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Laurier Centre for Economic Research & Policy Analysis

LCERPA Working Paper No. 2018-5

January 2018

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October 25, 2017

*An earlier version of the paper was presented at the Econometric Research in Finance (ERFIN 2016) Conference in Warsaw, at the 10th International Conference on Computational and Financial Econometrics (CFE 2016) in Seville and at the 10th Financial Risks International Forum (2017) in Paris. The authors are grateful for the comments by the seminar participants. We also thank two anonymous referees for helpful comments.

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Abstract

Chinese futures markets for agricultural commodities are among the fastest growing futures markets in the world and trading behaviour in those markets is perceived as highly speculative. Therefore, we empirically investigate whether speculative activity in Chinese futures markets for agricultural commodities destabilizes futures returns. To capture speculative activity a speculation and a hedging ratio are used. Applying GARCH models we first analyse the influence of both ratios on the conditional volatility of eight heavily traded Chinese futures contracts. Additionally, VAR models in conjunction with Granger causality tests, impulse-response analyses and variance decompositions are used to obtain insight into the lead-lag relationship between speculative activity and returns volatility. For most of the commodities, we find a positive influence of the speculation ratio on conditional volatility. The results relying on the hedging ratio are inconclusive.

JEL Classification: E44, F30, G12, G13, G15

Keywords— Speculation Ratio, Returns Volatility, Chinese Futures Markets, Agricultural Commodities

1 Introduction

Since the mid-2000s, commodity markets have witnessed turbulent times. Prices peaked in 2007-2008, and again in 2010-2011, and markets have also seen a surge in returns volatility. Furthermore, a sharp rise in the popularity of commodity investing has triggered a large inflow of investment capital into commodity futures markets. This phenomenon, known as the "financialization" of commodity markets, has encouraged an extensive debate (e.g. Cheng and Xiong, 2014). In particular, commodity index traders, who represent a new player in commodity futures markets, have become the centre of public attention. Hedge fund manager Michael W. Masters is a leading supporter of the claim that the spikes in commodity futures prices in 2007-2008 were mainly driven by long-only index investment. Masters argues that the index investment created massive buying pressure, which in turn led to a bubble in commodity prices with prices far away from their fundamental values (Masters, 2008; Masters and White, 2008). Nevertheless, the empirical literature has, so far, failed to find compelling evidence for the Masters hypothesis (Aulerich et al., 2013; Gilbert and Morgan, 2010; Irwin et al., 2009; Stoll and Whaley, 2009). Discussing several empirical findings on the influence of index traders, Irwin and Sanders (2012) conclude that index trading is unrelated to the recent price peaks.

While the academic debate about the effects of long-only index investment seems to be settled, the role of traditional speculators on commodity futures markets, the so called long-short investors,[1] still remains an empirical issue. Our research builds upon this debate and aims to investigate whether long-short speculators contribute to the observed price changes. Studies by Till (2009) and Sanders et al. (2010) come to the conclusion that long-short speculators on energy and agricultural futures markets are not to blame for the price developments in 2007-2008 because the rise in speculation was only a response to a rise in hedging demand. Brunetti et al. (2011) use Granger causality tests to analyse the relationship between changes in the net positions of hedge funds in three commodities, namely corn, crude oil and natural gas, and volatility. The authors find that such funds actually stabilize prices by decreasing volatility.[2] Miffre and Brooks (2013) also investigate the role of long-short speculators on five metals, five energy futures, four livestock futures, and twelve agricultural futures markets and conclude that speculators have no significant impact on volatility or cross-market correlation.

Only a few studies investigate the influence of futures speculation on spot returns volatility.

[1] Contrary to the long-only investors, the traditional speculators hold long (buy) but also short (sell) positions.

[2] The study is motivated by a significant increase in speculative participation from hedge funds on futures markets (Brunetti et al., 2011).

Bohl et al. (2012) analyse how expected and unexpected speculative volume and open interest of six heavily traded futures contracts impact conditional spot returns volatility. After applying their tests to two sub periods, which differ by the size of the market shares of speculators, they conclude that the financialization of commodity futures markets does not increase volatility of spot returns. Furthermore, Kim (2015) shows that speculation in futures markets can even contribute to reducing spot returns volatility, especially in recent periods, when commodities have become financial assets attracting diverse types of speculators.

The literature to date finds either no effect or even a stabilizing effect of speculation on returns volatility. However, it should be noted that all of the studies cited focus solely on commodity futures markets in the U.S. Little empirical research has been conducted to investigate the role of speculation on commodity futures markets in China. It is of great interest to find out how the results to date compare with futures markets with different market characteristics.

China's futures markets for commodities have grown rapidly in recent years. A loosening of regulations also permits foreign investors to participate in Chinese futures markets and trading volumes have increased substantially. Therefore, Chinese futures markets are increasingly gaining in global importance and Chinese prices have begun to affect global prices for commodities (Wang and Ke, 2005; Wang et al., 2016). Compared with U.S. futures markets, Chinese commodity futures markets are relatively young. However, in terms of trading volume, they already belong to the most liquid ones in the world. Additionally, anecdotal evidence suggests that trading behaviour in Chinese financial markets is highly speculative. For example, China's stock markets are often compared to casinos, with share prices bearing little connection to underlying economic conditions (The Economist, May 26, 2015). Due to strengthening stock market regulation, provoked by the collapse in Chinese stock markets in 2015, futures markets for commodities have also become very attractive to speculators lately. Recently, the Financial Times stated: "In the past month near mania has gripped China's commodity futures markets with day traders and yield-hungry wealth managers pouring into a lightly regulated sector, often with astonishing results." (Financial Times, April 27, 2016). In a similar vein, a report published by Citigroup Research describes Chinese investors as perhaps prone to being the most speculative in the world. Furthermore, the report points out that speculative trading volume on Chinese commodity futures markets has exploded in the last years and has created high returns volatility (Liao et al., 2016).

Due to its global importance and the above mentioned characteristics, it is of considerable interest to investigate speculation in Chinese futures markets. To analyse speculative behaviour, empirical studies are usally based on reports provided by the Commodity Futures Trading Commission (CFTC), which classifies weekly trading data into speculative and hedging activity. Since the often used CFTC database is only available for U.S. futures contracts, we use raw market activity data, namely trading volume and open interest, to analyse Chinese trading behaviour. This procedure provides the advantage of being able to analyse the daily patterns of speculation and is not limited to weekly observations. In particular, we use two ratios, namely the ones proposed by Garcia et al. (1986) and Lucia and Pardo (2010) that combine trading volume and open interest data to measure the relative dominance of speculative activity and hedging activity on a market. The extant literature on commodity futures markets has generally accepted the idea that volume contains information about speculative activity while open interest reflects hedging activity (Bessembinder and Seguin, 1993; Leuthold, 1983; Rutledge, 1979).

