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The impact of global oil price shocks on China's bulk commodity markets and fundamental industries

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HIGHLIGHTS

- We investigated the impact of global oil price shocks on China's bulk commodity markets and fundamental industries.
- The aggregate commodity market was affected by both expected and unexpected oil price volatilities.
- The impact of unexpected oil price volatilities became more complex after 2007.
- The metals and grains indices did not significantly respond to the expected volatility in oil prices.

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ABSTRACT

This paper investigated the reaction of aggregate commodity market to oil price shocks and also explored the effects of oil price shocks on China's fundamental industries: metals, petrochemicals, grains and oilfats. We separated the volatilities of oil price into expected, unexpected and negatively expected categories to identify how oil prices influence bulk commodity markets. We contrasted the results between different periods and among classified indices, in order to discover the significant changes in recent years and the differences at an industry level. Our results indicate that the aggregate commodity market was affected by both expected and unexpected oil price volatilities in China. The impact of unexpected oil price volatilities became more complex after 2007. The metals and grains indices did not significantly respond to the expected volatility in oil prices, in contrast to the petrochemicals and oilfats indices. These results not only contribute to advancing the existing literature, but also merit particular attention from policy makers and market investors in China.

1. Introduction

Over the past few years, a rising demand from emerging economies and limited supplies from oil producing countries due to political tensions have frequently pushed oil prices to dramatically high levels. However, China, whose economic growth increasingly depends upon energy consumption, was the second largest consumer of oil in the world after the United States from 2002 to 2011 and is now the largest energy consumer in the world. The Chinese government is now facing severe challenges from an energy supply gap. China's dependence on imported oil has increased to over 53.9%. With high oil prices and high energy consumption, the energy issue has become critical and strategic to long-term development in China.

Crude oil is the most influential resource of raw materials and primary energies. It has been deemed the life blood of industrial economics. China is playing a more important role in the world economy and is becoming more heavily dependent on imported oil. The volatility of crude oil prices will undoubtedly affect China's economy. Moreover, this volatility could be transferred to the bulk commodity markets through various transmission mechanisms and further impact relevant industries through the chains of manufacturing, transportation and maintenance closely linked with the global oil markets. Furthermore, the present development of the commodity future market in China is rapid. Not only its effectiveness and functionality is evident, but also its global position and influence has greatly advanced. Therefore, it is necessary to recognize the volatility spillover effects of oil price shocks on the bulk commodity markets and relevant industries in China.

This paper investigated the reaction of aggregate commodity market to oil price shocks and the effects of oil price shocks on China's fundamental industries. We employed the ARJI and its extended model (ARJI-h_t), incorporating with the EGARCH method, to interpret the jump behaviors and volatility processes of various commodity indices. Moreover, we separated the volatilities of oil price into expected, unexpected and negatively expected categories

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to identify how oil prices influence bulk commodity markets. We contrasted the results between different periods and among classified indices, in order to discover the significant changes in recent years and the differences at an industry level. Our results indicate that the aggregate commodity market was affected by both expected and unexpected oil price volatilities in China. The impact of unexpected oil price volatilities became more complex after 2007. The metals and grains index did not significantly respond to the expected volatility in oil prices, in contrast to the petrochemicals and oilfats index.

This research not only contributes to knowledge about the jump behaviors of China's commodity markets and the different effects of oil price shocks at an industry level, but also is conducive to analyzing the problems existing in the markets of China's petroleum and commodity futures. Our results merit particular attention from policy makers and market investors in China.

2. Literature review

The comprehensive influence of oil price shocks on economies is not only an important issue among various regulatory agencies, enterprise managers and market participants, but also under scrutiny by many economists. Early empirical studies have revealed a significant negative relationship between oil price volatilities and the state of the macroeconomy, evidence that shocks from the crude oil market were a contributing factor in economic recessions (Hamilton, 1983; Mork, 1989). Later research on transmission mechanisms from crude oil shocks to economic growth indicated similar conclusions based on various statistical techniques and data sources (Baláž and Londarev, 2006; Cunado and Perezdegracia, 2005; Gronwald, 2008; Miller and Ni, 2011).

Besides close connections between crude oil prices and the macroeconomy, shocks from global oil markets were also a contributing factor to volatilities at an industry level. For example, Jones et al. (2004) found that sensitivities of Australian industry returns to an oil price factor were significantly different. Fan and Jahan-Parvar (2012) revealed that the impacts of changes in oil prices were concentrated in a relatively small number of U.S. industries. By extending the number of industries to 38 in the Euro area for the period 1983–2007, Scholtens and Yurtsever (2012) verified that the response to oil price shocks differed among different industries, in spite of all industries presenting asymmetric reactions regarding oil price increases and decreases. Jiménez-Rodríguez (2008) examined the dynamic effect of oil price shocks on the output of main manufacturing industries in six OECD countries and reported that there was cross-industrial heterogeneity of oil shock effects within the EMU countries.

Due to properties similar to crude oil, energy commodities, such as natural gas, electric power, coal, and fuel, have also attracted the attention of researchers. Many have investigated the relationship between crude oil and energy commodities. Lescaroux (2009) examined the co-movements of prices between oil and energy commodities and reported that the relationship between oil and natural gas prices was the strongest. Ewing et al. (2002) studied the link between crude oil and natural gas prices and revealed that there is a clear diffusion effect of natural gas prices on crude oil prices. Moutinho et al. (2011) found an analogous link between fuel and crude oil prices. However, Mohammadi (2009) argued that there was no long-term correlation between electric power and crude oil.

In terms of non-energy commodities, agricultural materials were the most popular subjects of study. For example, Sari et al. (2012) examined the roles of futures prices of crude oil, gasoline, ethanol, corn, soybeans and sugar in the energy–grain nexus. Chang et al. (2012) examined asymmetric adjustments for ethanol and agricultural products. They found that the skyrocketing price of crude oil was a major force driving the rising prices of corn, soybeans, maize and other foods. Their explanation was traditional that high oil prices would push up the costs of fertilizers, chemicals and transportation. Currently, the cause of this transmission is often the substitution of oil by bio-energy derived from maize, wheat and soybeans, increasing the need for agricultural commodities and their prices (Chen et al., 2010). However, conclusions varied from country to country. One study from Turkey supported the neutrality of agricultural commodity markets to both direct and indirect effects of oil price changes (Nazlioglu and Soytas, 2011). Furthermore, some results have also yielded apparently contradictory results from different times, as in the research of Du et al. (2011), who showed that from November 1998 to January 2009, there was only evidence of spillover after 2006.

