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Volatility transmissions across international oil market, commodity futures and stock markets: Empirical evidence from China☆

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ABSTRACT

This paper uses a trivariate VAR-BEKK-GARCH model to investigate the dynamic relationship among the Chinese stock market, commodity markets and global oil price. We find significant unidirectional return spillover effect from oil market to stock market, suggesting a strong dependence of the Chinese stock market on the oil market. Our results show significant unidirectional return interaction from the Chinese stock market and global oil market to key commodities indicators in China. In particular, significant return contagions from the Chinese stock market to copper and aluminium futures and from oil market to silver, copper and aluminium markets are observed. Non-existence of return spillovers between gold and stock (oil) suggests the safe-haven role of the gold. In terms of the volatility spillovers, we find bidirectional shocks spillovers between oil and stock markets but unidirectional volatility spillovers from the oil market to the Chinese stock market. For commodities, we show evidence of strong uni-directional shock and volatility spillovers from stock market or oil market to commodities market. However there are no spillover effects from all the commodity markets to either stock market or oil market, implying potential diversification benefits from the Chinese commodity markets. Finally, the paper highlights the results which potentially have important implications for portfolio management and hedge strategies.

1. Introduction

The fast development in commodity markets leads to the rapid growth of investments over the past two decades, despite that the commodity prices experience substantial fluctuations. The booming global demand has been driving force behind the observed upwards swings in commodity prices in recent decades. However, the global financial crisis (GFC) which led many global economies into recession did also dramatically affect commodity markets. The observed turbulences in commodity markets across developed and developing countries has shortchanged financial investors to consider alternative investment asset classes to diversify their portfolio potentially. This has also increased research interests in commodity markets to re-examine direct and indirect market dynamics among global asset markets. As investors have to make important choices in the asset allocation process and enhanced access to information systems, the rapid growth of investment in commodities via commodity futures markets is observed in recent years. Differently, it is well known that crude oil, agricultural markets, metal commodities and stock markets are characterized by periods of sharp fluctuations and noisy signals. Given this more volatile dynamic properties, it is very crucial that portfolio managers and policymakers do understand these dynamic interdependencies among the widely traded commodities, the energy prices and the stock markets. This therefore calls for a deeper analysis of spillover effects among these markets.

From a theoretical perspective, the economic and financial factors that drive commodity and equity markets are not mostly different and there are many factors which drive stock and commodity markets together. Returns of these two asset classes are expected to be less or even negatively correlated, which may potentially lead to portfolio diversification benefits (Daskalaki and Skiadopoulos, 2011; Gorton and Rouwenhorst, 2006). Empirically, some existing studies highlight that by including commodities into the stock portfolio, the investors can be

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better off and hedge some risk (Jensen et al., 2000). Over time and as the awareness on this beneficial effect increases, more investors may reallocate portions of their investment into commodity markets, enhancing the commodity markets' liquidity and efficiency and fostering capital inflows. This may then further lead to market co-movements of some sort and increase attraction of certain commodities as an asset class (Belousova and Dorfleitner, 2012). Recent empirical studies indicate that interdependencies between commodity and equity may have become stronger and prices more volatile since the GFC (Delatte and Lopez, 2013; Creti et al., 2013; Silvennoinen and Thorp, 2013). The more recent and rapid growth of index investment in commodities markets may have contributed to the integration of these markets with the equity and bond markets (Tang and Xiong, 2012).

Within the commodity markets, the interaction between the crude oil market and other commodity has increasingly caught the attention of financial analysts. Commodity traders (particularly oil traders) concurrently pay close attention to both commodity and stock market movements in order to infer the directions as they optimise their investment portfolios (Choi and Hammoudeh, 2010). Some of the existing empirical studies have pointed out the existence of interdependencies between oil and non-energy commodities (including both metals and agriculture). Commodity prices may have tendencies to move together as some of the common macroeconomic factors such as interest rates, inflation rates and industrial production are able to influence different commodities simultaneously (Hammoudeh and Yuan, 2008). Ji and Fan (2012) indicate that the substitution of fossil fuels with biofuel along with some hedging strategies against inflation caused by high oil prices. This has also influenced the dynamic linkages between oil and other commodities in recent years. Increases in oil price could possibly create shortfalls in power supply in some countries so that the production of precious metal commodities may be affected (Sari et al., 2010). Although some research has been conducted on the market behaviours of commodities, information on how commodity prices respond to shocks from the equity and oil markets is limited. The interaction channels between price returns of the oil, stock and commodity markets, particularly for the largest emerging market, are also not clear. Is there a unidirectional relationship between them (who drives who)? Is this relationship between their returns and volatilities strong? Are metal commodities, such as gold[1] and silver, highly sensitive to the market movement of equity and energy? These questions are important for all market participants since better insight on the dynamics of these markets will help investors to build optimal portfolios. This will also help policymakers to establish sound fiscal and monetary policies regarding the local financial environment. These issues have motivated us to look deeper at volatility interactions. In addition to the global investor's viewpoint, there are recent literature that put more emphasize on the origin of the shocks (both demand and supply side) and the economic role of the country inspected (from the perspectives of commodity importer and commodity exporter) (see Bjørnland (2009), Henriques and Sadorsky (2008) and Baumeister and Kilian (2016)). These authors have not only attempted to highlight the transmission channels of oil shocks for macroeconomic behaviour and but also whether oil price increases boost aggregate wealth and stock returns (Bjørnland, 2009). With regards to the economic environment of individual countries inspected (e.g. Kilian and Park, 2009), Cunado and Perez de Gracia (2014) examine how energy prices shocks are transmitted to Chinese stock market and whether oil price volatility increases the speculations in mining index, manufacturing index and petrochemicals index.

The existing literature in this area focuses on global commodity markets and developed equity markets, whereas studies on spillover dynamics with regards to emerging market remain limited. While Chinese investors are becoming more important in terms of investment choices and in influencing the global trading, commodity futures market is taking off within and beyond China borders. Moreover, China's global importance has grown following its entry into the World Trade Organization and gradual reforms to open up Chinese markets for foreign investment. To our knowledge, there are not many studies that examine the contagion effects between oil price and Chinese non-energy commodity markets. Understanding the dynamic linkages between commodity and equity markets in merging countries is importance since volatility spillovers and its transmission are the central issues that affect asset allocations and asset substitutions strategies. Thus, the existing literature gap motivates us to investigate the spillover effects between these three markets, providing a deeper and rigorous analysis of interdependence structure. Our research focuses on the context of China because of the country's increasing financial integration and its transformation policies to attract more foreign capital and provide access to equity markets. While China's future markets are definitely becoming more influential by the day, the country has been launching more innovative financial instruments which could be helping investors mitigate the risks of price volatilities. Secondly, the role of China in global commodity markets is also changing after years of unprecedented economic growth rate. Due to the continuous urbanisation, industrialisation and openness to world trade, the demand for raw materials in China continues to increase. Today, China is already the world's largest consumer of several commodities with a significant rise in its share of global trade in commodities. In 2014, China, the main driving force of global growth, consumed more than half of the world production of iron ore, about half of the world's refined copper, primary aluminium and smelted and refined nickel, representing roughly half of global demand for major base metals. As the largest producer of iron ore and aluminium, the second largest producer of copper, China is also the centre of metal production indicating its importance in the world industrial production (IMF, 2015). In terms of oil consumption, China took over Japan to become the second largest world oil consumer and the world's largest net oil-importing country since 2003 (Zhang and Qu, 2015). Therefore, a greater dependence on imported crude oil would result in a tight link between global oil price and Chinese economy. This close correlation will further affect the Chinese financial markets. On the other hand, due to the increasing demand for energy and non-energy commodities simultaneously, the interlinkages between Chinese equity market, commodity markets and international oil price movements are expected to be enhanced.

The study will contribute to the emerging empirical research work on the dynamic relationship between key financial and commodity markets, especially in the post GFC period. Through applying the VAR-BEKK-GARCH models, we provide a deeper examination of the degree of the spillover and other time-varying effects across the Chinese equity market, commodity markets and international oil markets. We investigate the extent to which commodity market is able to provide diversification benefits for investors holding positions in equity and oil markets. We report significant unidirectional return and volatility spillover effect from both the Chinese stock market and international oil market to the Chinese commodity markets, providing important practical implications for investors and regulators. From the empirical literature, the dynamic cross-effects between oil and commodity market remain unclear. Few studies take oil and stock markets simultaneously into consideration when examining volatility spillover effects on the commodities market. In this analysis, we account for both oil and stock markets in considering volatility transmission to commodity market. Secondly, in addition to the bivariate GARCH models that are very popular in measuring the conditional volatilities, we use a trivariate GARCH structure in order to capture dynamic volatilities for the three financial markets more accurately. Finally, our analysis on the price interactions and volatility spillovers is aimed to examine portfolio diversification implications, to understand the spillover directions and magnitude of volatility transfers.

[1] It should be noted that, as compared to other standard commodities, gold is a special raw material due to being only used in parts in the industrial production process. However, it forms part of our analysis here.

The remainder of the paper is structured as follows. Section 2 briefly reviews the current literature. Section 3 presents the data used and the methodological framework. We then analyse the findings in Section 4 and Section 5 concludes the paper.

2. Brief literature review on commodity futures markets

Theoretically, the correlation between equity and commodity futures markets are expected to be low or negative because they are driven by different financial and economic factors. In this aspect, commodities may have the capacity to bring diversification benefit when added into investors' portfolio (Hammoudeh et al., 2014). There are a number of studies that have attempted to explore the dynamic interactions between commodity and stock markets. These studies have examined whether commodity futures in the traditional assets do actually have diversification and hedging benefits. While examining the relationship between commodity, equity and bond assets over 1959–2004, Gorton and Rouwenhorst (2006) find that commodity futures are negatively correlated with stocks and bonds. As a result, investors may be able to choose these commodities to diversify their portfolio and generate risk reduction benefits. This finding could possibly explain the better performance of commodity futures market during the unexpected inflation periods and risk management opportunities generated by commodity market in the periods where the cyclical variation of stocks and bonds is observed. Büyüksahin et al. (2010) report that the return co-movement between commodity futures and S&P500 index is weak, as both cross-correlations and dynamic conditional correlations (DCCs) are almost zero during much of the sample time. Even during the 2008 financial turbulent period, the DCCs remain at a low level despite the increase in the cross-correlations. They find little statistical evidence of a cointegration relationship in the long-run. Similar findings are Chong and Miffre (2010) who also use DCC GARCH approach. Their results reveal that the conditional correlations between 11 commodity futures and S&P500 returns tend to fall when traditional market risks rise. Lagesh et al. (2014) perform a similar empirical analysis in the context of Indian. Belousova and Dorfleitner (2012) highlight that because such correlation, investors have diversification opportunities through commodity instruments, confirming commodities as valuable investment tools.