Using this approach, our paper contributes to the literature on speculation in commodity futures markets in two respects. First, the measures allow to analyse daily patterns of speculation. Second, we concentrate on Chinese futures markets which receive, despite their growing global importance, much less attention than U.S. futures markets. Our empirical analysis relies on GARCH models and Granger causality tests to examine both contemporaneous and lead-lag relationships between speculative activity and conditional returns volatility in eight heavily traded agricultural commodities, namely soybean, soybean meal, soybean oil, palm oil, corn, rapeseed oil, cotton and sugar. In contrast to the available literature we find a positive influence of the speculation ratio on conditional returns volatility, which indicates that a rise in speculative activity leads to an increase in returns volatility. Moreover, for most of the commodity contracts the speculation ratio positively Granger causes conditional returns volatility and vice versa. The results of the hedging ratio are inconclusive.

The remainder of this paper is structured as follows: A short introduction of China's commodity futures markets and an overview of relevant literature is given in section 2. In section 3 we outline the speculation measures. After presenting data and preliminary tests in section 4 and econometric methods in section 5, we discuss the empirical results in section 6. Section 7 summarizes our findings and concludes.

2 Characteristics of Chinese Commodity Futures Markets

Chinese futures markets were established in the early 1990s and have been rapidly evolving since then. Currently, there are four futures exchanges in China, namely, the Dalian Commodity Exchange (DCE), the Zhengzhou Commodity Exchange (ZCE), the Shanghai Futures Exchange (SHFE) and the China Financial Futures Exchange (CFFEX). While metal futures are mainly traded on the SHFE and financial futures on the CFFEX, the DCE and the ZCE are specialized in trading futures for agricultural commodities. Therefore, our analysis is focused on the two last-mentioned. All four futures exchanges have exhibited an impressive development over the past decade. Due to loosen regulations, foreign investors now trade Chinese commodity futures and China's key contracts have become the most widely-traded commodity futures contracts in the world. According to the latest annual futures and options volume survey, published by the Futures Industry Association (FIA), the DCE's trading volume reached 1.54 billion contracts in 2016 and the DCE became the 8th largest exchange in the world. The ZCE is now the 11th largest exchange in the world with a total trading volume of 901 million contracts in 2016 (Acworth, 2017).

[Table 1 about here]

Table 1 shows trading volumes of the global top 20 agricultural commodity contracts in 2016. In terms of trading volume, eleven of the global top 20 commodity contracts are traded on Chinese exchanges. Obviously China with nine contracts among the top 10, is already the biggest player in the global agricultural futures markets. The ZCE and the DCE have fully functional electronic systems including trading, delivery, clearing, risk control, news release, member services, etc. (Wang et al., 2016). Soybean meal is the most liquid contract with a trading volume of 389 million contracts in 2016. But trading volumes in rapeseed meal, palm oil, corn and white sugar have also exceeded the trading volumes of their U.S. equivalents. The DCE corn futures contract, for example, showed a trading volume of 122 million contracts in 2016, while the Chicago Board of Trade (CBOT) corn contract was traded 85 million times in the same year.

Compared to U.S. futures markets which are already well established, Chinese futures markets are relatively young. Thus, academic research on China's futures markets is far less extensive. Most of the existing studies on Chinese commodity futures markets concentrate on price linkages and information transmission across markets (Zhao, 2015). For instance, Du and Wang (2004) compare the ZCE wheat futures price behaviour with the one of the CBOT and conclude that futures prices of the ZCE and the CBOT are interrelated but not co-integrated. In the same vein, Hua and Chen (2007) investigate the relationship between the Chinese and the world futures markets for copper, aluminium, soybean and wheat. Similarly, the authors do not find co-integration between the ZCE and CBOT wheat futures prices but their study shows that the futures prices for copper and aluminium contracts, traded on the SFE, are co-integrated with the futures prices of the London Metal Exchange (LME) for these contracts. They get the same results for soybeans futures prices of the DCE and the CBOT. Moreover, Fung et al. (2003) explore the pattern of the information flow and market efficiency between U.S. and Chinese commodity futures markets for copper, soybeans and wheat. Their results indicate that while the U.S. has a strong impact on the pricing of Chinese copper and soybean futures, there is no pricing interaction for wheat futures. The authors explain the latter result with the strong regulation of the Chinese wheat market.

Cross-correlation properties of agricultural futures markets between Chinese and foreign markets are examined by Li and Lu (2012) and Fung et al. (2013). Fung et al. (2013) analyse 16 Chinese commodity futures contracts and their linkages to corresponding foreign markets. They find significant cross-correlations for maize and wheat in the short-run. Lee et al. (2013) examine the effect of a structural change on the flow of information between the U.S. agricultural futures markets and China after 2002. Their tests show that cotton and soybeans futures markets were integrated, whereas the corn futures markets were not integrated after the structural change. A relatively new study by Motengwe and Pardo (2016) explores information flows across four wheat futures markets on four continents, namely ZCE, South African Futures Exchange (SAFEX), Euronext, Liffe and Kansas City Board of Trade (KCBT). The study finds no evidence for long-run relationships among the markets examined.

The literature indicates a continuing improvement in the efficiency of the young market and also a growing global importance over the years. However, Wang et al. (2016) show that Chinese agricultural futures markets are still not resilient against large market price movements. As a possible explanation for their results, the authors name speculative behaviour, which makes those markets less able to absorb order imbalances. Only two studies are directly related to our study. Chan et al. (2004) analyse the daily volatility behaviour in Chinese futures markets for copper, mungbeans, soybeans and wheat. The authors find that volume is positive related to volatility, whereas open interest has a negative impact on volatility. Their findings imply a positive effect of speculative activity on volatility. Another similar study, by Chen et al. (2004), investigates the relationship between returns and trading volume for copper, aluminium, soybean and wheat futures contracts. Using correlations and Granger causality tests, the authors report significant positive contemporaneous correlations between absolute returns and trading volume. They also find significant causality from absolute returns to trading volumes. A significant causality from trading volumes to absolute returns is found only for copper.

Although Chinese commodity futures markets have developed quickly, there is still not much investigation of the role of speculators on commodity futures markets in China. Except for the two studies cited earlier which indicate a positive influence of (speculative) trading volume there is only anecdotal evidence suggesting a highly speculative trading behaviour on Chinese commodities futures markets. In the latest report of the Citigroup research

2016,[3] Chinese investors are described as being the most speculative in the world. The Citi report also states that most trades on Chinese futures exchanges are conducted through high-frequency transaction with the average tenure of each contract less than four hours. Furthermore, the report points out that speculative trading volumes on Chinese commodity futures markets have exploded in the last years, which in turn created high returns volatility (Liao et al., 2016). Against this backdrop, the aim of our paper is to analyse the relation between speculative activity and returns volatility in Chinese futures markets of agricultural commodities.