As for correlations between crude oil and precious metals, most studies reported that they tended to move together (Lescaroux, 2009), owing to the factors of investment portfolios and hedging effects (Hammoudeh and Yuan, 2008; Lee et al., 2012; Narayan et al., 2010). Narayan et al. (2010) tested the cointegration relationship between gold and crude oil and found that crude oil prices can be used to forecast those of gold. Hammoudeh and Yuan (2008) found that oil shocks had calming effects on precious metals but not on copper by examining the volatility behavior of three metals: gold, silver and copper. However, Soytas et al. (2009) found no predictive power of oil prices on precious metals prices in Turkey.

In terms of analytical methodologies and econometric models, a framework covering several models or methods has recently become popular in the literature. A two regime Markov-switching method was connected with an EGARCH process to examine the relationship between oil price shocks and stock markets (Aloui and Jammazi, 2009). Wavelet decomposition and regime shifts were linked to VAR to explore the impacts of oil price shocks on stock returns (Jammazi and Aloui, 2010). By combining GARCH process to VAR model, Arouri et al. (2012) and Hanabusa (2012) investigated the effects of oil price shocks in Europe and Japan, respectively. Zhang and Chen (2011) applied the EGARCH process to China's stock returns, combined with the Autoregressive Conditional Jump Intensity (ARJI) method.

To sum up the extensive body of the literature on oil price shocks: most focus on U.S. or European economies, and only a few on developing countries. In contrast to the considerable numbers of papers concentrating on the relationship between crude oil and raw commodities in developed countries, we find there is little attention given to China. In particular, investigations at the industry level in China are still rare. Further work is needed in this area.

In this paper, we considered expected, unexpected and negatively unexpected components of global oil price volatility, using a theoretical technique based on Lee and Chiou (2009, 2011). We applied the EGARCH process to the returns of China's Commodity Index, combined with the Autoregressive Conditional Jump Intensity (ARJI) (Chan and Maheu, 2002) method to examine the influence of oil price shocks on China's bulk commodity markets during the period of October 10, 2001–September 30, 2006 and also the separate phases before and after 2007. In addition, to compare the different effects of oil price shocks at an industry level, we investigated their effects on China's fundamental industries: metals, petrochemicals, grains and oilfats.

3. Methodology

3.1. The ARMA–GARCH model

The traditional ARMA model is a good prediction method of time series, but the oil price time series has a feature of volatility clustering, meaning that conditional heteroskedasticity exists. While the generalized conditional heteroskedasticity GARCH model can reflect the conditional heteroskedasticity of oil price time series (Cheong, 2009). The GARCH model incorporating ARMA process (ARMA–GARCH model), on one hand, can eliminate the conditional heteroskedasticity; on the other hand, it can be used to distinguish different factors causing oil price fluctuation. To examine whether the volatility process of China's Commodity Index (CCI) is sensitive to the expected, (negatively) unexpected shocks of oil spots market, we decomposed the changes of oil price into expected and (negatively) unexpected components, based on the ARMA–GARCH model. The ARMA–GARCH model utilized to describe oil price's volatility is in the following form:

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j a_{t-j} + a_t \tag{1}$$

$$a_t = \sqrt{h_t}\varepsilon_t \tag{2}$$

$$h_t = \omega + \sum_{i=1}^{k} \beta_i h_{t-i} + \sum_{j=1}^{l} \alpha_j a_{t-j}^2 \tag{3}$$

where r_t is the changes of oil price, μ is constant term. p, q are the lag order of AR and MA, respectively. $\phi_i\{i=1,2,\ldots,p\}$, $\theta_j\{j=1,2\ldots,q\}$ are the coefficients of AR and MA, respectively. a_t is the error term assumed to follow a GARCH process of orders k and l, both equal to 1 in our empirical analysis. ω is constant term. $\beta_i\{i=1,2\ldots,k\}$ and $\alpha_j\{j=1,2\ldots,l\}$ are the coefficients of variables. ε_t is white noise series, h_t is conditional heteroskedasticity of series.

According to Eq. (1), the expected volatility (e_t) is reckoned as the difference between the changes of oil price and the estimated residual:

$$e_t = r_t - a_t \tag{4}$$

where e_t is taken as the expected oil price volatility, a_t is taken as the unexpected oil price volatility (up_t) and define $up_t^- =$ Min (up_t, $E(up_t)$) as the negatively unexpected component. Now it is feasible to take the expected (e_t), unexpected (up_t) and unexpected returns (up_t^-) into consideration within the framework of commodity indices' returns, as displayed in Eq. (5).

3.2. The ARJI–EGARCH model

On the basis of the methodologies originated by Chan and Maheu (2002), we further integrated the EGARCH framework with an ARJI method, postulating that the jump intensity varies in time and follows an ARMA process. Taking the different components of oil price shocks into account, the dynamic volatility of CCI returns could be described as follows:

$$R_t = \mu + \phi_1 R_{t-1} + \phi_2 \varepsilon_{1,t-1} + k_1 \mathrm{e}_t + k_2 up_t + k_3 up_t^- + \varepsilon_{1,t} + \varepsilon_{2,t} \tag{5}$$

Φ_1 and Φ_2 are the coefficients of AR (1) and MA (1), respectively. k_1, k_2 and k_3 are the impact coefficients of expected oil price volatility, unexpected oil price volatility and negatively unexpected oil price volatility, respectively. Two innovations are included in the volatility equation, separately representing the 'normal' ($\varepsilon_{1,t}$) and 'abnormal' ($\varepsilon_{2,t}$) vibrations of index change. $\varepsilon_{1,t}$ is a mean zero innovation with a normal stochastic course, assumed to be:

$$\varepsilon_{1,t} = \sqrt{h_t} Z_t, \quad Z_t \sim NID(0,1) \tag{6}$$

Define the information set at time t to be the history of index returns, $\phi_t = \{R_t, \ldots, R_1\}$. The conditional variance of $\varepsilon_{1,t}$ equals h_t, estimated in accordance with ϕ_t. Hence, the EGARCH (1, 1) process is expressed as follows:

$$h_t = \exp(\omega + \beta \ln h_{t-1} + d\varepsilon_{1,t-1}/\sqrt{h_{t-1}} + \alpha(|\varepsilon_{1,t-1}/\sqrt{h_{t-1}}| - \sqrt{(2/\pi)})) \tag{7}$$

As advancement to the GARCH model, Eq. (7) supplies the evidence of asymmetric effect when the index returns react to positive and negative outside innovations, d may reveal whether asymmetry of EGARCH (1) is significant or not.