This potential diversification opportunity, through commodity futures investment, has led to an increase the capital inflows into the commodity markets. Büyükşahin and Robe (2014) note that co-movements between commodity and equity are positively related to commodity market participation by speculators and hedge funds. The increased financialization of commodity markets together with other reforms may have led to the integration between commodity markets and traditional assets markets. However, this may eliminate diversification and inflation protection through commodities. This contradictory empirical evidence favours market integration between commodity and conventional assets. Daskalaki and Skiadopoulos (2011) could not find the publicised diversification benefits in their studies which considered the higher order moments of the portfolio returns distribution into the optimal portfolio, challenging the common view of commodities being a diversifying asset class. Silvennoinen and Thorp (2013) report evidence of decreased diversification benefits for portfolio investors holding commodities, equities and bonds, indicating some degree of integration across these markets. In addition, some investors may not have enough commodity-specific knowledge and make investment decisions based on their overall perceptions of the macroeconomic situation. Thus both energy and non-energy commodities can be influenced by rising global demand which also drives the equity prices (Lombardi and Ravazzolo, 2016).

Crude oil prices have huge impacts on stock prices directly by influencing the future cash flow and influencing corporations' production costs. Thus oil price has negative impacts on the real output and stock market return (Huang et al., 1996). Sadorsky (1999) highlights that oil price movements are important in explaining movements in stock returns and that positive shock to oil prices depress real stock returns. Ciner (2001) provides evidence of bidirectional nonlinear Granger causality between oil futures returns (both crude and heating oil) and stock index returns. In the case of emerging markets, Basher and Sadorsky (2006) examine the impact of oil price changes on 21 emerging stock market returns over the period 1992–2005. They show that oil price risk plays a significant role in emerging stock markets returns using both unconditional and conditional risk analysis. Similar evidence in developing markets is reported by (Park and Ratti, 2008; Mohanty et al., 2010; Arouri et al., 2011b; Arouri et al., 2011a; Fayyad and Daly, 2011; Cunado and Perez de Gracia, 2014). Oil prices have been found to influence not only equity prices but also other commodities markets and there are some preliminary findings suggesting co-movement between oil and non-energy commodities. The increased linkage could possibly be explained by the substitution of fossil fuels with biofuels and the hedging strategies against high oil prices (Ji and Fan, 2012).

In more recent years, researchers and analysts have been paying attention to the possible linkage between crude oil prices and agricultural markets following simultaneous surges and significant swings in both oil and foods prices. From neoclassical theoretical perspectives, since most primary agricultural products use various energy-intensive inputs, this production can directly be significantly influenced by the crude oil prices. Thus, higher crude oil prices will cause agricultural production costs to rise, shifting the supply curve of the agricultural commodities to the left and increasing their prices increase (Ahmadi et al., 2016). Also, this kind of market co-movements between energy and agricultural markets are likely driven by macroeconomic uncertainty and global warming related regulations (Mensi et al., 2014). On the demand side, the rapid economic growth in emerging markets may be triggering increases in the demand and consumptions of these commodities. As the most important driving force of the emerging market economies, oil price shocks will affect demand for biofuels and lead to rising demand for commodities such as corn and soybeans. Exchange rate effect is another indirect channel through which changes in price of crude oil can influence agricultural market since changes in oil prices, which are denominated in the US dollars, have a direct impact on local currencies. Any appreciation or depreciation of the local currency, may in return, affects the country's import or export and impact the prices of the agricultural commodity (Harri et al., 2009). Emerging empirical evidence show an overall increase in market co-movements between energy and agricultural commodities in recent years and that their returns are highly correlated (Nicola et al., 2016).

Different methodological framework as well as theoretical models have been used to explain how oil price shock influence stock and commodity prices. Zafeiriou et al. (2018) use the ARDL approach to examines the bivariate dynamic interactions of crude oil–corn and crude oil–soybean futures prices using monthly data from July 1987 to February 2015. Park and Ratti (2008) utilised a multivariate VAR analysis to capture the complexities of dynamic interactions between oil price shocks and real stock returns for US and 13 European countries between January 1986 to December 2005. Bai and Koong (2018) examine the link between oil price shocks, stock return and exchange rates in the two largest economies, US and China. While using dynamic conditional correlation diagonal BEKK-GARCH model, they report that aggregate demand shocks have significant influence on oils prices and that oil price shocks adversely affect Chinese stock market. Boldanov et al. (2016) examine the relationship between volatility of oil price and stock market returns using a Diagonal BEKK model and data from six major oil-importing and oil-exporting countries. They report that oil price volatility and stock market volatility relationships show heterogeneous patterns, suggesting that their correlation is not constant but changes over time.

From the empirical literature, there is some evidence pointing metal commodities are increasingly being used for hedging and portfolio management purposes, especially by investors who hold oil assets in their investments. Narayan et al. (2010) point out that a higher oil price would create inflationary pressures, thus encouraging investments in gold as a hedging instrument against inflation. While modelling the volatility behaviour of gold, silver and copper, Hammoudeh and Yuan (2008) find that past positive oil shocks have a cooling effect on current gold and silver volatilities but have no impact on copper volatility. Sari et al. (2010) find a weak relationship between oil price and metal commodities but significant linkages among commodities and between precious metals and exchange rates. Ji and Fan (2012) suggest that oil price has significant volatility spillovers on non-energy commodities, indicating a significant influence of oil on commodity markets. In fact, they observe a significant bi-directional price and volatility spillover effects between the crude oil and metal commodities before and after the GFC. By decomposing the oil price shock into oil supply shocks, global demand shocks and speculative oil demand shocks, Ahmadi et al. (2016) note significant differences for gold, silver and copper's responses to oil price shocks. It is reported that speculative demand shocks become effective after the crisis, somehow depressing the volatility of silver and enhancing the volatility of copper. In contrast, Dutta et al. (2017) find strong volatility transmission from the world oil market to metal and aggregate non-energy commodity indices. Fernandez-Perez et al. (2017) also demonstrate a significant causal effect from crude oil to platinum and palladium, highlighting the important role of crude oil on these commodities. However, Kang et al. (2017) find that both gold and silver were net information transmitters to the other commodity markets including the crude oil market, showing that gold and silver serve as origins of information transmissions over the other commodities. Finally, it should be mentioned that oil prices could drive commodities either as complementary or substitutes. Empirical analyses have looked at whether changes in agricultural commodity prices such as soybean and corn are more closely related to changes in oil prices. In this regard, the existence of complementary relationship would mean that agricultural commodity price shocks will reduce the expenditure on oil to the extent of reducing its price (Alvalos, 2013). Thus, Cooke and Robles (2009) show that the most recent increases in soybean and corn prices are significantly influenced by the global crude oil prices. In this aspect, energy is necessary to mine, smelt or harvest commodities (such as copper, aluminium, corn and soybean) and it can reasonably be said that energy costs have a high proportion of the costs of many consumer products. It is therefore not surprising to see a joint consumption of oil and other commodities and oil is in this sense being a complementary product. On the other hand, substitution effect may be expected in the case where increasing demand for corn and soybean oil will lead to a higher corn and soybean oil prices, forcing consumer to switch to other inputs in the production

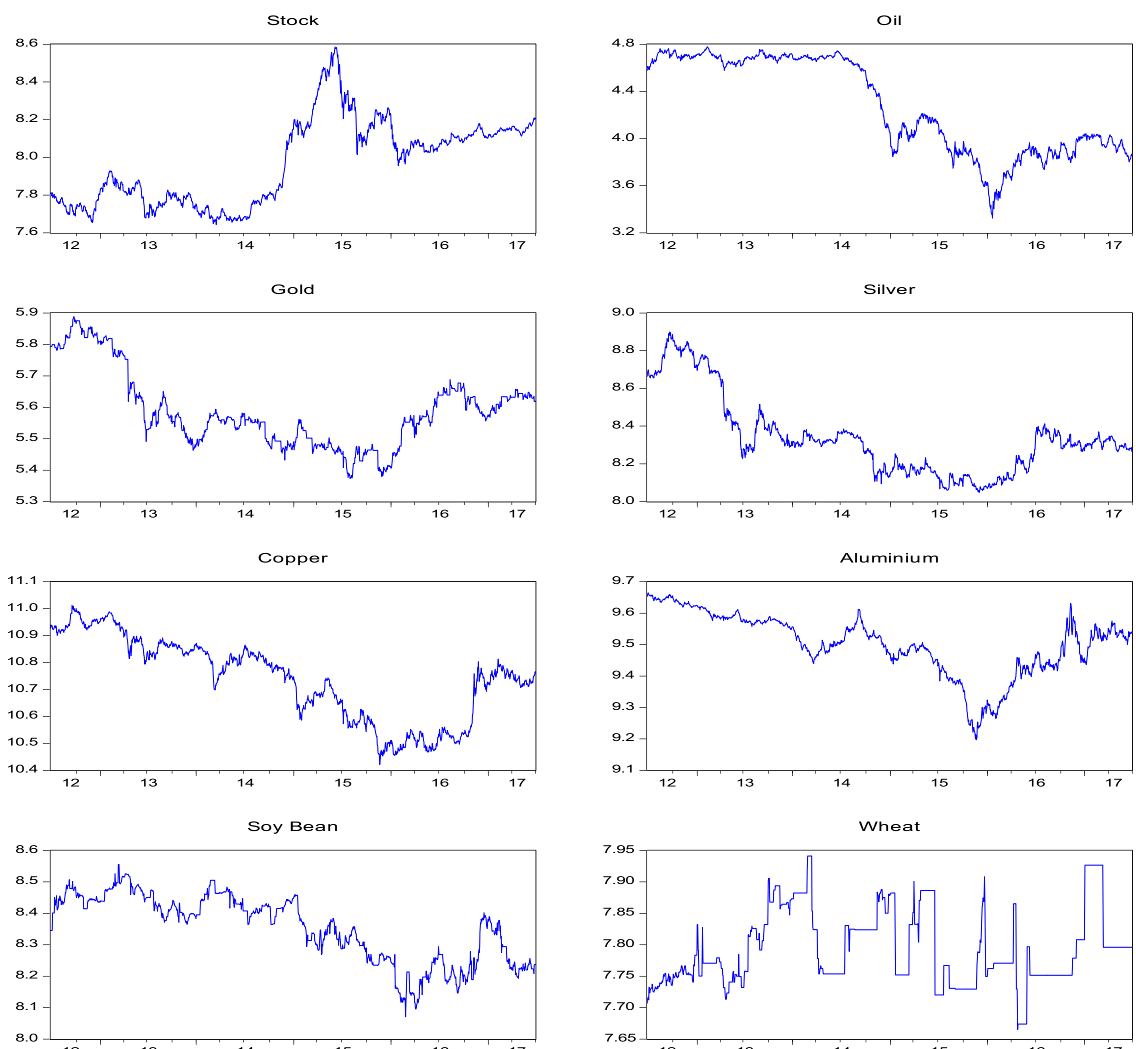

Fig. 1. Price movement of stock, oil and commodity markets.