3 Measures Construction

In the academic literature on futures markets, there are different methods for distinguishing between speculative and hedging activity. One very common way of approaching the question is to use data from the Commitments of Traders (COT) reports provided by the U.S. Commodity Futures Trading Commission (CFTC). The original COT report, which separates solely traders into commercial (hedgers) and non-commercial traders (speculators), has been put into question many times from diverse perspectives (Ederington and Lee, 2002; Peck, 1982). To deal with these concerns, the CFTC publishes two variations to the COT reports, the Disaggregated Commitments of Traders (DCOT) report and the Supplemental Commitments of Traders (SCOT).[4] Nevertheless, CFTC data are publicly available only at a weekly level and therefore not suitable for analyses which aim to examine the short term dynamics of commodity prices. To investigate the effects of speculative activity on returns volatility, empirical analyses should be based on data of at least daily frequency. Furthermore, the CFTC publishes only data for specific futures contracts traded on markets in the U.S. Hence, to investigate Chinese futures markets, different methods to separate hedging from speculative activity must be applied.

Therefore we compute two ratios, both of which combine daily figures of volume and open interest, to analyse the character of trading activity on a specific trading day. Daily trading volume captures all trades for a particular contract which are executed during a specified day. Open interest describes all positions of that contract which are neither equalized by an opposite futures position nor fulfilled by the physical delivery of the commodity or by cash settlement. The first ratio is proposed by Garcia et al. (1986) and is defined as daily trading

[3] The Citigroup report, a technical report, describes the recent developments on Chinas futures markets for commodities. Developments of trading volume and futures returns of several Chinese commodity futures contracts are analysed.

[4] For more details about the CFTC database see Stoll and Whaley (2009) as well as Irwin and Sanders (2012).

volume (TV_t) divided by end-of-day open interest (OI_t):

$$Ratio_t^{Spec} = \frac{TV_t}{OI_t}. \tag{1}$$

The speculation ratio measures the relative dominance of speculative activity in the contract analysed in comparison to the hedging activity. A high (low) speculation ratio indicates high (low) speculative activity with respect to hedging activity. Therefore, a rise in the speculation ratio reflects a rise in the dominance of speculators in the market.

The idea behind the speculation ratio lies in the assumption that hedgers hold their positions for longer periods, whereas speculators mainly try to avoid holding their positions over night. Based on different trading behaviours, speculators and hedgers influence the amount of trading volume and open interest in a different way. Speculators mostly impact on trading volume instead of open interest because they buy and sell contracts during the day and close their positions before trading ends. Thus outstanding contracts at the end of a trading day are mainly held by hedgers (Bessembinder and Seguin, 1993; Leuthold, 1983; Rutledge, 1979). Obviously, the ability of the ratio to measure the dominance of speculative activity depends on the assumption that hedgers and speculators sit on their trading position for different time periods. There is empirical evidence that seems to confirm the assumption that hedgers tend to hold their position for longer periods than speculators (Ederington and Lee, 2002; Wiley and Daigler, 1998).

We also use a second ratio, which is proposed by Lucia and Pardo (2010), to provide supportive results for the first one. The second ratio is also based on the different trading behaviour of speculators and hedgers, but relates daily trading volumes to open interest in a different way. The ratio gauges the relative importance of hedging activity instead of speculative activity on a specific trading day and is defined as the daily change in open interest ($\Delta OI_t = OI_t - OI_{t-1}$) divided by daily trading volume:

$$Ratio_t^{Hedge} = \frac{\Delta OI_t}{TV_t}. \tag{2}$$

The change in open interest during period t is a measure of net positions being opened or closed each day and held overnight and is used to capture hedging activity. Since the change of open interest during period t is in the range $[-TV_t, +TV_t]$, the hedging ratio can only take on values in the range of [1 and -1] (Lucia et al., 2015). While a positive value of the hedging ratio indicates that the number of opened positions has exceeded the number of closed positions, a negative value implies that the number of closed positions is greater than the number of opened ones. Therefore, a hedging ratio with a value close to one or minus one, indicates low speculative activity in contrast to hedging activity in the contract examined. A value close to zero indicates relatively high speculative activity (Palao and Pardo, 2012). The correlation between the two ratios used in this study should be negative.

Based on the speculation ratio (1) we are able to investigate the role of short term speculators on commodity futures markets. In a few studies, short term speculation in U.S. futures markets is explored by using the speculation ratio. For agricultural commodities Streeter and Tomek (1992) find a positive influence of the speculation ratio on returns volatility for soybeans. Robles et al. (2009) investigate speculative activity in four agricultural future markets and find a Granger causal relationship between the speculation ratio and prices for wheat and rice. Using GARCH models, Manera et al. (2013) find a positive influence of the speculation ratio on returns volatility for energy and for agricultural commodities traded in the U.S. More recently Chan et al. (2015) examine the role of speculators on oil futures markets by using the speculation ratio to proxy speculative activity and conclude that the oil futures market is dominated by uniformed speculators in the post-financialization period.[5] Only Lucia et al. (2015) apply both the speculation (1) and hedging ratios (2) to explore the relative importance of speculative activity versus hedging activity in the European carbon futures market. The authors show the different dynamics of speculative behaviour during three phases of the European Union Emission Trading Scheme.

4 Data and Preliminary Analysis

To examine China's agricultural commodity markets, we analyse eight heavily traded commodity futures contracts for soybeans,[6] soybean meal, soybean oil, palm oil, corn, rapeseed oil, cotton and sugar. The contracts for soybeans, soybean meal, soybean oil, palm oil and corn are traded on the DCE, whereas rapeseed oil, cotton and sugar contracts are traded on the ZCE. We have selected some of the most active agricultural contracts. According to their trading volumes, all of the chosen contracts belong to the top 20 liquid agricultural futures contracts (see Table 1). For all eight contracts, daily prices (settlement prices) and daily figures of trading volume and open interest (end of day) are obtained from Thomson Reuters Datastream. We use continuous futures price series, which are calculated by using the price of the nearest contract month as a starting point until the contract reaches its expiry date. Afterwards prices of the next trading contract month are taken. Prices of

[5] The speculation ratio has not only be used to investigate commodity markets. Chatrath et al. (1996), for instance, apply the speculation ratio to examine the influence of speculation on the volatility of exchange rates.

[6] In 2001, the DCE soybean futures contract has been divided into two types. Since a non-genetically modified contract (No. 1 soybean) and a genetically modified soybeans contract (No. 2 soybean) are traded on the DCE (Liu et al., 2015). In our analysis the no. 1 soybean contract is used.

contracts are quoted in Chinese Renminbi (RMB) per 10 metric ton (MT),[7] daily trading volumes represents the number of contracts traded during a day and open interest reflects the number of contracts outstanding at the end of a trading day. The sample periods extend from 2003 to 2017 for soybean meal and soybeans, from 2004 to 2017 for corn and cotton, from 2006 to 2017 for soybean oil and sugar, from 2007 to 2017 for palm oil and from 2012 to 2017 for rapeseed oil. Table 2 provides the key specifications for each futures contract.