In Eq. (5), where $\varepsilon_{2,t}$ denotes a jump innovation, at the same time independent of $\varepsilon_{1,t}$. It is induced by the extreme events or news and supposed to follow a compound Poisson process. Specifically, within any period t, n_t is on behalf of the discrete counting process dominating the number of jumps, which submits to a Poisson distribution with the parameter λ_t and has the following density function:

$$P(n_t = j|\Phi_{t-1}) = \exp(-\lambda_t)\lambda_t^j/j! \quad j = 0,1,2,\ldots \tag{8}$$

The conditional jump intensity λ_t is permitted to be varying in time and is assumed to follow the ARMA (1, 1) process:

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1} \tag{9}$$

where $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > \gamma$, $\gamma \geq 0$. Eq. (9) demonstrates that the conditional jump intensity at time t is forecasted by one past lag of itself and plus one lag of ξ_t. It is defined that $\lambda_t \equiv E[n_t/\phi_{t-1}]$, indicating the conditional expected value of the counting process, so the ex ante error ξ_{t-1} will capture the unexpected number of jumps in the preceding period and is calculated according to the following derivation:

$$\xi_{t-1} \equiv E[n_{t-1}|\Phi_{t-1}] - \lambda_{t-1} = \sum_{j=0}^{\infty} jp(n_{t-1} = j|\Phi_{t-1}) - \lambda_{t-1} \tag{10}$$

When ϕ_{t-1} is given, the conditional jump size $\pi_{t,k}$ is supposed to be independently and normally distributed, with mean θ_t and variance δ_t^2, just as the form $\pi_{t,k} \sim NID$ (θ_t, δ_t^2). $J_t = \sum_{k=1}^{n_t} \pi_{t,k}$ is the jump component influencing the returns of index from t-1 to t, so the jump innovation during the period t is expressed as follows:

$$\varepsilon_{2,t} = J_t - E[J_t|\Phi_{t-1}] = \sum_{k=1}^{n_t} \pi_{t,k} - \theta_t\lambda_t \tag{11}$$

Take notice of the specifications of the jump intensity and jump size, so that we can achieve some implications for the conditional volatility. If the model and process are properly specified, the conditional variance should be deduced as the following form:

$$\mathrm{Var}(R_t|\Phi_{t-1}) = \mathrm{Var}(\varepsilon_{1,t}|\Phi_{t-1}) + \mathrm{Var}(\varepsilon_{2,t}|\Phi_{t-1}) = h_t + (\delta_t{}^2 + \theta_t{}^2)\lambda_t \tag{12}$$

It is shown in Eq. (12) that the conditional variance is an increasing function of intensity varying in time and is in relation to the distributed characters of jump size.

After observing R_t and using the Bayes's rule, the ex post probability of occurring j jumps at period t can be certainly inferred from the following equation:

$$P(n_t = j|\Phi_t) = \frac{f(R_t|n_t = j, \Phi_{t-1})P(n_t = j|\Phi_{t-1})}{P(R_t|\Phi_{t-1})} \quad j = 0,1,2\ldots \tag{13}$$

where $P(n_t = j|\phi_t)$ is specified in Eq. (8). The probability of jump occurrence plays an important role in the volatility model, for it not only enters into Eq. (10), but also can be used for inference purposes. Now there is a completion for the conditional density of returns (R_t) by integrating out the discrete-valued variable n_t:

$$P(R_t|\Phi_{t-1}) = \sum_{j=0}^{\infty} f(R_t|n_t = j, \Phi_{t-1})p(n_t = j|\Phi_{t-1}) \tag{14}$$

Exclusive of all jumps occurring during the same interval, the conditional probability density function can be calculated as follows:

$$f(R_t|n_t=j,\Phi_{t-1})=\frac{1}{\sqrt{2\pi(h_t+j\delta_t^2)}}\exp\left(-\frac{(R_t-\mu-\phi_1 R_{t-1}+\theta_t\lambda_t-\theta_t j)^2}{2(h_t+j\delta_t^2)}\right) \tag{15}$$

Given the sample size ***T***, the log likelihood function of the ARJI–EGARCH model is naturally the sum of the conditional densities:

$$L(\Psi)=\sum_{t=1}^{T}\ln f(R_t|\Phi_{t-1};\Psi) \tag{16}$$

where ψ represents the set of all parameters to be estimated.

3.3. An extension of ARJI: the ARJI-h_t model

The inference is established on the postulation that the jump size is following the distribution of Gaussian, while ignoring the case of dynamic change in the conditional mean and variance. Therefore, a developed model of ARJI allowing the conditional mean of the jump size to be a function of lagged returns (R_t) and the variance to be varied with h_t, referred as ARJI-h_t:

$$\theta_t=\eta_0+\eta_1 R_{t-1}D(R_{t-1})+\eta_2 R_{t-1}(1-D(R_{t-1})) \tag{17}$$

$$\delta_t^2=\zeta_0^2+\zeta_1 h_t \tag{18}$$

In Eq. (17), $D(x)$ is an indicator function that equals 1 if $x>0$ and 0 otherwise, and η_0, η_1, η_2, ζ_0, ζ_1 are coefficients to be estimated. The specification of the conditional mean of jump size is renewed to better describe the cluster effect of jumps. For example, when the returns of the last period increase, the conditional mean of the current period will be $\eta_0+\eta_1 R_{t-1}$, vice versa. Therefore, the distribution form of conditional mean during this period is decided largely by the last volatility of index returns. In addition, Eq. (18) is a set up to investigate whether the conditional variance is influenced by contemporary volatility of the whole market and if ζ_1 significantly rejects the hypothesis of being zero, indicating that the variance of jump size is related to the GARCH process of index returns.

Table 1
Summary statistics (2001–2011).