Table 1
Descriptive statistics for market returns.

	CSI	OIL	GOLD	SLVR	COP	ALU	SB	WHT
Mean	0.033	−0.058	−0.014	−0.033	−0.013	−0.010	−0.009	0.007
Median	0.056	−0.063	0.000	−0.025	0.000	0.000	0.000	0.000
Maximum	6.499	9.561	5.396	6.414	6.709	3.833	6.973	12.319
Minimum	−9.154	−8.811	−13.399	−8.846	−5.266	−6.942	−10.736	−16.606
Std. Dev.	1.590	2.000	1.070	1.489	1.101	0.823	1.256	1.341
Skewness	−0.899	0.314	−2.010	−0.259	0.096	−0.292	−0.542	−1.656
Kurtosis	8.897	6.013	28.344	7.700	7.369	10.023	13.836	59.049
JB	1927	480	33,390	1134	970	2519	6014	159,857
Q(20)	99.443	40.925	44.925	31.766	27.912	64.269	28.773	17.753
Unit root tests								
ADF^L	−1.110	−0.739	−1.909	−1.736	−1.562	−1.948	−1.921	−4.046
PP^L	−1.153	−0.758	−1.905	−1.729	−1.531	−1.879	−1.660	−4.200
$KPSS^L$	2.705	3.859	1.594	2.502	3.219	2.267	3.485	0.248
ADF^R	−33.037	−37.104	−39.074	−37.476	−35.950	−32.240	−37.673	−34.671
PP^R	−33.049	−37.033	−39.215	−37.387	−35.964	−32.164	−38.019	−34.671
$KPSS^R$	0.087	0.129	0.237	0.158	0.190	0.180	0.075	0.026

Note: The descriptive statistics (return data) are in %. CSI stands for Chinese stock market, SLVR means silver, COP stands for copper, ALU for aluminium, SB for Soy Beans and WHT for Wheat. When conducting ADF and PP tests, we include an intercept in the test equation. ADF^L, PP^L and $KPSS^L$ are for level data while ADF^R, PP^R and $KPSS^R$ are for the first difference of the level data which are the return series. ADF^R and PP^R are all significant at 1% level whereas ADF^L and PP^L are not significant except for wheat. For KPSS test, since its null hypothesis is that the time series is stationary, $KPSS^L$ are all significant at 1% level whereas $KPSS^R$ are not significant with the exception of wheat. Please see Section 3 for specific details of each variable (and the nature its contract).

process. In support of this, Zafeiriou et al. (2018) note that "given corn is the major input for ethanol, a substitute for crude oil prices, the behaviour of crude oil prices may well reflect the behaviour of corn prices" p.7.

3. Data used and methodological framework

We investigate the return and volatility transmissions among global oil price, equity and commodity markets in China. To avoid aggregation bias of commodity prices, we use individual commodity futures including agriculture, industrial metals, and precious metals. We use the daily data which is compiled from SIRCA. The sample period starts from 2 July 2012 to 30 June 2017, which covers several episodes of wide instabilities for both stock and commodity markets. We consider using the CSI300 index to represent Chinese stock market, because it is a capitalization-weighted index covering the 300 largest and most liquid stocks traded in the Shanghai Stock Exchange and Shenzhen Stock Exchanges, representing about 60% of the total market capitalization. Commodities are classified into three categories. Precious metals refer to gold and silver, industrial metals comprise copper and aluminium, and agriculture commodities include soy bean and wheat. Since commodity markets show heterogeneity characteristics, our selection here provides deeper insights into dynamic links between various commodities. In terms of global oil price, we choose the Brent oil price to represent the international crude oil market since it is widely viewed as the benchmark of the global oil market to price (El Hedi Arouri et al., 2011).[2] Since our focus is Chinese financial market, we have considered using China's new crude oil futures contract which were launched in March 2018. After carefully examining and comparing the recent China's crude oil futures data and the Brent oil price movements, we observe closely matching common patterns and trends. For this reason, we believe the Brent oil price is a representative proxy not only for international energy market but also for the Chinese domestic energy market. Following the literature, our commodity futures continuous price series are constructed using the closing price of the nearest to maturity contract until the last trading day and then rolling over to the next nearest-to-maturity contract. This is because the nearest contract is often expected to be the most liquid and actively traded. We take the natural logarithms of the prices and returns are calculated as $R_t = 100^*\ln(P_t/P_{t-1})$, where P_t is the futures price at time t. Fig. 1 demonstrates the price trend for the markets under review. We see that the Chinese stock market increases dramatically from 2014 and reaches the top in the mid-2015. It then shows a significant downward swing from then and stabilises after 2016. In contrast, the global oil price shows a downward shift in 2014 and bottom-up in early 2016. The Chinese commodity markets follow the similar trend except for wheat.

Table 1 provides descriptive statistics of log prices and returns for global oil market, Chinese stock and commodity markets. We see that the average returns for most commodity markets are negative with exceptions of the wheat market. The Chinese stock market has a positive average return which is much higher than those in commodity markets. The large value of kurtosis ranging from the lowest of 6.01 for oil to the highest of 59.05 for wheat indicates the return is highly leptokurtic with fat tails compared to a normal distribution. The non-normality is also confirmed by the Jarque–Bera test statistics which reject the null hypothesis of normality for all the market returns under study at 1% level significance level. These preliminary descriptive statistics demonstrate significant asymmetry and excess kurtosis. Thus, our use of GARCH family models to measure the volatility of returns is justified and appropriate. The Ljung-Box Q test residual autocorrelation is significant at 10% significance level for all returns series except wheat. This shows that market returns exhibit serial correlation and that VAR modelling framework is suitable. We employ Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) tests together with KPSS tests to examine trend stationarity. As noted in Table 1, all the tests results indicate that price level data display a non-stationary feature with the exception of wheat.[3] Table 2 provides the unconditional correlation matrix among market returns. The low correlation between indicators implies the potential portfolio diversification benefits and hedging opportunities. However, the correlations between gold and silver and between copper and aluminium are higher compared with other commodity pairs.

[2] Also, the majority of oil futures contracts are traded on Brent oil with better inventory levels in Cushing compared with WTI oil. Oil: ICE Brent Crude Futures (ICE means Intercontinental Exchange); Gold: SHFE Gold Futures (SHFE means Shanghai Futures Exchange); Silver: SHFE AG Futures (SHFE means Shanghai Futures Exchange); Copper: SHFE CU Futures (SHFE means Shanghai Futures Exchange); Aluminium: SHFE Al Futures (SHFE means Shanghai Futures Exchange); Soy Bean: DCE Bean#1 (DCE means Dalian Commodity Exchange); Wheat: CZCE Wheat (CZCE means China Zhengzhou Commodity Exchange).

[3] Due to food security issues, the Chinese government has strong interventions on the prices of wheat, stabilising its prices and resulting in its stationarity.

Table 2
Correlations matrix.

	CSI	OIL	GOLD	SLVR	COP	ALU	SB	WHT
CSI	1.000							
OIL	0.083	1.000						
GOLD	0.040	−0.068	1.000					
SLVR	0.115	−0.006	0.372	1.000				
COP	0.195	0.055	0.168	0.372	1.000			
ALU	0.159	0.080	0.071	0.147	0.413	1.000		
SB	0.038	0.015	−0.012	−0.016	0.059	0.065	1.000	
WHT	0.046	0.036	−0.035	−0.009	−0.038	−0.039	0.037	1.000

Note: CSI stands for Chinese stock market, SLVR means silver, COP stands for copper, ALU for aluminium, SB for Soy Beans and WHT for Wheat.

3.1. Estimation framework

We use both Johansen and Juselius (1990) and Pesaran et al. (2001) bounds tests to check for cointegration relationship among the series of P_t^{st}, P_t^{oil} *and* P_t^{cm}. Thus we initially assume the following VAR:

$$P_t = A_0 + \sum_{i=1}^{p} A_i P_{t-i} + \varepsilon_i \tag{1}$$

where $P_t = (P_t^{st}, P_t^{oil}, P_t^{cm})'$

Eq. (1) can be rewritten as:

$$\Delta P_t = A_0 + \Pi P_{t-p} + \sum_{i=1}^{p-1} \Gamma_i \Delta P_{t-i} + \varepsilon_i \tag{2}$$

where $\Delta P_t = A_0 + \Pi P_{t-p} + \sum_{i=1}^{p-1} \Gamma_i \Delta P_{t-i} + \varepsilon_i$

The corresponding likelihood ratio statistics for Trace and Maximum Eigenvalue tests are calculated as:

$$\text{Trace statistic}: \lambda_{Trace}(r) = -T \sum_{i=r+1}^{n} \ln\left(1-\hat{\lambda}_i\right)$$

$$\text{Maximum eigenvalue statistic}: \lambda_{Max}(r) = -T \ln\left(1-\hat{\lambda}_{r+1}\right),$$

where T is the sample size and $\hat{\lambda}_i$ is the *i*th largest canonical correlation.