[Table 2 about here]

To control for macroeconomic factors that are important to commodity returns and its volatility we follow, among others, Kim (2015) and Manera et al. (2016) and add five different economic variables in our estimated specifications. Since these papers deal with U.S. commodity futures markets, we have tried to find equivalent variables suitable for China. The first is the RMB exchange rate vis-à-vis the U.S. Dollar. Since prices for the eight commodity contracts are quoted in RMB, changes in the exchange rate are assumed to affect the commodity prices. For instance, exchange rate changes influence exports and imports of commodities. Oil price shocks influence commodity prices in different ways. A surge in oil prices, for example, increases transportation costs and thus can affect commodity supply. Moreover, an increase in oil prices may boost demand for agricultural commodities that are used in biofuel production. Therefore, the ICE Brent crude oil futures contract, which can be seen as a benchmark for the world price of oil, is used as the second control variable. The usage of the two mentioned variables is motivated, for instance, by Chen et al. (2010), Ji and Fan (2012) and Nazlioglu and Soytas (2012).

Furthermore, following Frankel (2006) and Akram (2009), we model interest rate changes to control for effects of Chinese monetary policy decisions, by applying Chinese ten years treasury bond futures contract. In line with Tang and Xiong (2010), we apply the MSCI World Index of equity prices to proxy for world demand and the MSCI Emerging Markets Index to proxy for the demand in emerging economies such as China, Brazil and Russia. Since the MSCI Emerging Markets Index reflects economic conditions in China, we assume changes in this variable can influence Chinese commodity futures prices. All five macroeconomic time series are obtained from Thomson Reuters Datastream as well.

Table 3 displays summary statistics for returns (r_t), open interest (OI_t), trading volume (TV_t), the speculation ratio ($Ratio_t^{Spec}$) and the hedging ratio ($Ratio_t^{Hedge}$) for all eight commodities examined. The table also shows summary statistics for the five macroeconomic variables. For all time series, mean, maximum (Max), minimum (Min), standard deviation

[7] Solely for cotton the contract size is 5 MT.

(Std.Dev.), skewness, kurtosis and Jarque-Bera statistics are given.

[Table 3 about here]

Several interesting observations can be made from Table 3. Mean returns are close to zero and positive for most of the time series examined. According to the distance of the extreme values (minimum, maximum) and the standard deviation of the returns, the market for palm oil displays the highest volatility. Skewness and kurtosis parameters indicate that none of the eight return time series follows a normal distribution. This is confirmed by the Jarque-Bera statistics. Regarding the results of Jarque-Bera tests the null hypothesis of normal distribution is rejected for all time series at the 1 percent level.

[Figure 1 about here]

Figure 1 shows log returns for the eight commodity contracts examined. The graphs visualize volatility clusters. Since returns are characterized by conditional heteroscedasticity, we apply non-linear processes such as the GARCH model. Additionally, the graphs indicate that years between 2007 and 2009 were highly volatile for most of the commodities examined. When looking at Figure 2, the speculation ratios for sugar and palm oil futures have the highest means with 1.39 and 1.30. The ratio for corn futures shows the lowest mean with 0.48. Note that a high ratio implicates a high amount of speculative activity compared to hedging activity. In addition, the speculation ratio of cotton futures appears to be most volatile as indicated by its high standard deviation. The mean values of the hedging ratios are close to zero and negative for all contracts except for rapeseed oil. A ratio close to zero indicates high speculative activity. Palm oil and sugar show the highest speculation, as their means for the hedging ratio are the closest to zero.

[Figure 2 about here]

In international comparison, trading on Chinese futures markets is assumed to be highly speculative. To investigate this assertion, we compare the speculative activity on Chinese markets to speculation on U.S. markets. For that reason, we calculate the speculation ratio not only for the eight Chinese contracts, but also for equivalent commodity contracts, traded on U.S. markets. Since for palm oil and rapeseed oil there are no comparable U.S. contracts, we use a Malaysian palm oil contract and a Canadian rapeseed oil contract instead. Figure 2 visually compares the calculated speculation ratios for the eight Chinese contracts to the calculated speculation ratios for the eight other markets. The graphs clearly show that the speculation ratios of Chinese contracts are generally higher than the ones calculated for the U.S., Malaysian and Canadian contracts. This implies that in contrast to these markets, Chinese markets are dominated by short term traders, who go in and out of the market during the same day and therefore raise the trading volume instead of the open interest. On U.S. markets, however, hedgers that hold their position for longer periods and therefore mainly impact on open interest, play a more dominant role than short term speculators.

To draw a comparison based on the hedging ratio, we follow Palao and Pardo (2012, 2014) and calculate the number of days on which the hedging ratio is between [-0.025, 0.025]. Trading days in this interval are characterized by an abnormal number of short term traders. While values close to one indicate days on which traders massively opening positions, and values close to minus one identify those days where traders massively close positions, values close to zero indicate days dominated by traders that open and close positions on the same day. Again, we count the number of days on which the hedging ratio is between [-0.025, 0.025] not only for the eight Chinese commodity contracts but also for the eight equivalent U.S., Malaysian and Canadian contracts. The number of days on which the hedging ratio is close to zero is greater for most of the Chinese contracts. Only for U.S. soybean and corn contracts the number of days, marked by an abnormal number of short term traders, is higher.

[Figure 3 about here]

In Figure 3 the monthly development of the number of days when the hedging ratio for the eight commodities of Chinese and U.S. markets is between [-0.025, 0.025] are displayed. The number of days, that show an abnormal number of short term speculation per month is, on average, always higher for Chinese contracts than for U.S., Malaysian and Canadian contracts, except for soybean and corn contracts.

To test for stationarity we apply the augmented Dickey and Fuller (1979) (ADF) unit root tests on prices, returns, speculation ratio and hedging ratio for all eight commodities examined. The number of lags are selected in accordance with the Schwarz information criterion. Results of ADF tests are presented in Table 4. The results show that prices contain a unit root, whereas the ADF test clearly rejects the unit root hypothesis for returns and both ratios for all eight contracts, as well as for the five macroeconomic time series (log differences) considered. Thus, each of the time series used in the empirical tests is stationary. To test for conditional heteroscedasticity we perform Engle's Lagrange Multiplier (LM) test (Engle, 1982) on returns. The test results, also displayed in Table 4, show that GARCH effects, which imply volatility clusters, are present in all time series. The results of LM tests motivate the usage of the GARCH model. Therefore, our variable of interest, namely the volatility of returns, is proxied by conditional variances estimated via the GARCH model. As shown by the summary statistics none of the return series are normal distributed. Hence, we follow Nelson (1991) and use the Generalized Error Distribution (GED) for the GARCH models.