Var	Mean	Std.	Skewness	Kurtosis	Jarque–Bera	Q^2 (15)
WTI	0.0542	2.7057	−0.2317***	4.7195***	2190.75***	1270.63***
CCI	0.0350	0.9571	−0.5033***	2.4993***	707.23***	1364.11***

*** Significance at the 1% level.

4. Data and experimental results

To examine the volatility spillovers between oil price and the bulk commodity prices in China, we collected 2335 daily data, over the period from October 8, 2001 to September 30, 2011, for the main two series in this paper. The first series is Wenhua China's Commodity Index (CCI), employed to represent the performances of Chinese bulk commodity markets as a whole, obtained from the official database of China's Webstock (http://www.wenhua.com.cn/). Because they can not only capture the prices changes of the most important nineteen bulk commodities, but also be used to investigate the dynamic impacts at an industry level. The second series is West Texas Intermediate (WTI) spot price, highly correlated with other crude oil markets, obtained from the Energy Information Administration (EIA), the U.S. Department of Energy.

Returns are defined as 100 times the first difference in the logarithm of the closing price/index and for the following different model specifications, parameters are estimated using the maximum likelihood estimation (MLE) method with the Winrats 7.0 statistical software.

4.1. Descriptive statistics

As shown in Table 1, the high degrees of kurtosis reveal a fat-tail distribution of both returns and the skewness coefficient is negative, indicating the rejection of the normality condition for the two series at the 1% level, along with the Jarque–Bera tests. According to the standard deviations, the volatility of WTI is significantly stronger than that of CCI. Strong evidence of autocorrelations and conditional heteroskedasticity for both markets are provided by the Ljung–Box Q and Q^2 statistics, therefore, the GARCH class process contained in the model is adaptable to capture this market phenomenon.

According to Fig. 1, the volatility clustering is apparent, high volatility in this period tends to be followed by high volatility in the next period, indicating the plausibility of GARCH effects of both return series.

To test the unit-root (non-stationarity) of the prices and the first-order differences regarding to WTI and CCI, we used the Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) unit root tests. Furthermore, the Kwiatkowski et al. (KPSS) stationary test based on the null hypothesis of trend stationary is also considered, in order to figure out whether the series existing long-term memories. If the result of KPSS is significant, it demonstrates a long-term memory, that is, non-stationarity.

According to the results shown in Table 2, the null hypothesis of existing unit roots for ADF and PP is accepted in level but not in the first-order difference, converse in the case of KPSS test. Therefore, it can be concluded that WTI and CCI are non-stationary in

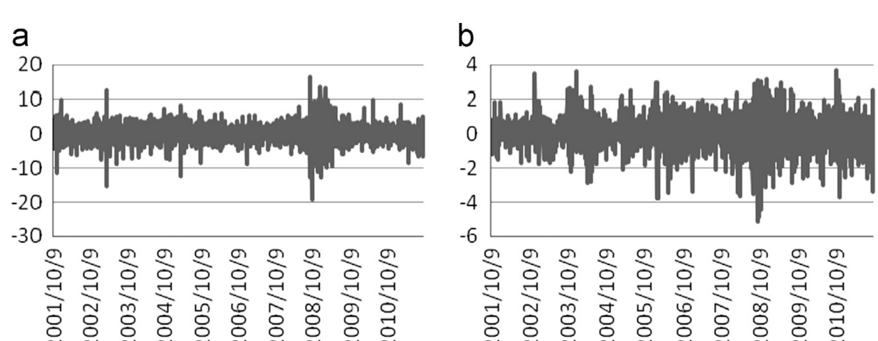

Fig. 1. (a) Returns of WTI spot price and (b) returns of the composite CCI.

level but stationary in the first-order difference, indicating that they are both integrated with order 1, I (1).

4.2. Application of ARMA–GARCH to WTI price changes (2001–2011)

As shown in Table 3, the coefficients of ARMA model, Φ_1 and θ_1 are both significant, indicating the instant WTI returns are decided by its one-lagged value and the last period's error. Positive value of α_1 and β_1, sum of them smaller than one, all match the conditions of the GARCH process and the significance of them demonstrates the GARCH effect is apparent. The relatively small Q^2 statistic provides evidence for not existing ARCH effect, indicating that the model is appropriately simulated.

Table 2
Unit root and stationary tests.

Variable	Levels			First difference		
	ADF	PP	KPSS	ADF	PP	KPSS
WTI	−1.757	−1.764	3.931	−51.289***	−51.350***	0.067***
CCI	−0.770	−0.919	4.180	−30.062***	−47.711***	0.082***

*** Significance at the 1% levels.

Table 3
ARMA (1, 1)–GARCH (1, 1) model on the WTI spot price changes (2001–2011).

Parameter	Coefficients	Standard error	*T*-statistics	Signif. lvl.
μ	0.163898661**	0.075880512	2.15996	0.03077598
Φ_1	−0.633620328***	0.117993998	−5.36994	0.00000008
θ_1	0.593640028***	0.124234235	4.77839	0.00000177
ω	0.228704985***	0.057853070	3.95320	0.00007711
α_1	0.071573114***	0.010611501	6.74486	0.00000000
β_1	0.893195128***	0.017254078	51.76719	0.00000000
Q^2 (10)	9.827 (statistic)	[0.455790]		

Notes: Q^2 (10) is the Ljung–Box test statistics for serial correlation in the squared standardized residuals with 10 lags. The value in the square bracket indicates the significance level.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

4.3. Application of ARJI–EGARCH to the composite CCI changes

We analyzed the impacts of WTI price volatilities on the CCI changes not only during the whole period from October 10, 2001 to September 30, 2006, but also during the separate phases before and after 2007 and compared the results. In addition, in order to explain the volatility spillover effects at an industry level, we further investigated the impacts of oil price shocks on four primary commodity indices.

Empirical estimates on the overall period (2001–2011) are shown in Table 4. With regards to the jump size distribution of CCI, the values of all coefficients (η_0, ζ_0, λ_0, ρ and γ) significantly reject the null hypothesis of zero, suggesting the relative effectiveness of ARJI model in describing the dynamic behaviors of China's bulk commodity market. Especially, the significant coefficients (ρ and γ) of jump intensity (λ_t) indicate the presence of jumps varying in time on the arrival of new events. The positive value of ρ (0.940934) measuring the persistence in the conditional jump intensity suggests that a high probability of many (few) jumps today tends to be followed by a similar high probability tomorrow. The coefficient of γ examining the jump sensitivity of λ_t to the most recent intensity residual (ξ_{t-1}) is also significantly positive (0.547119), implying that a unit of increase in ξ_{t-1} will probably lead to enhanced jump intensity in the period *t*.

As shown in Table 4, as for the volatility spillover from WTI spot price shocks to the composite CCI returns, the statistical significance of k_1 (-0.069061) demonstrates that the expected volatility of WTI price has significantly negative impact on the CCI returns. On the contrary, the impact from the unexpected volatility of WTI price is positive (k_2=0.038968). In addition, the asymmetric effects between unexpected volatility and CCI returns do not exist according to the insignificant k_3.