The bounds testing procedure requires the use of the Autoregressive Distributed Lag (ARDL) technique which can be used without considering whether the time series are either I(0) or I(1). Unlike the other commonly used cointegrating approaches, ARDL approach therefore can test co-integration among time series integrated of different orders less than I(2). We can specify our equation as:

$$\Delta P_t^{st} = a_i + \sum_{i=1}^{q_1} b_i \Delta P_{t-i}^{st} + \sum_{i=1}^{q_2} c_i \Delta P_{t-i}^{oil} + \sum_{i=1}^{q_3} d_i \Delta P_{t-i}^{cm} + \lambda_1 P_{t-1}^{st} + \lambda_2 P_{t-1}^{oil} + \lambda_3 P_{t-1}^{cm} + \varepsilon_t \tag{3}$$

where Δ denotes the first difference operator, q_1, q_2 and q_3 are the lag lengths, b_i, c_i, d_i are the short term coefficients whereas λ_1, λ_1 and λ_1 are the long-run coefficients. In order to determine the existence of a cointegrating relationship among P_t^{st}, P_t^{oil} *and* P_t^{cm}, we test the null hypothesis that is there is no cointegration relationship: $\lambda_1 = \lambda_2 = \lambda_3 = 0$ against the alternative of cointegration: $\lambda_1 \neq \lambda_2 \neq \lambda_3 \neq 0$ by computing F-statistics. The calculated F-statistics will be compared with two different asymptotic critical values provided by Pesaran et al. (2001).

Moving to the conditional volatility, (General) Autoregressive conditional heteroskedasticity [(G)ARCH] models are widely used in forecasting market volatility. This is because of their ability to capture the time-varying conditional variances and show time series features such as volatility clustering. Multivariate GARCH models are found to have the forecasting ability to examine the dynamics of stock market volatility among different financial institutions. By specifying the conditional variance and covariance equations, MGARCH models have widely been used to examine how the correlation and covariance between different variables change over time. Multivariate volatility models such as BEKK (Baba, Engle, Kraft and Kroner), CCC (Constant Conditional Correlation) or DCC (Dynamic Conditional Correlation) specifications with dynamic covariances and conditional correlations are more relevant than univariate models when investigating volatility interdependence and transmission mechanisms among different financial time series (Arouri et al., 2011b).

A number of existing empirical studies confirm the superiority of these models (Chang et al., 2011; Agnolucci, 2009; Hammoudeh et al., 2009; see Hassan and Malik, 2007). However, the existing studies examining volatility transmissions using MGARCH only focus on the bivariate relationship. Our paper examines the trilateral dynamics of the mentioned markets. In terms of interpreting and capturing the spillovers between commodity and other markets, a GARCH model with BEKK specification has successfully been utilised (Salisu and Oloko, 2015; Jouini and Harrathi, 2014). Here we follow the trivariate BEKK-GARCH approach (Engle and Kroner, 1995) to investigate the return and volatility transmission in China. By adding VAR(1) term into BEKK-GARCH, we can specify our model under the conditional mean equation and conditional variance equation. The conditional mean model of VAR(1) can be outlined as:

$$R_t = \mu + G R_{t-1} + \varepsilon_t, \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \tag{4}$$

where R_t denotes a vector of stock market return, oil market return and commodity market return: $R_t = (R_{st,\ t}, R_{oil,\ t}, R_{cm,\ t})'$, G is a (3 × 3) matrix of VAR coefficients, ε_t represents a vector of Gaussian error: $\varepsilon_t = (\varepsilon_{st,\ t}, \varepsilon_{oil,\ t}, \varepsilon_{cm,\ t})'$ and μ is a vector of constants: $\mu = (\mu_{st}, \mu_{oil}, \mu_{cm})'$.

In terms of conditional variance, several different multivariate GARCH specifications have been developed in the literature. Bollerslev et al. (1988) introduced a general VECH GARCH where the conditional variance and covariance are a linear function of all lagged squared errors and conditional variance and covariance. However this results in another econometric challenge because the number of parameters is very large. It is also hard to guarantee a positive conditional variance and covariance matrix H_t without restrictions on parameters. By reducing the number of parameters, Engle and Kroner (1995) proposed a BEKK-GARCH model which simplifies the estimation process so that VECH parameterization problems can be overcome. This model uses the quadratic forms to release the positive restriction on the conditional variance matrix and further simplifies the estimation process. The conditional variance equations are specified as follow:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{5}$$

where

$$H_t = \left[h_{11,t}\, h_{12,t} h_{13,t} h_{21,t} h_{22,t} h_{23,t} h_{31,t} h_{32,t} h_{33,t}\right], C = \begin{bmatrix} c_{11} & & \\ c_{21} & c_{22} & \\ c_{31} & c_{32} & c_{33} \end{bmatrix},$$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \text{ and } B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33.} \end{bmatrix}$$

where C is a 3 × 3 lower triangular matrix with six parameters. A is a 3 × 3 matrix, indicating how conditional variances are correlated with past shocks. B is also a 3 × 3 matrix, showing the effects of past conditional variances on current conditional variances. The total number of estimated parameters for our trivariate variance equations is 24.

Following Hassan and Malik (2007), the conditional variance for each market, ignoring the constant coefficients, can be expanded as follow:

$$\begin{aligned} h_{11,t} = {} & a_{11}^2\varepsilon_{st,t-1}^2 + 2a_{11}a_{12}\varepsilon_{st,t-1}\varepsilon_{oil,t-1} + 2a_{11}a_{31}\varepsilon_{st,t-1}\varepsilon_{cm,t-1} \\ & + a_{21}^2\varepsilon_{oil,t-1}^2 + 2a_{21}a_{31}\varepsilon_{oil,t-1}\varepsilon_{cm,t-1} + a_{31}^2\varepsilon_{cm,t-1}^2 + b_{11}^2h_{11,t-1} \\ & + 2b_{11}b_{12}h_{12,t-1} + 2b_{11}b_{31}h_{13,t-1} + b_{21}^2h_{22,t-1} \\ & + 2b_{21}b_{31}h_{23,t-1} + b_{31}^2h_{33,t-1} \end{aligned} \tag{6}$$

$$\begin{aligned} h_{22,t} = {} & a_{12}^2\varepsilon_{st,t-1}^2 + 2a_{12}a_{22}\varepsilon_{st,t-1}\varepsilon_{oil,t-1} + 2a_{12}a_{32}\varepsilon_{st,t-1}\varepsilon_{cm,t-1} \\ & + a_{22}^2\varepsilon_{oil,t-1}^2 + 2a_{22}a_{32}\varepsilon_{oil,t-1}\varepsilon_{cm,t-1} + a_{32}^2\varepsilon_{cm,t-1}^2 + b_{12}^2h_{11,t-1} \\ & + 2b_{12}b_{22}h_{12,t-1} + 2b_{12}b_{32}h_{13,t-1} + b_{22}^2h_{22,t-1} \\ & + 2b_{22}b_{32}h_{23,t-1} + b_{32}^2h_{33,t-1} \end{aligned} \tag{7}$$

$$\begin{aligned} h_{33,t} = {} & a_{13}^2\varepsilon_{st,t-1}^2 + 2a_{13}a_{23}\varepsilon_{st,t-1}\varepsilon_{oil,t-1} + 2a_{13}a_{33}\varepsilon_{st,t-1}\varepsilon_{cm,t-1} \\ & + a_{23}^2\varepsilon_{oil,t-1}^2 + 2a_{23}a_{33}\varepsilon_{oil,t-1}\varepsilon_{s3t,t-1} + a_{33}^2\varepsilon_{cm,t-1}^2 + b_{13}^2h_{11,t-1} \\ & + 2b_{13}b_{23}h_{12,t-1} + 2b_{13}b_{33}h_{13,t-1} + b_{23}^2h_{22,t-1} \\ & + 2b_{23}b_{33}h_{23,t-1} + b_{33}^2h_{33,t-1} \end{aligned} \tag{8}$$

The diagonal elements of matrices A(a_{11}, a_{22} and a_{33}) and B(b_{11}, b_{22} and b_{33}) capture the effect of previous shocks and historical volatility to the current conditional variance, respectively. On the other hand, the off-diagonal elements of matrices A(e.g. a_{12}, $a_{13}$and a_{21}) and B(e.g. b_{12}, b_{13} and b_{21}) measure the volatility spillovers across the markets.[4] In the estimation process, the following logarithm likelihood function should be maximised with a normal distribution for the error terms:

$$L(\theta) = \sum_{t=1}^{T} L_t(\theta) \tag{9}$$

The log-likelihood function of the joint distribution is given as:

$$L_t(\theta) = -\ \ln(2\pi) - \frac{1}{2}\ \ln|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1}\varepsilon_t \tag{10}$$

where θ denotes the vector of parameters to be estimated and T is the number of observations. Since the above function is non-linear, we will employ BFGS (Broyden, Fletcher, Goldfarb, and Shanno) algorithms as the maximization technique to obtain the initial condition and the final parameter estimates of the variance–covariance matrix.

In this set-up, the conditional variance for the commodity market, for example, is not impacted only by its own past shocks and past conditional variance, but also by those of the stock and oil markets. This captures the direct shocks and volatility transmission between one market and another.

4. Major findings and analysis

As noted in Table 1, we conclude that the prices for Chinese stock market, oil, gold, silver, copper, aluminium, and soy bean integrated of order 1 (I(1)). In contrast, the wheat prices are stationary. As a result, we only apply the bounds test for the group of stock market, oil prices and wheat prices. Table 3 reports results of both Johansen and Juselius and bounds tests. The ARDL bounds tests suggest that there is no cointegration among the Chinese stock market, the global oil market and all the Chinese commodity markets. The F-statistic for all cases is lower than the lower bound of the critical values. In another word, there is no common driving force for these three variables in the long run. Our findings here are in line with Sari et al. (2010) who find no evidence of long-term equilibriums for the oil prices, precious metal prices, and exchange rates. Results from the Johansen and Juselius cointegration tests also show no obvious long-run cointegration relationship among the stock market, crude oil prices and the major Chinese commodity markets. Further analysis shows that oil prices and soy bean futures tend to move together in the long-term. This supports findings by Nazlioglu and Soytas (2012) who argue that oil prices are important factors in determining the long-run behaviours of agricultural commodity markets.

4.1. VAR-BEKK-GARCH results

Our estimation results of VAR(1)-BEKK-GARCH(1,1) are provided in Table 4 which consist of two sections. The first part presents VAR results based on the estimation of conditional mean equations. Through these estimations, we aim to identify the return spillovers among these markets. The second part shows results from the conditional variance equations modelled by BEKK GARCH where we analyse volatility spillovers.