[Table 4 about here]

5 Methodology

5.1 GARCH-Model

To analyse the impact of speculative activity, proxied by the speculation and the hedging ratio, on returns volatility, a generalized autoregressive conditional heteroscedasticity (GARCH) model (Bollerslev, 1986), is used. Our AR(1)-GARCH(1,1) model is written as follows:

$$r_t = a_0 + a_1 r_{t-1} + \sum_{j=1}^{5} b_j X_{j,t} + \varepsilon_t \tag{3}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 Ratio_t^{Spec,Hedge} \tag{4}$$

where $r_t = (ln(P_t) - ln(P_{t-1})) \times 100$ is the return on day t, σ_t^2 is the conditional variance on day t and $Ratio_t^{Spec,Hedge}$ describes the speculation ratio on day t in the first specification and the hedging ratio on day t in the second specification.[8] The mean equation (3) models the returns as a first-order autoregressive (AR) process and includes the set of five macroeconomic factors denoted by $X_{j,t}$. We use log differences of the five macroeconomic variables to induce stationarity. The relationship between conditional variances and speculative activity has been modelled by the variance equation (4). The parameter α_1 captures the ARCH effect, which measures the reaction of conditional variance to new information, whereas β_1 describes the GARCH effect, which displays the duration of a shock to die out.

The influence of speculative activity, proxied either by the speculation or the hedging ratio, is captured by the parameter γ_1. Regarding the speculation ratio, a positive sign

[8] We apply a GARCH model of order p = 1 and q = 1, since a number of researchers have frequently demonstrated the suitability of GARCH (1,1) models to represent the majority of financial time series (Bera and Higgins, 1993). For example, Kim (2015) and Manera et al. (2013, 2016) have used a GARCH(1,1) model to estimate conditional volatility on agricultural commodity futures markets. Our preferred model is chosen based on the ARCH LM test.

of γ_1 implies that speculative activity amplifies returns volatility, whereas a negative sign indicates that speculative activity decreases returns volatility.

In order to ensure a linear relationship between the hedging measure and intraday speculation, we include absolute values of the hedging ratio in the analysis. The lower the absolute value of the hedging ratio, the higher the intraday speculation. Therefore, a negative sign of γ_1 indicates that speculation drives volatility, while a positive sign means that speculation stabilizes the market. Furthermore, the GARCH (1,1) model has a number of restrictions to ensure a positive conditional variance, i.e., $\alpha_0 > 0, \alpha_1 \geq 0, \beta_1 \geq 0, \alpha_1 + \beta_1 \leq 1$.

5.2 VAR-Model

The previously introduced GARCH model measures the possible influence of speculative activity on conditional volatility and not vice versa. Since not only speculation can drive returns volatility, but high returns volatility also can attract speculators' attention and thus lead to speculative activity, we are also interested in the lead-lag relationship between the two variables. To investigate the dynamic relationship between returns volatility and speculative activity, we use the following vector autoregressive (VAR) model:

$$\sigma_t^2 = a_{1,t} + \sum_{i=1}^{k} b_{1,t}\sigma_{t-i}^2 + \sum_{i=1}^{k} c_{1,t} Ratio_{t-i}^{Spec,Hedge} + \varepsilon_t \tag{5}$$

$$Ratio_t^{Spec,Hedge} = a_{2,t} + \sum_{i=1}^{k} b_{2,t}\sigma_{t-i}^2 + \sum_{i=1}^{k} c_{2,t} Ratio_{t-i}^{Spec,Hedge} + \upsilon_t. \tag{6}$$

In the VAR equations the conditional variance (σ_t^2), the speculation ratio $Ratio_t^{Spec}$ and the absolute value of the hedging ratio $Ratio_t^{Hedge}$ are dependent on their own lagged values and on the lagged values of the respective other variable. Returns volatility is proxied by conditional variance estimated from the previous AR(1)-GARCH(1,1) model ((3) and (4)) but omitting the influence of the ratios in the variance equation.

Optimal lag lengths (k) for each variable for the VAR models are determined by minimizing the Schwarz information criterion. We set a maximum lag length of kmax=20 (four trading weeks). For this purpose, all possible combinations between 1 and 20 lags of the variables are estimated. ϵ_t and μ_t represent the residuals of the regression, which are assumed to be mutually independent and individually i.i.d. with zero mean and constant variance.

Based on (5) and (6), we perform three further analyses, namely Granger causality tests, variance decompositions and impulse response estimations. Granger causality tests (Granger, 1969) are applied to gain information about the lead-lag relationship between returns volatility and the speculation ratio or, alternatively, the hedging ratio. The test will help to answer the question of whether speculative activity causes conditional volatility in a forecasting sense and/or vice-versa. To test for Granger causality we estimate a standard F-test and test the null hypothesis, that speculative activity (conditional volatility) does not Granger cause conditional volatility (speculative activity). The hypothesis is rejected if coefficients of the lagged values are jointly significantly different from zero ($\beta_1 \neq \beta_2 \neq ... \neq \beta_k \neq 0$).

Next, we obtain the variance decompositions. These measure the percentage of the forecast error of a variable that is explained by another variable. It indicates the conditional impact that one variable has upon another variable within the VAR system. Variance decompositions provide an indication of the economic significance of each one of the variables in the VAR model as a percent of the total forecast error variance (Fung and Patterson, 1999). To find out whether the causal relationships are positive or negative we then compute impulse response functions. These show the impact of an exogenous shock in one variable on the other variables of the VAR system. We uses these to visually represent and analyse the behaviour of volatility on simulated shocks in the speculation ratio or in the hedging ratio respectively and vice versa.

6 Empirical Results

6.1 GARCH - Results

Table 5 and 6 contain the empirical findings of the GARCH(1,1) models using the speculation and the hedging ratio, respectively. The interpretation of the mean equations is similar for both tables. The MCSI Emerging Markets Index, which is used to proxy the general influence of the Chinese economy, has a significant positive influence for all of the examined commodities. Whereas, the MSCI World Index, which presents the development of the world economy, shows a significant negative influence on the majority of the eight contracts, except for soybean meal and palm oil. Furthermore, the results indicate a significant positive influence of the oil price for most of the contracts, with the exception of palm oil, sugar and rapeseed oil. A highly significant negative influence of the exchange rate is observed except for corn and sugar. Interest rates are statistically insignificant in most of the cases.

[Table 5 and 6 about here]

The variance equation models the relationship between conditional volatility and speculative activity, measured by the two ratios. Table 5 displays the empirical results relying on the speculation ratio. In the majority of cases GARCH and ARCH parameters are highly statistically significant and positive, except for cotton. Stationarity requirements that shocks die out in finite time are met for all contracts. The constant, which represents the time-invariant level of conditional variance, is positive and highly significant for the majority of the contracts examined. The significant positive parameters of the speculation ratio implicate that conditional volatility is driven by speculative activity in each case, with the sole exception of palm oil.

