</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>0.06264***</td>
<td>0.04668</td>
<td>0.09523**</td>
<td>0.05293</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>$-0.06007^{**}$</td>
<td>$-0.02881$</td>
<td>0.00324</td>
<td>$-0.03703$</td>
</tr>
<tr>
<td>$\phi_2$</td>
<td>0.04920**</td>
<td>0.01749</td>
<td>0.07414***</td>
<td>0.05742***</td>
</tr>
<tr>
<td>$k_1$</td>
<td>0.02759***</td>
<td>0.05562***</td>
<td>0.07216***</td>
<td>0.04229***</td>
</tr>
<tr>
<td>$k_2$</td>
<td>0.04864***</td>
<td>0.00139</td>
<td>0.07770***</td>
<td>0.05491***</td>
</tr>
<tr>
<td>$d_1$</td>
<td>$-0.23236^{*}$</td>
<td>$-0.55411^{***}$</td>
<td>$-0.93759^{***}$</td>
<td>$-0.39742^{***}$</td>
</tr>
<tr>
<td>$d_2$</td>
<td>$-0.05641^{*}$</td>
<td>0.03263</td>
<td>0.44718*</td>
<td>0.42447*</td>
</tr>
<tr>
<td>$\omega$</td>
<td>0.01193**</td>
<td>0.01170***</td>
<td>0.07152***</td>
<td>0.01876**</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.07130***</td>
<td>0.17783***</td>
<td>0.09148***</td>
<td>0.07872***</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.91512***</td>
<td>0.88966***</td>
<td>0.87296***</td>
<td>0.91362***</td>
</tr>
<tr>
<td>$Q^2(15)$</td>
<td>4.0245</td>
<td>20.4168</td>
<td>12.8748</td>
<td>10.6947</td>
</tr>
<tr>
<td>Likelihood value</td>
<td>$[0.998]$</td>
<td>$[0.157]$</td>
<td>$[0.612]$</td>
<td>$[0.774]$</td>
</tr>
</tbody>
</table>

Notes: (1) $Q^2(15)$ is the Ljung–Box test statistics for serial correlation in the squared standardized residuals with 15 lags. (2) The value in the square bracket indicates the significance level. (3) $k_1$ and $k_2$ are the coefficients of positive shocks and negative shocks, respectively, defined in Eq. (11). (4) $d_1$ and $d_2$ measure the impacts of current jump intensity and first-order lag jump intensity of crude oil, defined in Eq. (11). (5) $\omega$, $\alpha$, and $\beta$ are the parameters of GARCH (1, 1) model, defined in Eq. (13).
price. The US, Japan, Germany and France have already established oil reserve systems and efficiently reduced the risk of oil price fluctuations. Second, it is recommended to support the development of new technologies in alternative energies. Other energies such as biofuels and solar energy are renewable and also more environmentally friendly. These energies need to be developed and exploited so as to diversify the energy consumption structure and reduce the dependence on imported oil. Third, it is necessary to improve the pricing mechanism of petroleum to become more market-oriented in China. Due to the time-delay between changes in oil prices and policy adjustments, irrational expectation and overreaction to policy changes could increase speculation so as to raise the degree of uncertainty. Therefore, a more market-oriented pricing mechanism can make markets more efficient and reduce irrational speculations. Fourth, it is important to develop the crude oil futures market in China. In the lack of hedging tools, when global crude oil price changes fiercely, it is likely to cause panic in the domestic market and increase market volatility. And the risk can be further transmitted to other markets. Due to the efficient use of agricultural and metal futures, the impacts of oil price shocks on the grains market and the metals market have been reduced and the two markets do not tend to “overreact” to the jump behavior in the crude oil market. Similarly, in order to stabilize domestic petroleum and petrochemicals markets, crude oil futures should be used to effectively manage the risk of oil price fluctuations and further make the other markets more stable.

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References

Campiche, J.L., Bryant, H.L., Richardson, J.W., Outlaw, J.L., 2007. Examining the evolving correspondence between petroleum prices and agricultural commod-
ity prices. Selected Paper Prepared for Presentation at the American Agricultural Economics Association Annual Meeting. Portland, OR.