In investigating returns Spillovers, we first examine the return behaviours for equity, oil and commodity markets based on our estimation from the conditional mean equations. We observe that the AR(1) parameter g_{22} for oil return is statistically significant for most groups at the 10% significance level. Therefore oil return shows an autoregressive characteristic, suggesting that one-period lagged oil returns significantly influence the current values. Similarly, some of the Chinese commodity markets (gold, silver and copper) also have autoregressive features as g_{33} are statistically significant for their market returns. Thus current market returns for gold, silver and copper are significantly affected by their past values and therefore show short-term predictability. However, we do not find strong evidence of serial correlation for the returns of Chinese stock market, aluminium, soy bean and wheat markets.

When examining the return spillover effects, the lagged values of returns in the oil market are found to affect the current returns of the Chinese stock market significantly, since the coefficient g_{12} are statistically significant for all groups. This shows that the Chinese stock market returns in the current time strongly depend on the past return in the oil market. This indicates that there is significant return spillover from the oil to the Chinese stock market. Looking at the sign of the coefficient, the positive sign indicates that the higher return in the oil market will possibly drive higher stock market return. Our results here is in contrary to the previous result found by Cong et al. (2008) who report insignificant impact of oil price shocks on real stock returns for most of the Chinese Stock market indices. This is not surprising since China is the world's largest net oil-importing country. In this regard, the oil market is expected to influence the Chinese stock market due to the strong dependence of its economy on oil import. The oil market is often treated as the leading economic indicator. Thus, rising oil prices due to oil demand increases reflect the expectation of future higher economic growth of the consuming country. This signals a higher stock market return. Consistent with our finding, Bai and Koong (2018) and Park and Ratti (2008) report that oil price shocks have significant and robust impacts on real stock returns of the US and 13 European countries. Basher and Sadorsky (2006) also argue that oil price increases have positive impacts on excess stock returns in emerging markets. In contrast, there is no evidence of return spillover from the Chinese stock market to the oil market, since the coefficient g_{21} is statistically insignificant for all groups. Therefore we can see that the oil market tends to behave independently from the Chinese stock market. Our findings here are supported by Arouri et al. (2011b) who find strong market interdependence from lagged oil returns to stock market return for most GCC countries, where the reverse does not hold. However, our results are contrary to Singhal and Ghosh (2016) who indicate insignificant spillovers from international crude oil returns on Indian stock market returns.

Looking at the return spillovers between Chinese stock and commodity markets, we find strong unidirectional return spillovers from the stock market to copper and aluminium markets respectively. The coefficient g_{31} is statistically significant at least at the 5% level for the

[4] In interpreting the coefficients of the conditional variance equation, the sign of our parameter estimates does not matter since their squared values affect the conditional variance as noted by Kim et al. (2015)

Table 3
Cointegration test results.

Johansen and Juselius Cointegration Test Results												
H_0	Gold		Silver		Copper		Aluminium		Soy Bean		Wheat	
	Tr	Max	Tr	Max	Tr	Max	Tr	Max	Tr	Max	Tr	Max
None	21.13	12.91	17.36	10.26	17.05	10.41	20.77	13.97	30.14*	22.03*	NA	
At most 1	8.23	7.25	7.10	5.94	6.63	6.32	6.80	6.47	8.11	7.50	NA	
At most 2	0.98	0.98	1.16	1.16	0.32	0.32	0.32	0.32	0.61	0.61	NA	
ARDL Bounds Test Results												
F-statistic	0.65		0.71		0.79		0.70		0.57		1.91	
Significance	10%		5%		2.5%		1%					
I(0) Bound	2.63		3.1		3.55		4.13					
I(1) Bound	3.35		3.87		4.38		5					

Note: We allow for linear deterministic trend and intercept in cointegration equation when conducting Johansen and Juselius cointegration test and the lag selection is based AIC. As the wheat prices are stationary according to ADF, PP and KPSS tests, so it is inappropriate to use Johansen and Juselius Cointegration Test. Tr and Max refer to Trace statistic and Max-Eigen statistic respectively. * represents the rejection of the null hypothesis at 5% level. Since the prices of wheat are stationary, only ARDL bounds test can be applied on wheat meanwhile we also conduct ARDL bounds test for the other series.

groups of copper and aluminium. Looking at the coefficient signs, the impacts of the Chinese stock market to both copper and aluminium are negative. This indicates that a higher stock return will lead to the fall of copper and aluminium markets. However, we see no evidence of mean spillover effect from commodities to stock market. These results are similar to the findings reported by Nguyen et al. (2015) who highlight that the causality from equity returns to copper futures returns is significant whereas the causality from commodity futures to equity is less pronounced.

The similar results are also observed when examining the interdependence between the global oil market and Chinese commodity markets. Silver, copper and aluminium markets are found to be possibly

Table 4
VAR-BEKK-GARCH results.

	Gold		Silver		Copper		Aluminium		Soy Bean		Wheat	
Mean equation												
Dependent variable: R_{st}												
Constant	0.043	(0.183)	0.057*	(0.079)	0.053	(0.114)	0.055*	(0.086)	0.039	(0.245)	0.078**	(0.015)
$R_{st}(-1)$---g_{11}	0.036	(0.254)	0.025	(0.403)	0.044	(0.167)	0.034	(0.287)	0.014	(0.654)	0.042	(0.166)
$R_{oil}(-1)$---g_{12}	0.048***	(0.007)	0.040**	(0.030)	0.035*	(0.058)	0.049***	(0.009)	0.046***	(0.007)	0.058***	(0.001)
$R_{cm}(-1)$---g_{13}	−0.023	(0.474)	0.004	(0.866)	0.027	(0.312)	−0.028	(0.373)	0.027	(0.292)	−0.011	(0.651)
Dependent variable: R_{oil}												
Constant	−0.041	(0.334)	−0.024	(0.565)	−0.083*	(0.069)	−0.043	(0.312)	−0.035	(0.425)	−0.060	(0.158)
$R_{st}(-1)$---g_{21}	−0.023	(0.483)	−0.027	(0.407)	−0.025	(0.471)	−0.011	(0.736)	−0.018	(0.579)	−0.021	(0.515)
$R_{oil}(-1)$---g_{22}	−0.057*	(0.059)	−0.054*	(0.074)	−0.044	(0.169)	−0.052*	(0.086)	−0.054*	(0.074)	−0.082**	(0.011)
$R_{cm}(-1)$---g_{23}	−0.012	(0.781)	−0.008	(0.807)	−0.040	(0.394)	−0.074	(0.291)	0.010	(0.796)	0.049	(0.157)
Dependent variable: R_{cm}												
Constant	−0.018	(0.576)	−0.050	(0.224)	−0.013	(0.650)	−0.025	(0.133)	0.006	(0.857)	0.076*	(0.052)
$R_{st}(-1)$---g_{31}	−0.026	(0.216)	0.006	(0.805)	−0.043**	(0.030)	−0.033***	(0.001)	0.003	(0.892)	0.030	(0.315)
$R_{oil}(-1)$---g_{32}	0.017	(0.318)	0.084***	(0.000)	0.105***	(0.000)	0.043***	(0.000)	0.011	(0.518)	0.021	(0.320)
$R_{cm}(-1)$---g_{33}	−0.113***	(0.000)	−0.106***	(0.004)	−0.066**	(0.050)	−0.007	(0.824)	−0.024	(0.559)	0.017	(0.710)
Conditional variance equations												
C(1,1)	0.053	(0.164)	−0.054	(0.143)	0.111***	(0.000)	0.062**	(0.026)	0.067***	(0.005)	−0.027	(0.495)
C(2,1)	−0.033	(0.695)	−0.021	(0.808)	−0.122***	(0.000)	−0.019	(0.778)	−0.013	(0.850)	−0.058	(0.758)
C(2,2)	0.104***	(0.008)	0.104***	(0.004)	0.012	(0.739)	0.111***	(0.000)	−0.102**	(0.017)	−0.109	(0.360)
C(3,1)	−0.037	(0.854)	−0.285	(0.580)	0.118*	(0.060)	0.028	(0.395)	−0.271	(0.116)	−1.024**	(0.021)
C(3,2)	0.049	(0.751)	0.088	(0.774)	0.298***	(0.000)	0.019	(0.414)	−0.065	(0.800)	−0.223	(0.908)
C(3,3)	0.110	(0.154)	0.470	(0.100)	0.000	(1.000)	−0.037	(0.238)	0.457***	(0.000)	0.000	(1.000)
A(1,1)	−0.231***	(0.000)	−0.214***	(0.000)	0.220***	(0.000)	−0.222***	(0.000)	−0.205***	(0.000)	−0.214***	(0.000)
A(1,2)	−0.042*	(0.056)	−0.056**	(0.013)	−0.003	(0.879)	−0.047*	(0.054)	−0.053**	(0.020)	−0.079***	(0.005)
A(1,3)	−0.022**	(0.023)	−0.006	(0.842)	−0.069***	(0.000)	−0.010	(0.249)	−0.086***	(0.000)	−0.319***	(0.000)
A(2,1)	0.027**	(0.026)	0.023**	(0.035)	0.021	(0.106)	0.027**	(0.017)	0.019	(0.129)	0.020	(0.134)
A(2,2)	−0.211***	(0.000)	−0.204***	(0.000)	−0.199***	(0.000)	−0.194***	(0.000)	−0.216***	(0.000)	−0.191***	(0.000)
A(2,3)	0.015*	(0.084)	0.009	(0.739)	−0.005	(0.769)	−0.001	(0.934)	−0.041*	(0.055)	0.173***	(0.000)
A(3,1)	0.041	(0.113)	−0.020	(0.483)	−0.004	(0.833)	−0.007	(0.671)	−0.024	(0.289)	0.012	(0.506)
A(3,2)	0.026	(0.433)	0.040	(0.176)	0.016	(0.635)	−0.067	(0.183)	−0.004	(0.925)	−0.012	(0.654)
A(3,3)	0.059***	(0.000)	−0.348***	(0.000)	0.337***	(0.000)	−0.242***	(0.000)	0.370***	(0.000)	−0.293***	(0.000)
B(1,1)	0.973***	(0.000)	0.978***	(0.000)	0.973***	(0.000)	0.975***	(0.000)	0.978***	(0.000)	0.974***	(0.000)
B(1,2)	−0.007	(0.224)	−0.009	(0.122)	0.014***	(0.005)	−0.008	(0.195)	−0.009*	(0.093)	−0.009	(0.161)
B(1,3)	−0.007***	(0.005)	0.009	(0.355)	0.021***	(0.000)	−0.002	(0.354)	0.001	(0.867)	0.009	(0.856)
B(2,1)	0.005*	(0.075)	0.003	(0.110)	0.004**	(0.042)	0.004**	(0.046)	0.004	(0.163)	0.004	(0.108)
B(2,2)	0.975***	(0.000)	0.977***	(0.000)	0.978***	(0.000)	0.978***	(0.000)	0.975***	(0.000)	0.978***	(0.000)
B(2,3)	0.001	(0.524)	0.002	(0.769)	0.004	(0.400)	−0.001	(0.555)	−0.015**	(0.034)	0.006	(0.878)
B(3,1)	0.005	(0.616)	−0.015	(0.453)	−0.006	(0.553)	−0.002	(0.600)	0.008	(0.575)	0.046	(0.350)
B(3,2)	−0.007	(0.582)	0.002	(0.920)	0.000	(0.975)	−0.012	(0.337)	0.006	(0.854)	−0.104	(0.276)
B(3,3)	0.991***	(0.000)	0.860***	(0.000)	0.887***	(0.000)	0.970***	(0.000)	0.821***	(0.000)	−0.377***	(0.000)