Results of the second specification, when the hedging ratio is used as an explanatory variable are presented in Table 6. Again for all contracts examined, GARCH and ARCH parameters are highly significant and positive. Additionally, all stationarity requirements are met. The influence of the hedging ratio is inconclusive. The hedging ratio has a significantly negative influence on conditional volatility only in the case of cotton, indicating a stabilizing influence of hedging activity and supporting the results of the first GARCH model. However, there is no significant influence of the hedging ratio for corn, sugar and rapeseed oil and a significant positive influence in the case of soybean meal, soybean oil, soybeans and palm oil.[9]

6.2 VAR - Results

Table 7 reports the results of Granger causality tests between the speculation ratio (hedging ratio) and conditional volatility for all eight commodities examined. The table also contains the number of observations, F-statistics, probability values and the number of lags of Granger causality relations. Starting with the results relying on the speculation ratio, we can reject the null hypothesis of no Granger causality for soybean meal, soybean oil, soybeans, sugar and cotton in both directions. Hence, the speculation ratio Granger causes conditional volatility and conditional volatility causes the speculation ratio in the Granger sense. These results imply that the amount of speculative activity in relation to hedging activity contains information about changes of volatility in the future. Additionally, current volatility involves information about futures speculative activity. For corn no Granger causality relationship is observable. Palm oil and rapeseed oil show only one way relationships. In particular, conditional volatility of the palm oil contract Granger causes speculative activity but not vice versa, while speculative activity in the rapeseed oil market Granger causes conditional volatility but not vice versa.

[Table 7 about here]

[9] GARCH-in-Mean (GARCH-M) tests are also applied to the data but GARCH terms in the mean equations are not significant. Higher order AR terms added in the mean equation are either insignificant or do not change the conclusions.

Again the results of the hedging ratio are less conclusive. For soybean meal, soybeans, and palm oil the null hypothesis can be rejected for both directions, indicating a Granger causal feedback relationship. In the case of soybean oil and sugar, the results indicate that the hedging ratio Granger causes conditional volatility but not vice versa. We can not find a significant Granger causality relationship for corn and rapeseed oil. Conditional volatility in the cotton market Granger causes the hedging ratio but not vice versa.

The VAR estimation results are also used to perform a variance decomposition for all commodities examined. Results of the variance decompositions for volatility and speculation ratio as well as the hedging ratio are presented in Table 8. Table 8 presents results in percent for trading days 1, 5, 15 and 20. Across all contracts examined, we observe similar results. Variations in volatility are mostly caused by their own lagged values, while the speculation ratio appears to play only a minor role in explaining return volatility. Own lagged values of the speculation (hedging) ratio are also mainly responsible for its own variation. Thus lagged volatility only explains a small effect of the variation of the two ratios.

[Table 8 about here]

Figures 4, 5, 6 and 7 display impulse response functions for all commodities examined. We only present impulse response functions for commodities for which we were able to find significant Granger causality relations. Shocks are defined as one standard deviation and are regarded over a period of 20 trading days. Figure 4 shows the responses of conditional volatility to shocks in the speculation ratio, whereas Figure 5 displays the responses of the speculation ratio to volatility shocks. Regarding the speculation ratio, for all commodities, the responses of conditional volatility to shocks in the speculation ratio are positive, which implies that a rise in speculative activity leads to a rise in returns volatility. The rise of volatility persists up to five days for soybeans, up to nine days for soybean meal and up to twelve days for sugar and afterwards each volatility converged to its mean. However, only the responses for soybeans and sugar volatility to shocks in the speculation ratio are significant for all 20 trading days. Responses of soybean meal and cotton volatility become significantly positive only after four trading days and after eight trading days for soybean oil. The response of rapeseed oil volatility becomes insignificant after three days. Volatility shocks, visualized in Figure 5, also produce only positive responses of the speculation ratio for all commodities, with one exception for palm oil. The response of palm oil is insignificant and therefore not interpretable. In all the other cases, speculative activity is driven by increases in volatility.

Responses of conditional volatility to shocks in the hedging ratio are presented in Figure 6 and responses of the hedging ratio to volatility shocks are displayed in Figure 7. The responses of volatility to shocks in the hedging ratio are significantly positive for soybean oil, soybeans, palm oil and sugar. The results stand in contrast to the observed results using the speculation ratio. Negative responses of the hedging ratio to shocks in volatility are shown in Figure 7 for soybean meal, soybeans and cotton. The findings indicate that high volatility attracts mainly speculators and fewer hedgers. In most of the cases, the results of the VAR model support the results obtained with the GARCH models.

[Figures 4, 5, 6 and 7 about here]

7 Conclusion

Motivated by periods of high returns volatility and the ongoing financialization of agricultural commodity futures markets, we investigate the impact of speculative activity on returns volatility in Chinese commodity futures markets. We focus on Chinese futures markets because these markets are believed to be highly speculative. Additionally, China's futures markets for commodities have grown rapidly in the last few years and their global importance is increasing. However, the impressive development of Chinese commodity futures markets is not matched by research on those markets. In particular, empirical studies on speculation in Chinese futures markets are limited.

Therefore, we consider a speculation ratio, defined as trading volume divided by open interest, to capture the relative dominance of speculative activity in China's futures markets. To examine the robustness of our results we use a second ratio which captures the relative importance of hedging behaviour instead of speculative behaviour by combining volume and open interest data in a different way. To estimate the influence of speculative activity, proxied by the two ratios, on returns volatility, we estimate both GARCH and VAR models. The empirical tests enable us to get insight into the contemporaneous and the lead-lag relationships between speculative activity and returns volatility of eight heavily traded Chinese futures contracts, namely soybeans, soybean meal, soybean oil, palm oil, corn, rapeseed oil, cotton and sugar. From the GARCH model we find a positive influence of the speculation ratio on returns volatility for most of the commodities examined. Indicated by the results, a rise in speculative activity can lead to an increase in returns volatility. This deduction is supported by the Granger causality tests which show that the speculation ratios for most of the commodities Granger cause conditional volatility and vice versa. The findings imply that the amount of speculative activity in relation to hedging activity can contain information about changes in futures volatility.

The positive influence of the speculation ratio is in line with the results of Manera et al.

(2013), who analyse speculation on agricultural futures markets in the U.S. The authors rely on the same speculation measure as we do, but additionally include measures based on CFTC position data into a GARCH model of the same kind employed in this study. They find that the speculation ratio has a significant positive impact on returns volatility, while the CFTC speculation measures exhibit a negative effect. However, CFTC position reports provide weekly data and capture rather the long term than the short term dynamics of speculation. We are not able to carry out the same analysis for Chinese futures markets since trading position data reports like the CFTC reports are not available for China.

To summarize, our results show that short term speculation, captured by the speculation ratio, tends to amplify returns volatility for Chinese agricultural commodity futures returns. Since the positive influence of the speculation ratio is not supported by the results of the hedging ratio, our results are inconclusive but they do not support various markets reports (e.g. Liao et al., 2016) which conclude that Chinese futures markets are rife with speculative activity. Further research is needed to analyse speculative trading behaviour on Chinese futures markets. This study is to be seen as a basis for future research, which will contribute to a better understanding of speculation and its relation to returns volatility on Chinese futures markets.