Similar to the whole period, both of the variables show significant volatility clustering with a lot of abnormal spikes during 2001–2006 (Fig. 2), indicating that the GARCH class model should also be used to describe their volatility process.

Table 4
ARJI–EGARCH – estimation by BFGS (2001–2011).

Variables	Coefficients	Standard error	*T*-statistics	Signif. lvl.
μ	0.112635900	0.025874709	4.35313	0.00001342
Φ_1	−0.177335432	0.073392841	−2.41625	0.01568130
Φ_2	0.079467382	0.073850264	1.07606	0.28190002
k_1	−0.069061559***	0.009430032	−7.32358	0.00000000
k_2	0.038968385***	0.010844671	3.59332	0.0003264
k_3	0.003191573	0.016205568	0.19694	0.84387214
ω	−0.059287508***	0.014868769	−3.98739	0.00006681
α	0.054896176***	0.014983601	3.66375	0.0002485
β	0.989896280***	0.004295916	230.42730	0.00000000
d	0.044492448***	0.01210446	3.67571	0.00023719
η_0	−0.164987915**	0.065434265	−2.52143	0.01168789
ζ_0	0.982862729***	0.109869514	8.94573	0.00000000
λ_0	0.021627196**	0.008780455	2.46311	0.01377390
ρ	0.940934176***	0.019527836	48.18425	0.00000000
γ	0.547119043***	0.157840831	3.46627	0.00052773
Q^2 (15)	10.997 (statistic)	[0.35773]		

Notes: Q^2 (15) denotes Ljung–Box test for serial correlation in the squared standardized residuals with 15 lags. The value in the square bracket indicates the significance level. Φ_1 and Φ_2 are the coefficients of AR (1) and MA (1), respectively, defined in Eq. (5). *k*1, *k*2 and *k*3 are the impact coefficients of expected oil price volatility, unexpected oil price volatility and negatively unexpected oil price volatility, respectively, defined in Eq. (5). ω, α, β and *d* are the parameters defined in Eq. (7). *d* may reveal whether asymmetry of EGARCH is significant or not. η_0 and ζ_0 are the parameters defined in Eqs. (17) and (18). λ_0, ρ and γ are the coefficients of jump intensity λ_t, defined in Eq. (9).
** Significance at the 5% level.
*** Significance at the 1% level.

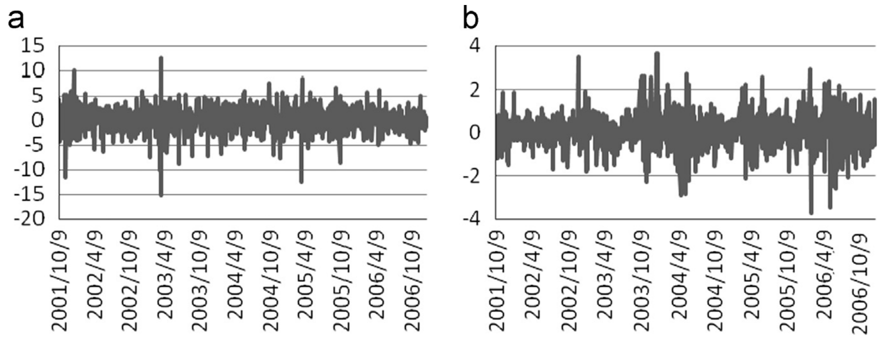

Fig. 2. (a) Returns of the WTI spot price and (b) returns of the composite CCI. The period of the both variables is from October 9, 2001 to September 30, 2006.

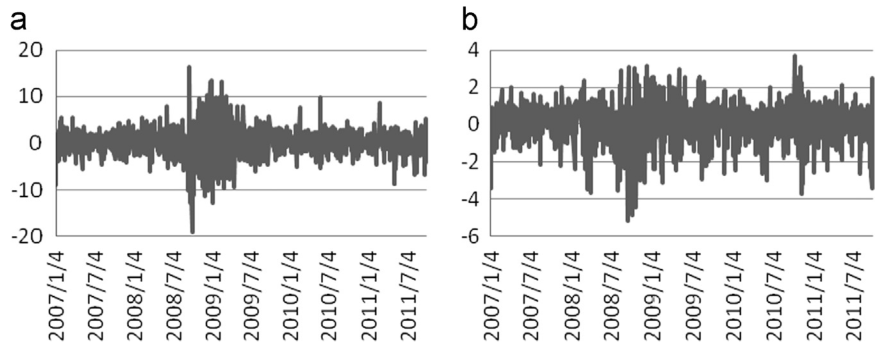

Fig. 3. (a) Returns of the WTI spot price and (b) returns of the composite CCI. The period of the both variables is from October 9, 2007 to September 30, 2011.

The period of the both variables is from October 9, 2001 to September 30, 2006.

Compared to the early period, the frequency of two variables' volatility is higher and the amplitudes of them also become wider in the recent period (Fig. 3). Especially in 2008 and 2009, the severe volatility and its characteristic of WTI price are paralleled with those of CCI, suggesting a closer relationship between them.

The period of the both variables is from October 9, 2007 to September 30, 2011.

According to Tables 5 and 7, the significance of all the coefficients demonstrates that the changes of WTI prices can be mainly explained by the autoregressive and moving average model. With respect to the oil price changes, the coefficients of AR and MA process in the recent years are larger than those in the early period, verifying that the oil price changes are influenced by the historical information more significantly in the latest years. The sum of α and β of GARCH is almost equal to one, indicating that the volatility clustering effect of WTI price changes lasts longer than before, and the impact of oil price shocks is more difficult to be removed in short time.

With regards to the volatility spillover effects on CCI from oil price shocks, it is revealed from Table 6–8 that the responses of CCI to expected oil price shocks are similar in two stages, according to both negative and significant k_1. However, the asymmetric effect of the reaction to the unexpected oil price shocks is only manifested in the later period, evidenced by the significant k_3 just after 2007.

In order to explain the volatility spillover effects at an industry level, we investigated the impacts of oil price shocks in different industries: metals, petrochemicals, grains and oilfats. We mainly focus on the recent period of 2007–2011. There are about 1120 observations of each variable. In the light of saving space, the specifically statistic descriptions and tests of each returns will be left out in the following empirical analysis, and we only provide the results of each returns (Fig. 4).