Note: The figures in brackets are *P*-values which indicate the statistical significance of the coefficients.
*, **, *** indicate statistical significant level at 10%, 5%, and 1% respectively.

influenced by oil return, given that the coefficient g_{32} is statistically significant at the 1% level. The positive sign of the coefficient indicates that a higher oil price will boost the markets of silver, copper and aluminium. Although we see here evidence of close interactions between crude oil and copper and aluminium markets, which may indicate that the two are compliments, we argue that this needs further empirical analysis in support of a substantial complementary effect. The positive interdependence between oil and other commodities may be due to the influence of common macroeconomic drivers such as interest rates, inflation rates and industrial production (Hammoudeh and Yuan, 2008). We do not find the return spillovers from the commodity markets to the oil market. Interestingly, both copper and aluminium are very sensitive to the shocks from both the Chinese stock market and global oil market. This suggests that these two commodity markets are vulnerable to the external effects or shocks. The lack of relationship between gold and stock and gold and oil markets indicate that the gold plays a safe-haven role which has also been pointed out by Baur and McDermott (2010). For agricultural commodities, we cannot find significant evidence of spillover effects, implying weak integration among agricultural commodities, stock market and oil market. Our findings here indicate potential diversification benefits between some commodities (gold, soy bean and wheat) and Chinese stock market and between those and oil markets. It is very interesting to note that the oil and wheat show no substitute effects from our results. Our finding here is in contrast with Liu (2013) who report significant cross-correlations between oil and price returns of agricultural commodities such as corn and soybean.

We further conduct the impulse response analysis based on the VAR model to forecast shock effects on our selected financial markets. The results are illustrated in Fig. 3a, b, c, d, e and f. As we can see, all markets seem to react more significantly to shocks from their own markets compared with their cross markets' effects. Moving to the cross markets' effects, China's stock market responds more strongly to oil shocks compared with the shocks from other commodity markets. On oil market, the shocks from the Chinese stock market have stronger effects than those from commodity markets. Overall, the interactions between stock and oil markets are more obvious whereas the commodity markets have little influence on both stock and oil markets. For commodity markets, we can see that those metal commodity (especially silver, copper and aluminium) markets respond significantly to the shocks from both stock and oil market. These results are consistent with the informational feedback process previously reported, indicating robustness of our results.

4.2. Volatility spillovers based on BEKK GARCH

We next examine the volatility spillovers based on conditional variance equations. Ross (1989) emphasises that the market volatility is significantly influenced by the rate of information flow. Therefore it is possible that linkages across financial markets not only exist in the returns but also in the market volatility. As noted in Table 4, the estimated coefficients for ARCH and GARCH models [A(1,1), A(2,2), A(3,3) and B(1,1), B(2,2), B(3,3)] in our conditional variance equations for all the groups are statistically significant at the 1% significant level. This shows that the Chinese stock market, Brent oil market and all the Chinese commodity markets (gold, silver, copper, aluminium, soy bean and wheat) have strong ARCH and GARCH effects. These results point out that the conditional variances of these financial markets are significantly influenced by their own lagged shocks and their own lagged conditional variance. Our findings are consistent with Beirne et al. (2013) who provide strong evidence of ARCH and GARCH effects in emerging markets and emphasis on the appropriateness of the GARCH family models in these analyses. Moreover, the reported ARCH coefficients are relatively small in size compared with the GARCH coefficients. This suggests that the conditional volatility of corresponding markets does not change rapidly if there is a shock but rather fluctuate gradually over time. It also suggests that past value of their own volatility plays a more crucial role in forecasting their future volatility compared with their own shocks.

To analyse volatility transmissions, we first look at the nature of spillover mechanisms between the Chinese stocks and the international oil market. The statistical significance of the off-diagonal coefficients in the matrix A and B of the BEKK model's variance equation (Eq. (5)),[5] we can examine how shocks and volatility spillovers are transmitted. Our results show significant transmission of shock spillovers from the Chinese stock market to the oil price as the coefficients A(1,2) are significant at the 10% level for most groups except for copper. Thus past shocks in the Chinese stock market have significant effects on the oil market's volatility over the sample period. Looking at the opposite effect, we see shock volatility spillover effect from the crude oil to the Chinese stock market is intermediate, as the coefficients A(2,1) are significant only for half of the groups. In terms of volatility spillovers, we find that the fluctuation in oil returns induce positive and significant volatility spillovers to mainly gold, copper and aluminium returns. However, the coefficient B(1,2) is only significant for the groups of copper and soy bean. These later results indicate that the volatility spillovers from the stock market to the oil market are weak.

Our findings demonstrate a bi-directional shocks spillover between the Chinese stock market and oil market but a uni-directional volatility spillover from oil to stock market. These results remain qualitatively unchanged when we swap our methodology to bivariate models.[6] Our findings here are in line with Jouini and Harrathi (2014) who show evidence of bilateral shock transmission between the oil and UAE/Bahrain stock markets. It is also consistent with Arouri et al. (2011b) who found past oil shocks to have significant effects on stock market volatility for 13 GCC countries. Overall, our results suggest that the shocks from both Chinese stock market and oil price have important effects on the other markets' volatility. However, volatility from oil market only has an impact on the Chinese stock market. These results support the view that the Chinese markets are integrating with the rest of the world following governments commitments for the gradual financial liberalisation reforms over the last few years. We believe this could also be explained by the fact that China is the top oil importer of oil. As financial liberalisation and the financialisation of commodity markets are enhanced, Chinese financial markets are becoming more responsive to the fluctuation in global oil prices. Thus international oil market volatility is able to exert a strong negative (both in terms of shock and volatility) into the stock market in China.

We next analyse shock and volatility spillover between stock and commodity markets. As reported in Table 4, the off-diagonal elements of matrix A—A(1,3) are statistically significant at the 5% level for most commodity markets (e.g. gold, copper, soy bean and wheat). This evidence highlights significant shock spillovers from stock market to commodity markets. The highest absolute value of coefficient A(1,3) is given as 0.319 for wheat and is significant at the 1% level, implying the wheat market is the most sensitive market to the shocks from the Chinese stock market.

Regarding the off-diagonal elements of matrix B—B(1,3), we do observe volatility spillover effect from stock market to gold and copper as the corresponding coefficients are significant at the 1% level. In terms of the absolute value of the coefficient, it is relatively small compared with A(1,3). This suggests that the volatility spillover effect from stock to commodity is marginal compared with shock spillovers. In the opposite direction, we find no evidence of both shock and volatility spillover effects from commodity to stock markets, as neither A(3,1)

[5] The off-diagonal elements of matrices A(ij) capture the shock spillover effects from market i to market j. Similarly, the volatility spillovers are measured by the off-diagonal elements of matrix B(ij).

[6] The full robust test results are available upon request. Here we only show the results for the coefficients of shock and volatility spillovers. A(1,2): −0.053 (0.030); A(2,1): 0.026 (0.047); B(1,2): −0.010 (0.110); B(2,1): 0.005 (0.058).

nor B(3,1) are statistically significant for all groups. It can also be seen that both gold and copper are influenced by past shocks and volatility from stock market while soy bean and wheat are only influenced by past shocks. However, we see no statistical evidence of shock and volatility spillovers from the Chinese stock market in the cases of silver and aluminium. In summary, our results indicate unidirectional shock (strong) and volatility (moderate) spillover effects from the stock market to the commodity markets in China.

Moving to the interdependence between the oil market and the Chinese commodity markets, there is strong evidence of shock spillovers from oil prices to gold, soy bean and wheat markets. Those respective A(2,3) coefficient are statistically significant. For volatility spillovers, we can only find contagion from oil to soy bean market as the respective B(2,3) coefficient is significant at the 5% level. In terms of the magnitude, the oil market has the largest impact on the wheat market with A(2,3) valued at 0.173. Similarly, our results reveal no shock and volatility spillover effects from all the commodity markets to global oil market as A(3,2) and B(3,2) coefficients remain insignificant. In line with the findings of Ji and Fan (2012), we find crude oil market has significant volatility spillover effects on non-energy commodity markets, showing oil market's core global influences.

Overall, our evidence suggests that metal futures are more sensitive to the fluctuation in the local stock market while the agricultural commodities react more to the shocks in the oil market. Our empirical results are robust with regard to the lack of significant spillovers from commodity markets to either stock market or oil market. However, the spillover levels of the stock and/or oil market to commodity markets depend on the individual commodity. It is interesting to see that volatility spillover effects are not homogenous across commodity markets. We believe the mixed results on volatility transmissions reflect the different level of financial integration in these commodity markets with the stock/oil market. This is also partly contributed by the nature of the commodity, size and liquidity of the markets, the degree of financial liberalisation and other deeper causes not limited to those financial factors. China has undertaken a number of major reform policies (both domestic and foreign) in recent years to open up its capital market. Wang et al. (2017) notes that although Chinese policy initiations between 2010 and 2015 were launched to deepen and open-up financing and investment mechanisms to improve long-term development of the Chinese financial market, reforms such as integration, stabilization and bailout policies have mainly affected the stock market. While pointing out the greater role and eminence of China in the global financial arena, Bai and Koong (2018) argue that “the Chinese stock market is the second largest stock market in the world, and the Chinese currency has expanded its usage and to be included in one of the five major currencies in the SDR basket”. Through these gradual reforms, Chinese stock market was able to better link with other regional markets and permit spillovers from China to other foreign markets. The implementation of market liberalisation policies has also enhanced interdependences between China and overseas markets (Li, 2012).