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Table 1: Top 20 Global Agricultural Contracts

	Contract	Volume Jan-Dec 2016
1	**Soybean Meal Futures, DCE**	388,949,970
2	**Rapeseed Meal Futures, ZCE**	246,267,758
3	**Palm Oil Futures, DCE**	139,157,899
4	**Corn Futures, DCE**	122,362,964
5	**White Sugar Futures, ZCE**	117,293,884
6	**Rubber Futures, SHFE**	97,371,256
7	**Soybean Oil Futures, DCE**	94,761,814
8	Corn Futures, CBOT	85,625,219
9	**Cotton No. 1 Futures, ZCE**	80,530,129
10	**Corn Starch Futures, DCE**	67,445,264
11	Soybean Futures, CBOT	61,730,753
12	Sugar Futures, ICE Futures U.S.	33,115,334
13	**No. 1 Soybean Futures, DCE**	32,570,158
14	Chicago Soft Red Winter Wheat Futures, CBOT	31,059,726
15	Soybean Oil Futures, CBOT	29,429,298
16	**Rapeseed Oil Futures, ZCE**	27,312,246
17	Soybean Meal Futures, CBOT	25,953,938
18	Corn Options, CBOT	22,794,484
19	**Egg Futures, DCE**	22,474,739
20	Soybean Options, CBOT	20,109,648

Notes: This table presents trading volume for top 20 global agricultural futures contracts in 2016. Data are obtained from FIA 2016 Annual Volume Survey (Acworth, 2017).

Table 2: Contract Specifications

Contract	Exchange	Contract Size	Currency	Sample	Obs.
Soybean Meal	DCE	10 MT	RMB	9/09/2003 7/10/2017	3139
Soybean Oil	DCE	10 MT	RMB	1/09/2006 7/10/2017	2064
No. 1 Soybeans	DCE	10 MT	RMB	9/08/2003 7/10/2017	3142
Palm Oil	DCE	10 MT	RMB	10/31/2007 7/07/2017	3475
Corn	DCE	10 MT	RMB	9/22/2004 7/10/2017	3475
White Sugar	ZCE	10 MT	RMB	1/10/2006 7/10/2017	2738
Rapeseed Oil	ZCE	10 MT	RMB	12/31/2012 7/10/2017	2487
Cotton	ZCE	5 MT	RMB	6/01/2004 7/10/2017	2487

Notes: This table displays contract specifications for the eight commodity contracts examined. The No. 1 Soybean contract refers to the non-genetically modified contract. A genetically modified soybeans contract (No. 2 soybean), also traded at the DCE, is not considered in this paper.

Table 3: Descriptive Statistics

	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
				Soybean Meal			
$\mathrm{r_t}$	0.008	8.431	-14.644	1.481	-1.313	15.008	19761.720***
$\mathrm{OI_t}$	1573220	5837670	59806	1338847	0.569	2.153	263.227***
$\mathrm{TV_t}$	1301990	11868480	1800	1322928	2.146	9.832	8514.901***
$Ratio_t^{Spec}$	1.054	8.379	0.010	0.833	2.343	11.641	12637.940***
$Ratio_t^{Hedge}$	-0.005	0.256	-0.999	0.067	-4.100	48.177	275737.500***
				Soybean Oil			
$\mathrm{r_t}$	0.008	7.286	-11.003	1.590	-0.339	6.311	982.481***
$\mathrm{OI_t}$	612673	1367448	26382	388496	-0.097	1.697	149.203***
$\mathrm{TV_t}$	548723	2295448	922	357016	0.850	4.331	401.035***
$Ratio_t^{Spec}$	1.165	6.293	0.007	0.837	1.955	7.677	3196.854***
$Ratio_t^{Hedge}$	-0.003	0.336	-0.927	0.060	-3.815	51.724	209174.800***
				Soybeans			
$\mathrm{r_t}$	0.014	6.189	-9.594	1.098	-0.483	11.174	8868.911***
$\mathrm{OI_t}$	425139	1116542	87022	173455	0.741	3.618	337.175***
$\mathrm{TV_t}$	331549	2677400	5030	312034	2.191	9.909	8762.382***
$Ratio_t^{Spec}$	0.748	7.099	0.015	0.593	2.464	14.501	20495.690***
$Ratio_t^{Hedge}$	-0.012	0.844	-0.990	0.086	-2.326	28.400	87294.990***
				Palm Oil			
$\mathrm{r_t}$	-0.035	14.448	-24.793	2.345	-0.616	17.278	11398.640***
$\mathrm{OI_t}$	473038	1111466	2942	301418	0.107	1.650	103.688***
$\mathrm{TV_t}$	533271	2334592	936	406486	0.996	3.864	261.428***
$Ratio_t^{Spec}$	1.304	6.798	0.028	0.864	2.636	13.522	7686.309***
$Ratio_t^{Hedge}$	-0.002	0.484	-0.698	0.077	-1.692	23.213	23309.980***
				Corn			
$\mathrm{r_t}$	0.014	12.242	-16.486	1.090	-1.517	56.789	339944.100***
$\mathrm{OI_t}$	407102	4702794	17528	464604	2.640	12.843	14612.510***

$\mathrm{TV_t}$	0.476	3.742	0.044	0.353	2.174	11.971	11641.060***
$Ratio_t^{Spec}$	0.477	3.742	0.044	0.354	2.165	11.852	11385.520***
$Ratio_t^{Hedge}$	-0.011	0.747	-0.809	0.119	-0.266	9.446	4899.375***
Sugar							
$\mathrm{r_t}$	0.010	10.796	-10.370	1.197	-0.094	15.414	17586.300***
$\mathrm{OI_t}$	799725	1556438	7732	359485	-0.382	2.562	88.358***
$\mathrm{TV_t}$	1060040	5438290	932	818226	1.493	5.802	1913.507***
$Ratio_t^{Spec}$	1.388	7.594	0.029	0.879	1.705	8.037	4220.881***
$Ratio_t^{Hedge}$	-0.002	0.241	-0.774	0.046	-3.586	54.635	310039.000***
Rapeseed Oil							
$\mathrm{r_t}$	-0.052	7.562	-10.329	1.346	-0.294	11.258	2113.435***
$\mathrm{OI_t}$	287385	546678	2974	102340	0.197	2.507	12.283***
$\mathrm{TV_t}$	160765	989184	1566	126845	1.964	8.982	1578.895***
$Ratio_t^{Spec}$	0.515	1.856	0.074	0.274	1.463	6.225	584.565***
$Ratio_t^{Hedge}$	0.003	0.867	-0.643	0.105	1.391	22.708	12214.920***
Cotton							
$\mathrm{r_t}$	0.001	8.377	-17.268	1.038	-1.837	38.321	159950.100***
$\mathrm{OI_t}$	271570	1024536	1458	226748	0.795	2.789	326.804***
$\mathrm{TV_t}$	282011	4543210	1396	506734	3.164	14.280	21226.170***
$Ratio_t^{Spec}$	0.808	10.114	0.025	0.959	3.382	19.584	40685.270***
$Ratio_t^{Hedge}$	-0.009	0.685	-0.967	0.102	-1.384	15.213	19889.640***
Macroeconomic Variables							
Ex.rate	6.981	8.278	6.041	0.757	0.637	1.925	363.5017***
CrudeOil	510.887	1000.794	183.437	168.407	0.115	2.055	123.843***
Tbond	3.676	4.951	2.660	0.513	0.449	2.425	148.867***
MSCI_W	9512.135	13201.260	4710.284	1685.923	-0.109	2.504	38.450***
MSCI_EM	5978.874	10004.520	3117.703	1276.767	-0.137	3.083	10.701***

Notes: This table presents descriptive statistics of the investigated time series of the eight futures contracts. r_t, OI_t and TV_t describe the returns, end-of-day open interest and daily trading volume on day t. The speculation ratio is represented by $Ratio_t^{Spec}$ and the hedging ratio by $Ratio_t^{Hedge}$. Descriptive statistic of the five macroeconomic variables is displayed in the bottom of the table. JB stands for Jarque-Bera statistics and significance at the 1% level is represented by ***. All data is taken from Thomson Reuters Datastream.