The period is from October 9, 2007 to September 30, 2011.

According to the empirical results shown in Table 9, as to the volatility clustering of the four returns, they all can be properly analyzed by the GARCH model. Unlike the cases in other three indices, d is significantly positive for the oilfats index returns, meaning that only oilfats index returns have asymmetric responses to the outside increased or decreased innovations.

By contrasting the effectiveness of applying CJI and ARJI model to each index, we find that the jump intensity of metals and petrochemicals indices returns is relatively constant, whereas that of the grains and oilfats indices returns varies in time. Furthermore, the extended model of ARJI-h_t is adaptable to examine the jump behavior of grains index returns, implying that the conditional mean and variance of jump size are no more constant, but vary with contemporary returns volatility, evidenced by significant coefficients of η_1, η_2 and ζ_1.

According to Tables 9, k_1 in the model of metals and grains is not significant, indicating that the responses of their indices returns are not sensitive to expected volatility of WTI price. This is contrary to the results of petrochemicals and oilfats. It is found that the reactions to the unexpected oil price volatility of the four indices returns are all apparent, in view of the significant k_2. In addition, there is apparent asymmetric effect during the period of 2007–2011, verified by significant k_3.

5. Discussions

5.1. Impacts of global oil price shocks on the composite CCI

There have been volatility clustering and an asymmetric effect in the bulk commodity markets since 2001. The response to increased innovation is stronger than the response to decreased innovation. The explanation may be that the rise of bulk commodity prices has meant higher costs of raw materials for the correlated companies, which leads to falling profits and reductions

Table 5
ARMA (1, 1)–GARCH (1, 1) model on the WTI spot price changes (2001–2006).

Variables	Coefficients	Standard error	T-statistics	Signif. lvl.
μ	0.174769673	0.105074483	1.66329	0.09625376
Φ_1	−0.602597328	0.158706130	−3.79694	0.00014649
θ_1	0.559912811	0.170477130	3.28439	0.00102205
ω	0.763356168	0.384115363	1.98731	0.04688809
α_1	0.084433989	0.024588227	3.43392	0.00059492
β_1	0.780871838	0.089420372	8.73259	0.00000000
Q^2 (15)	9.402 (statistic)		[0.855554]	

Notes: Q^2 (15) denotes Ljung–Box test for serial correlation in the squared standardized residuals with 15 lags. The value in the square bracket indicates the significance level.

Table 6
CJI–EGARCH model on the CCI returns – estimation by BFGS (2001–2006).

Variables	Coefficients	Standard error	T-statistics	Signif. lvl.
μ	0.011465442	0.025001384	0.45859	0.64652697
k_1	−0.052325071	0.007127560	−7.34123	0.00000000
k_2	0.030399233	0.010547396	2.88216	0.00394965
k_3	−0.017960069	0.016417648	−1.09395	0.27397735
ω	−0.152692341	0.034141342	−4.47236	0.00000774
α	0.158118163	0.031849658	4.96452	0.00000069
β	1.008257425	0.005800490	173.82279	0.00000000
d	0.047705248	0.009980859	4.77967	0.00000176
η_0	0.117972064	0.056969972	2.07078	0.03837971
ζ_0	0.628743757	0.085253224	7.37501	0.00000000
λ_0	0.410715818	0.132742837	3.09407	0.00197430
Q^2 (15)	5.591 (statistic)		[0.985825]	

Notes: Q^2 (15) denotes Ljung–Box test for serial correlation in the squared standardized residuals with 15 lags. The value in the square bracket indicates the significance level.

Table 7
ARMA (1, 1)–GARCH (1, 1) model on the WTI spot price changes (2007–2011).

Variables	Coefficients	Standard error	T-statistics	Signif. lvl.
μ	0.215079114	0.119769138	1.79578	0.07252939
Φ_1	−0.845836362	0.129890458	−6.51192	0.00000000
θ_1	0.813995974	0.139154105	5.84960	0.00000000
ω	0.314346336	0.072568245	4.33173	0.00001479
α_1	0.126545354	0.021183165	5.97386	0.00000000
β_1	0.834212391	0.024031987	34.71259	0.00000000
Q^2 (15)	17.167 (statistic)		[0.309004]	

Notes: Q^2 (15) denotes Ljung–Box test for serial correlation in the squared standardized residuals with 15 lags. The value in the square bracket indicates the significance level.

in production or shifts to another industry, leading, in turn, to decreases in the demand for and price of bulk commodities.

The dynamic jump intensity in the volatility of China's bulk commodity markets varied during the period of 2001–2011. This result shows that CCI changes are strongly sensitive to exterior shocks, could be brought on by unexpected innovation, and vary in intensity over time.

This study suggests that an expected volatility in WTI prices has a significant negative impact on CCI changes. However, Chiou and Lee report different results (Chiou and Lee, 2009; Lee and Chiou, 2011). These suggested that oil price fluctuations had no significant impacts on financial returns, while we found that an expected volatility of WTI price has a significant negative impact on CCI changes. This may be because China still lacks oil futures, so that related companies do not have sufficient experience to predict what will happen in terms of oil prices. Secondly, China's producers and investors tend to overreact in response to oil price changes; their anticipations are irrational. Thirdly, the incomplete pricing mechanism of petroleum in China means that global oil price changes cannot be expeditiously and accurately transferred to the oil market, and that the volatility spillover effect on bulk commodity markets is also influenced by the obstructed transferring channel.

Unexpected volatility of the WTI price has a positive but slight effect on CCI changes. The transferring coefficient is positive but very small and there are no asymmetric responses of CCI changes to the increased or decreased innovations of unexpected oil price shocks. Generally, the influence of oil price shocks often comes from the unexpected component of volatility and asymmetry is also demonstrated in the volatility spillover effects (Lee and Chiou, 2011). As for the empirical results of CCI, besides the inaccuracies in pricing petroleum, another explanation could be that the energy sources consumed in China are still dominated by coal. The dependence on coal by China is about 70.4%, reducing, to some extent, the influence of unexpected volatility in the global oil price.

5.2. Impacts of oil price shocks on the CCI during different periods

The jump intensity of the CCI changes varied in time only during the period 2001–2007. There could be two explanations for this result. On one hand, during the early years, China's bulk commodity markets were relatively independent of the global market, so that they were less affected by international fluctuations, and jumps in the market were relatively invariant. What is more, over-confidence in markets may also have contributed to abating external influences (Ko and Huang, 2007). After 2007, as the country developed a closer relationship with world markets, it was inevitable for China's bulk commodity markets to be more strongly influenced by outside shocks, making the volatility features of domestic and foreign bulk commodity markets more similar.