4.3. Optimal portfolio designs and hedging ratios

Understanding volatility spillover effects are crucial for risk management and efficient portfolio diversification. Given the insignificant volatility spillover effects from commodity market to stock/oil market, potential opportunities for portfolio diversification are substantial by investing in both stock/oil and commodity markets. To mitigate risk exposures of volatile markets and wild price swings, portfolio managers need to quantify both optimal weights and hedging ratios to minimise the extra risks without decreasing the expected returns. Similarly, investors can also achieve greater diversification gains by investing in both stock and commodity or oil and commodity markets. To illustrate the implications of our empirical findings on optimal portfolio design and risk hedging, we consider a portfolio of stock and commodity (oil and commodity) in mitigating the risks exposure to both the Chinese stock and global oil markets. We apply the estimation results from our trivariate VAR-BEKK-GARCH model to compute the optimal portfolio weights of as well as the optimal hedge ratios.

Based on the method developed by Kroner and Ng (1998), we calculate the optimal portfolio weights by constructing a risk minimized portfolio without reducing expected returns. The optimal portfolio weight of holdings of two assets (e.g. stock and commodity or oil and commodity) is given by:

$$\begin{aligned} W_{st-cm} &= \frac{h_{33,t}-h_{13,t}}{h_{11,t}} - 2h_{13,t} + h_{33,t} \ or\ W_{cm-st} \\ &= \frac{h_{11,t}-h_{13,t}}{h_{11,t}} - 2h_{13,t} + h_{33,t} \end{aligned} \tag{11}$$

$$\begin{aligned} W_{oil-cm} &= \frac{h_{33,t}-h_{23,t}}{h_{22,t}} - 2h_{23,t} + h_{33,t} \ or\ W_{cm-oil} \\ &= \frac{h_{22,t}-h_{23,t}}{h_{22,t}} - 2h_{23,t} + h_{33,t} \end{aligned} \tag{12}$$

where $W_{i-j} = \{ 0, if\ W_{i-j} < 0 W_{i-j}, if\ 0 \le W_{i-j} \le 1 1, if\ W_{i-j} > 1$, represent the weight of asset i in a one-dollar portfolio of asset i and asset j at time t, particularly W_{st-cm} refer to the weight of stock market in a one-dollar portfolio of stock and commodity while the optimal weight of commodity in the considered portfolio is W_{cm-st} and W_{oil-cm} is the optimal weight of oil in the considered portfolio of oil and commodity whereas W_{cm-oil} represents the optimal weight of commodity in the same portfolio.[7]

We also compute the optimal hedge ratio for their portfolio according to Kroner and Sultan (1993). The risk of this portfolio is minimal if a long position of one dollar in the stock/oil market can be hedged by a short position of β_t dollar in the Chinese commodity market. Hedge ratio is computed using the formula:

$$\beta_{cm-st} = \frac{h_{13,t}}{h_{33,t}} \tag{13}$$

$$\beta_{cm-oil} = \frac{h_{23,t}}{h_{33,t}} \tag{14}$$

The average values of optimal portfolio weights and hedging ratios for the 6 commodities are detailed in Table 5.

Firstly, we look at the optimal portfolio weights of the commodity market in a portfolio constituting of the Chinese stock and commodity holdings. From our results, most commodity weights are >50% except silver,[8] varying from 50.52% in wheat being the lowest to the highest of 75.66% for aluminium. This means that 50.52% (75.66%) of the portfolio's value should be invested in the wheat (aluminium) futures market and the remaining 49.48% (24.34%) should be held in the Chinese stock market. The results indicate the allocation of the commodity in a one-dollar portfolio consisting of both stock and commodity is more than half for most cases, implying that investor should hold more commodities than stock in order to reduce the portfolio's risk without decreasing its expected return. In terms of the optimal portfolio weights of the commodity for a portfolio constituting of the oil and commodity holdings, similar results are observed with a maximum of 85.61% for aluminium and minimum of 58.18% for silver. The results can be interpreted as that the allocation of the commodity in a one-dollar portfolio is 85.61 cents and 58.18 cents for aluminium and silver respectively. The results indicate that investors need to invest more in the commodity market than oil market in terms of the capital allocation to decrease the risk of the investment portfolio. The findings may serve as an incentive to raise the investment in commodity markets. These findings are in line with the view that investors in stock or oil markets

[7] $W_{oil-cm} + W_{cm-oil} = 1\ and\ W_{st-cm} + W_{cm-st} = 1$

[8] The weight for silver is 46.48% which is only slightly below 50%.

Table 5
Optimal portfolio weights and hedging ratios.

	W_{cm-st}	W_{cm-oil}	W_{st-cm}	W_{oil-cm}	β_{cm-st}	β_{cm-oil}
Gold	0.5838	0.6853	0.4162	0.3147	0.0329	−0.1380
Silver	0.4648	0.5818	0.5352	0.4182	0.1282	0.0050
Copper	0.6577	0.7339	0.3423	0.2661	0.3395	0.1062
Aluminium	0.7566	0.8561	0.2434	0.1439	0.4446	0.1567
Soy Bean	0.5557	0.6560	0.4443	0.3440	0.0546	−0.0080
Wheat	0.5052	0.6236	0.4948	0.3764	0.0482	0.0623

Note: Optimal portfolio weights—W_{cm-st} and W_{cm-oil} are the weights of the commodity in one-dollar portfolio which consists of commodity and stock/oil. Therefore the corresponding weights for stock market (oil market) are W_{st-cm}=1-W_{cm-st} (W_{oil-cm}=1-W_{oil-st}). The table only reports the average values of optimal portfolio weights and hedging ratios across the sample period.

are able to gain diversification benefits. They are also consistent with Öztek and Öcal (2017) who provide empirical evidence that commodity markets deliver better portfolio diversification opportunities. Investors are able to hedge financial risk when they invest in both commodity and stock markets.

Moving on the average hedge ratios calculated in Eqs. (13) and (14), the ratios differ greatly across commodities. We observe positive values of the average hedge ratios for all pairs of commodity-stock. The ratio varies from the minimum of 0.445 for aluminium-stock to the maximum of 0.033 for gold-stock. We can see that the ratios are kept at low levels in general, suggesting excellent effectiveness in hedging the risk in the Chinese stock market. Taking aluminium for example, a highest average hedge ratio is observed for aluminium-stock portfolio which means this is the most expensive hedge. The ratio (0.445) indicates that hedging a one-dollar long position (buy) in the Chinese stock market requires a short position (sell) of 0.445 cents in the aluminium futures market. In terms of the average hedge ratios for commodity-oil, we observe negative values for gold and soy bean.

The interesting results show that the short position should be changed to the long position since the oil market returns are negatively correlated with the returns of gold or soy bean, on average, during the sample period. For the remaining commodities, the hedging ratios are positive, implying that oil price risk exposure can be hedged by shorting in the commodity markets. Regarding the absolute value, it ranges from lowest of 0.005 for silver to the highest of 0.157 for aluminium. The small size of the ratios implies that the markets movements of the non-energy commodities are not highly correlated with crude oil prices, indicating an effective hedge. For example, for one dollar that is the long position in the oil market, investors should short or sell 10.62 and 15.67 cents in the copper and aluminium futures markets respectively.

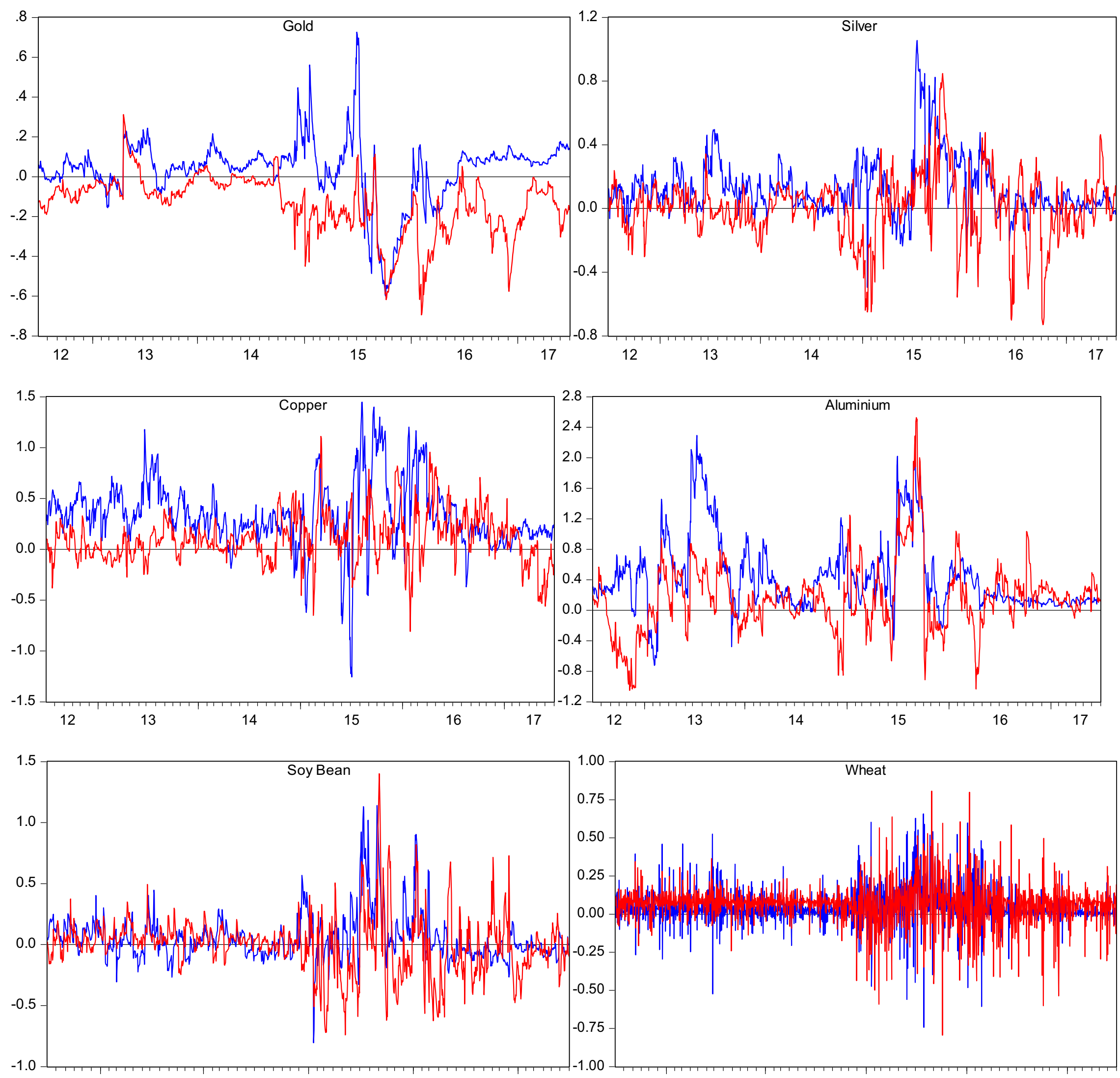

Fig. 2. The Time-varying hedge ratios Note: The blue line and red line refer β_{cm-st} and β_{cm-oil} respectively.

Overall, our empirical results indicate that inclusion of a commodity in a well-diversified portfolio of stock or oil can reduce risk without sacrificing the return. Additionally, the Chinese commodity markets can help investors to hedge their risk exposure from both local stock market and global oil market. As a result, the findings are important for investors to improve the risk-adjusted performance by establishing more diversified portfolios and executing the hedge strategy more effectively. Moreover, the hedge ratios seem to be very volatile showing that the market are not insulated from external crisis and that Chinese investor should hold a well-diversified portfolio.

Fig. 2 illustrates the evolutions of the time-varying hedge ratios for both commodity-stock and commodity-oil pairs over the sample period. The graphs indicate considerable variability across the sample period, implying that investors need to adjust their hedging strategies frequently when the market conditions change. More importantly, the patterns for hedge ratios differ across commodities under study, suggesting that those commodities have different functions in hedge strategy due to their unique characteristics.

5. Conclusion

The aim of this research is to examine the dynamic relationship among the Chinese stock market, international oil price and commodity markets. We employ dynamic frameworks to investigate the market interdependence between three different financial markets. Firstly, we undertake the bounds and Johansen and Juselius tests to examine cointegration relationships among our key market variables. We then apply the well-known VAR-BEKK-GARCH framework to capture both mean and volatility spillover effects. The estimated results indicate significant unidirectional return and volatility interaction from the Chinese

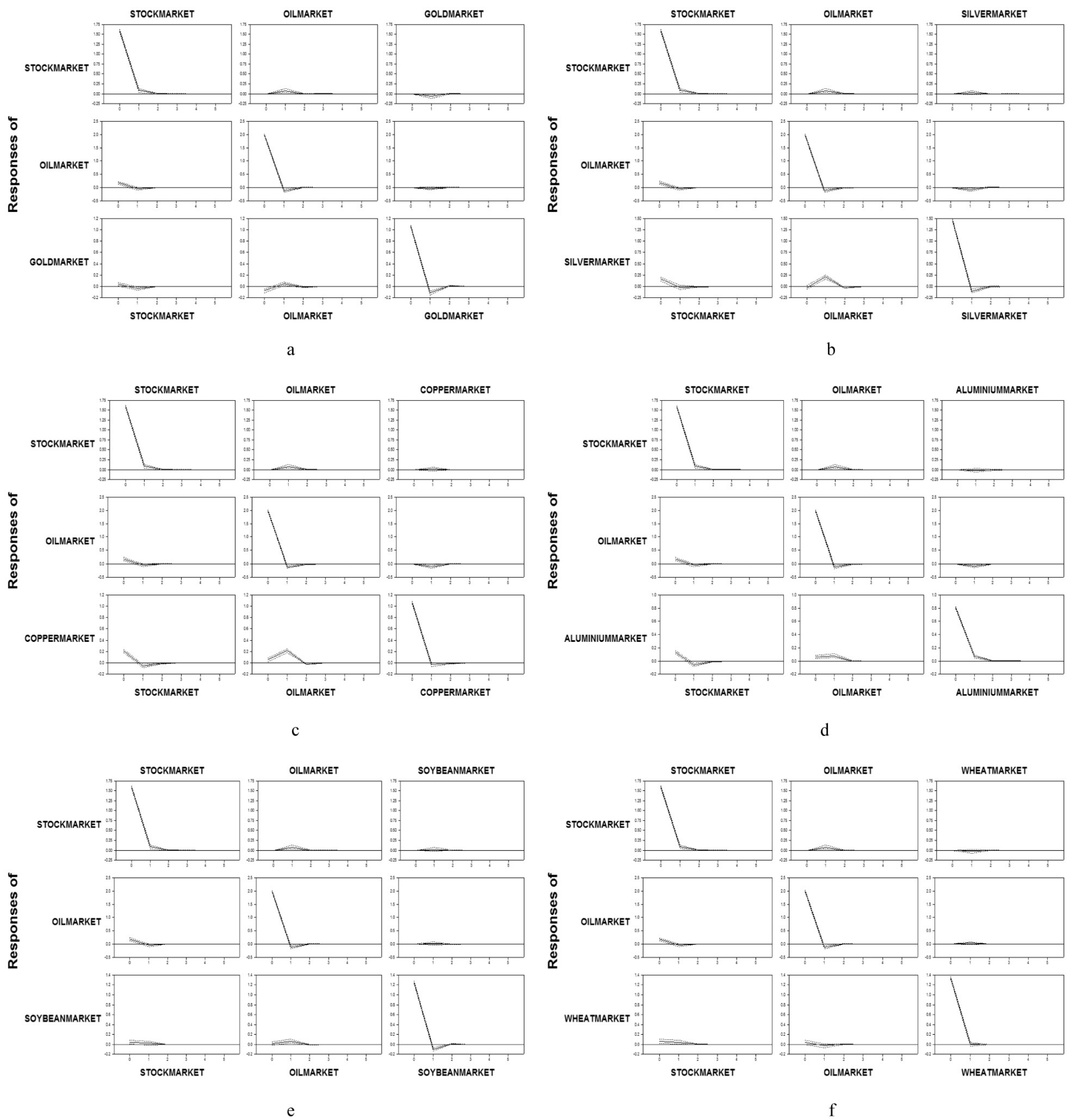

Fig. 3. a: Impulse Response for Stock, Oil and Gold Markets b: Impulse Response for Stock, Oil and Silver Markets c: Impulse Response for Stock, Oil and Copper Markets d: Impulse Response for Stock, Oil and Aluminium Markets e: Impulse Response for Stock, Oil and Soy Bean Markets f: Impulse Response for Stock, Oil and Wheat Markets

stock market and global oil markets to our key selected commodities. Particularly, we find the return spillover effect is from the international oil market to the Chinese stock market, showing strong dependence in this case. However, the oil market tends to behave independently from the Chinese stock market since there are no return spillovers from stock to oil market. In terms of the spillover effect in the returns between the stock and commodity markets in China, we can see significant contagion from the Chinese stock market to copper and aluminium futures. Similar results are observed for the interdependence between the global oil market and Chinese commodity markets. To a large extent, silver, copper and aluminium markets are found to be influenced by oil returns. In terms of forecasting, we see that a higher oil price more likely to boost the prices of silver, copper and aluminium futures. However, we find no evidence of the return spillover effects from commodity markets to both the Chinese stock market and the oil market. The may imply weak information efficiency for the Chinese commodity futures. Interestingly, we see no return spillovers between gold and stock and gold and oil market, suggesting the safe-haven role of the gold. The insignificant spillover effects between the returns of the agricultural commodities and stock/oil markets suggest weak integration of agricultural commodities.

From the volatility behaviours, we report a significant ARCH and GARCH effects in all the markets. Our results demonstrate that both shocks and volatility in oil market are able to be transmitted to the Chinese stock market. The findings highlight that the Chinese stock market is now more integrated with the international global markets, although still being less efficient in terms of information transmission. We see a strong uni-directional shock spillover from stock market to most commodity markets (e.g. gold, copper, soy bean and wheat) and volatility spillover effect from stock market to a few commodities like gold and copper. Interestingly, we note that metal futures are more sensitive to the fluctuation in the local stock market whereas the agricultural commodities react more to the shocks in the oil market. Not surprisingly, the heterogeneous volatility spillover effects across commodity markets reflect the different level of integration between these commodities and stock or oil markets.

Given the high level of uncertainties and volatile nature of financial markets in today's world, it is necessary to adopt effective risk management and hedging strategies. Our results for optimal portfolio weights and hedging ratios suggest that by adding the Chinese commodity futures into a well-diversified portfolio of stock or oil, the investment risk can be minimized without sacrificing portfolio performance. From the optimal portfolio weights, we observe both a portfolio constituting of the Chinese stock and commodity, and a portfolio holding of a commodity and oil products are more than half, except for silver. It therefore provides better hedging opportunities for investors to hold more commodities to reduce their portfolio's risk. The time-varying hedge ratios imply that investors need to adjust their hedging strategies frequently. In terms of policy implications, our findings provide valuable insights to investors, policymakers and portfolio managers. We observe that the interactions are uni-directional from both the Chinese stock market and the international oil market to other markets. Therefore these two markets provide important signals that may drive a change in investors' sentiments and approach. The weak market integration of the Chinese commodity markets indicates their usefulness in portfolio management and providing hedging opportunities. Given the increased level of integration, regulators should carefully monitor systemic financial risks and carefully act when they observe extreme market movements. Policy makers are suggested to enhance financial liberalisation reforms on commodity markets in order to enhance information transmission. With gradual financial openness policy pursued in recent years and as a major oil consumer and importer of oil, China is now more likely to be affected by the extreme fluctuations. Such market swings may also have stronger spillover and contagion effects onto its local stock market. Finally, given the continuous market reforms being conducted in China, which may have already contributed to China's increased regional interaction, further research will be critical in understanding the impact of unexpected oil price hikes on agricultural commodity markets. Importantly, further research is also necessary to examine the extent of substitution or complementary effects between markets.

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Appendix A. Supplementary data

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