The expected volatility of WTI price had a negative impact on the CCI in both periods. This result is consistent with that of the whole period (2001–2011), again suggesting that irrationality and over-reactivity always exist in China's bulk commodity markets.

An asymmetric impact of the unexpected volatility of WTI prices appeared just after 2007. The CCI changes appeared sensitive to the negatively unexpected volatility component of oil price in this later period, in contrast to earlier years. This suggests that the degree of linkage with the world and information efficiency of the China's bulk commodity markets was both greatly enhanced after 2007.

5.3. Impacts of global oil price on classified commodity indices

Volatility clustering phenomena were apparent in all four indices, while only the volatility of the oilfat index displayed an asymmetric effect. The estimated coefficients in the GARCH process of each classified index were significant, suggesting that it is suitable to apply the GARCH model to them, in accord with the study of Du et al. (2011).

Besides the oilfats index, the other three indices do not exhibit asymmetric responses to good and bad news. For the metal and grain indices, the main reason for this may be that both the metal and grain future markets have developed to a high state of efficiency. They do not behave much differently in the face of positive and negative shocks. At the same time, this feature of the two indices suggests that the investing risk of metal and grain future markets is relatively small.

The volatility of the petrochemicals index does not have asymmetry. Petrochemical prices are more independent of external markets except for oil and other energies, so they do not react differentially to general bad and good news.

Table 8
ARJI – EGARCH (1, 1) model on the CCI returns (2007–2011).

Variables	Coefficients	Standard error	*T*-statistics	Signif. lvl.
μ	0.24422268	0.04161712	5.86832000	0.00000000
Φ_1	−0.16841853	0.07950745	−2.11827000	0.03415191
Φ_2	0.00460240	0.08475213	0.05430000	0.95669282
k_1	−0.05417437	0.01588641	−3.41011000	0.00064937
k_2	0.05689365	0.01611724	3.52999000	0.00041558
k_3	0.04847460	0.02399895	2.01986000	0.04339754
ω	−0.11286277	0.03135847	−3.59912000	0.00031930
α	0.11868419	0.03607071	3.29032000	0.00100073
β	0.98901701	0.00778071	127.11134000	0.00000000
d	0.06963208	0.02042450	3.40924000	0.00065143
η_0	−0.33866541	0.13240314	−2.55784000	0.01053260
ζ_0	0.84028633	0.12562690	6.68875000	0.00000000
λ_0	0.02629724	0.01451009	1.81234000	0.06993331
ρ	0.94287683	0.02642287	35.68411000	0.00000000
γ	0.46036262	0.16922615	2.72040000	0.00652032
Q^2 (15)	13.115 (statistic)			[0.217320]

Notes: Q^2 (15) denotes Ljung–Box test for serial correlation in the squared standardized residuals with 15 lags. The value in the square bracket indicates the significance level. Φ_1 and Φ_2 are the coefficients of AR (1) and MA (1), respectively, defined in Eq. (5). $k1$, $k2$ and $k3$ are the impact coefficients of expected oil price volatility, unexpected oil price volatility and negatively unexpected oil price volatility, respectively, defined in Eq. (5). ω, α, β and d are the parameters defined in Eq. (7). d may reveal whether asymmetry of EGARCH is significant or not. η_0 and ζ_0 are the parameters defined in Eqs. (17) and (18). λ_0, ρ and γ are the coefficients of jump intensity λ_t, defined in Eq. (9).

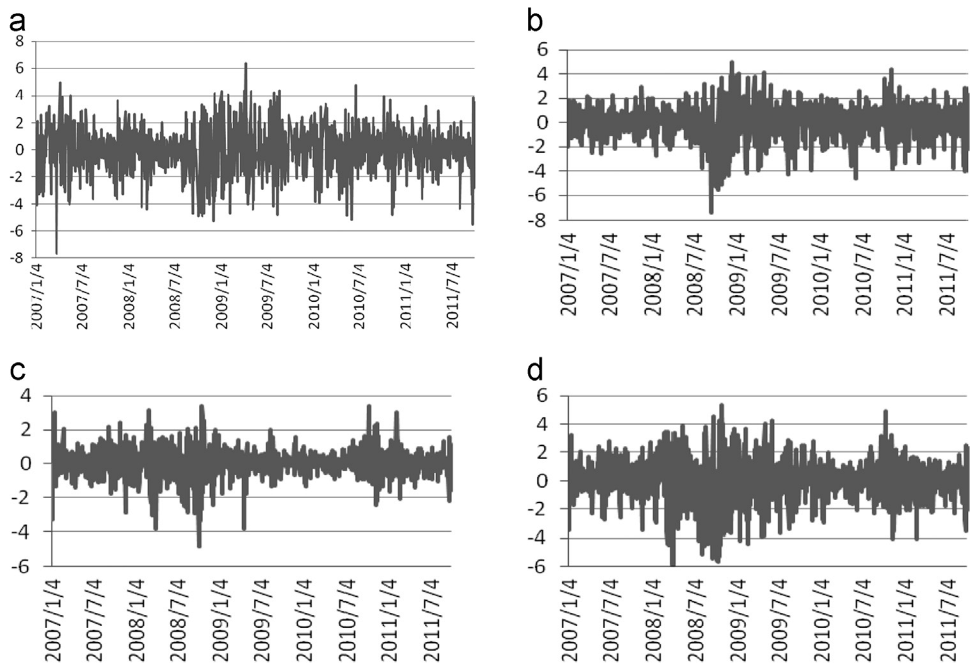

Fig. 4. (a) Returns of the metals index; (b) returns of the petrochemicals index; (c) returns of the grains index; and (d) returns of the oil and fats index. The period is from October 9, 2007 to September 30, 2011.

In contrast to the other three indices, the oilfats index has asymmetric effects in volatility. It reacts to bad news more significantly than good news. The coefficient value (d) of its asymmetry is close to that of the composite CCI, indicating that the asymmetric effect in composite CCI is caused mainly by the oilfats commodities. Therefore, in hedging and future portfolios, investors should pay more attention to the impacts of external shocks on oilfats commodities.

The response of the metal and grain indices to the expected volatility of WTI price is not obvious, while its response to unexpected volatility is not only significant but also asymmetric.

Expected shocks from the global oil market do not affect the metals remarkably. According to one study by Hammoudeh and Yuan (2008), there are relatively few activities of arbitraging between copper or aluminum futures and crude oil, so that the prices of main metals are not easily influenced by expected oil price volatility. In addition, the efficiency of China's metal future market is gradually improving and is better equipped to resist impacts from outside, especially the expected shock of related commodities like crude oil. It also implies that investors in the metal futures market should focus on hedging and risk-diversification.

Expected impact on the grains index is not apparent. On one hand, the global position of China's grain future market has improved notably, such as the market of soybean futures with the second largest transaction volume in the world. Therefore, it is more efficient for making use of the grain future market to avoid or calm the expected volatility risk. On the other hand, a variance from the case in the U.S. or other developed areas (Natanelov et al., 2011), the price linkage between China's soybean or corn and global oil is not strong, and oil price volatility as yet has not transferred to China's grain market.

Table 9
Volatility spillovers of WTI price shocks on four classified CCI (2007–2011).

Var.	Metals (CJI)	Petrochemicals (CJI)	Grains (ARJI-h_t)	Oilfats (ARJI)
μ	0.1785798	0.2896695	0.1205671	0.2227429
Φ_1	0.1474239***	−0.0816072	−0.3630329***	−0.1863318***
Φ_2	−0.3929809***	−0.0042843	0.0604860	0.0438559
θ_1	−0.2738962***			
θ_2	0.4935543***			
k_1	−0.0122789	−0.0973901***	0.0036312	−0.0589972***
k_2	0.0602449***	0.0575418***	0.0227004***	0.0619216***
k_3	0.0950643***	0.0741176**	0.0302719**	0.0587849***
ω	−0.2014905***	−0.2373416***	−0.1488545***	0.0002359
α	0.2604084***	0.1945759***	0.0879858***	−0.0011322***
β	0.9673609***	1.04362842***	0.9890276***	0.9937958***
d	−0.02943936	0.02362023	0.0098851	0.0691574***
η_0	−1.05401848**	−0.09825451**	−0.0446950	−0.2306463**
η_1			0.2572417***	
η_2			−0.2665415***	
ζ_0	2.3540416***	0.73650901***	−0.0000062	1.4415196***
ζ_1			3.2091908***	
λ_0	0.0836416***	1.45792983***	0.0279359*	0.0122005*
P			0.9662196***	0.9715099***
γ			−0.0422789	0.5051326***
Q^2 (15)	14.239[0.50746]	14.958[0.45443]	11.435[0.17823]	21.211[0.2170]

Notes: Q^2 (15) denotes Ljung–Box test for serial correlation in the squared standardized residuals with 15 lags. The value in the square bracket indicates the significance level.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

An unexpected volatility in oil price influences the metal and grain indices significantly and asymmetrically. Since 2007, metal and grain indices return rationally and fully react to external shocks to some extent. There is probably asymmetric spillover from an unexpected volatility of oil price. Moreover, it is found that the transmission coefficients of unexpected volatility (k_2 and k_3) are both larger for the metal indices than for the grain indices, because metal-related industries make more use of oil in manufacturing and processing. They are more susceptible to the oil price volatility.

Either expected or (negatively) unexpected volatilities of WTI price have a significant impact on the petrochemicals and oilfats indices. Compared to other two indices, the petrochemical and oilfat future markets are less developed and efficient, so they are sensitive not only to unexpected volatilities but also to expected ones.

The petrochemical industry is most strongly linked to the oil market. Therefore, the petrochemicals index is subject to the expected oil price volatility. Baffes (2007) drew a similar conclusion. Furthermore, owing to overreaction, the petrochemicals' index even responds in an opposite direction to the expected volatility.

As to the oilfats' index, it is also sensitive to expected volatilities in oil price, which may result from the crucial contribution of crude oil to processing and refining. Meanwhile, in contrast to the behavior of the petrochemicals index, whose response to the expected volatility is the strongest (k_1), it is the weakest in the case of oilfats. A reasonable explanation is that though oilfat commodities are somewhat affected by the global oil market, this limited because they are mainly extracted from soybeans or vegetable seeds and have a higher elasticity of oil demand.

6. Conclusions and policy implications

This paper examined the volatility spillover effects of crude oil price shocks on China's bulk commodities markets. We employed the ARJI and its extended model (ARJI-h_t), incorporating with the EGARCH method to interpret the jump behaviors and volatility processes of various commodity indices. Moreover, we separated the volatilities of oil price into expected, unexpected and negatively expected categories to identify how oil prices influence bulk commodity markets. We contrasted the results between different periods and among classified indices, in order to discover the significant changes in recent years and the differences at an industry level. The main conclusions are summarized as follows:

Firstly, the composite CCI has been significantly influenced by the expected volatility of global oil price during 2001–2011. Due to irrationality, the imperfection of the petroleum-pricing mechanisms and the lack of oil futures in China, the transmission channel of prices between the global and China's oil market is somewhat obstructed, leading producers and investors to over-react to oil price changes.

Secondly, the jump intensity of composite CCI returns varies in time, while its response to expected volatility lessens. An asymmetry response to unexpected volatilities has appeared in recent years, suggesting that the information efficiency of China's bulk commodity markets has improved and the impacts of unexpected oil price shocks have become more complex.

Finally, the jump intensity of industrial indices is constant and their volatility processes do not have asymmetric effects, unlike those of agricultural indices. The insignificant response of the metal and grain markets to the expected volatility of oil prices demonstrates that they are more efficient, and that it is more effective for the producers and investors to make use of them to spread the risks of price volatilities, whereas the development of the petrochemical and oilfat markets lag behind the others, so that they are more sensitive to expected volatilities in oil prices.

These results have several important policy implications. Firstly, the imperfections of the mechanism of petroleum pricing in China induce irrational expectations and overreactions to oil prices and should be improved to become more market-oriented so as to lower the uncertain risks. Secondly, providing a sum of subsidies for the enterprises that are seriously influenced by oil price shocks would make sense to maintain the stability of economic production. Thirdly, it is necessary to begin utilizing the technologies which employ corns, soybeans, and wheat to produce bio-energy, helping to reduce the dependence on traditional energies and importing oil from abroad for China. Finally, if crude oil futures come into China's commodity future markets, petrochemical related industries would spread risks more effectively. While in view of the more efficient future markets of metals and grains, relative industries should take advantage of them to hedge against prices volatilities.

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