Table 4: Augmented Dickey Fuller (ADF) Test and Lagrange Multiplier (LM) Test

	Price	Log-Returns	$Ratio_t^{Spec}$	$Ratio_t^{Hedge}$	$AbRatio_t^{Hedge}$
Soybean Meal	-2.970*	-52.442 ***	-3.915***	-15.437***	-9.733***
Soybean Oil	-2.108	-24.315***	-3.339**	-39.688***	-10.111***
Soybeans	-2.153	-25.165***	-5.526***	-14.070***	-9.325***
Palm Oil	-2.421	-9.852***	-6.278***	-13.578***	-10.743***
Corn	-1.766	-25.566***	-5.738***	-13.544***	-5.914***
Sugar	-1.260	-25.770***	-5.497***	-50.881***	-9.126***
Rapeseed Oil	-3.617***	-28.370***	-4.107***	-11.853***	-11.247***
Cotton	-2.005	-11.894***	-3.831***	-16.932***	-4.962***
	Level	Log-Difference			
Ex.rate	-2.022	-9.552***			
Crude Oil	-2.019	-11.314***			
Tbond	-2.866**	-11.707***			
MSCI_W	-0.831	-9.531***			
MSCI_EM	-2.648*	-12.618***			

	LM(1)	LM(5)	LM(10)	LM(15)	LM(20)
Soybean Meal	28.973***	8.822***	4.703***	3.216***	4.537***
Soybean Oil	69.929***	22.134***	11.878***	7.926***	6.105***
Soybeans	36.260***	12.165***	5.213***	3.975***	3.975***
Palm Oil	3.676*	8.079***	4.489***	3.007***	2.346***
Corn	10.479***	3.500***	1.804*	1.212	0.913
Sugar	18.256***	7.869***	8.503***	5.699***	3.920***
Rapeseed Oil	2.322	0.645	0.890	0.498	0.842
Cotton	14.857***	4.672***	2.845***	2.215***	2.104***

Notes: First rows show results of the ADF test for time series of the eight commodities examined and for the five macroeconomic variables. Lower rows show results of the LM tests for the eight commodity returns. Reagrding the ADF test, we include a constant in each test equation and select the lag structure based upon the Schwarz information criterion (SIC). Critical values are taken from MacKinnon et al. (1999). Numbers of lags for each LM test are given in parenthesis. *,**,*** denote statistical significance at the 10, 5, and 1 percent level, respectively.

Table 5: GARCH estimation based on $Ratio_t^{Spec}$

	Soybean Meal	Soybean Oil	Soybeans	Palm Oil	Corn	Sugar	Rapeseed Oil	Cotton
				Mean Equation				
C	0.034**	0.020	-0.006	-0.011	-0.011**	-0.008	-0.028	-0.005
r_{t-1}	0.068***	-0.001	0.011	-0.038	0.035***	0.083***	-0.004	0.076***
ExRate	-0.438***	-0.413***	-0.168**	-0.670***	-0.021	0.148	0.206*	-0.108*
Oil	0.015**	0.033***	0.012**	0.010	0.010***	0.009	0.002	-0.011***
TBond	-0.001	0.005	-0.010*	0.040*	-0.023***	-0.006	0.021	-0.003
MSCI	0.011	-0.071**	-0.037**	-0.057	-0.021**	-0.048***	-0.179***	-0.041***
MSCIE	0.111***	0.187***	0.104***	0.177***	0.045***	0.122***	0.189***	0.073***
				Variance Equation				
C	0.323***	0.095	0.106***	0.642***	0.088***	-0.120***	-0.239***	0.008
ARCH(1)	0.287***	0.26***	0.358***	0.399***	0.685***	0.195***	0.302***	0.192***
GARCH(1)	0.176***	0.529***	0.179***	0.590***	0.090***	0.265***	0.149**	0.008
$Ratio_t^{Spec}$	0.787***	0.413***	0.683***	-0.092**	0.627***	0.623***	2.466***	0.983***
Arch LM	0.396	0.262	0.429	2.836**	0.081	0.475	1.102	0.067

Notes: Results of the mean equation (3) and for the volatility equation (4), including the influence of the speculation ratio, are presented. $Ratio_t^{Spec}$ stands for the computed speculation ratio and captures speculative activity. The error distribution is GED. *,**,*** denote statistical significance at the 10, 5, and 1 percent level, respectively.

Table 6: GARCH estimation based on $AbRatio_t^{Hedge}$

	Soybean Meal	Soybean Oil	Soybeans	Palm Oil	Corn	Sugar	Rapeseed Oil	Cotton
Mean Equation								
C	0.039***	0.020	0.000	-0.028	0.000	0.003	-0.045*	0.001
r_{t-1}	0.072***	0.000	0.025	-0.040	0.025*	0.078***	0.025	0.083***
ExRate	-0.489***	-0.417***	-0.168*	-0.481**	-0.019	0.119	0.208	-0.198***
Oil	0.009	0.027***	0.011**	0.010	0.014***	0.004	0.007	-0.013***
TBond	-0.007	0.007	-0.007	0.024	-0.025***	-0.005	0.019	-0.002
MSCI	0.017	-0.065**	-0.036**	-0.050	-0.043***	-0.057***	-0.148***	-0.040***
MSCIE	0.105***	0.185***	0.103***	0.186***	0.047***	0.125***	0.200***	0.076***
Variance Equation								
C	0.511***	0.190***	0.146***	-0.042	0.218***	0.039**	0.401**	0.110***
ARCH(1)	0.316***	0.271***	0.359***	0.288***	0.667***	0.137***	0.323***	0.253***
GARCH(1)	0.411***	0.617***	0.549***	0.532***	0.248***	0.830***	0.420***	0.664***
$Ratio_t^{Hedge}$	2.433**	3.999***	0.666**	26.907***	0.288	0.542	2.078	-0.181*
Arch LM	0.761	0.567	1.275	2.018*	0.227	0.612	0.368	0.453

Notes: Results of the mean equation (3) and for the volatility equation (4), including the influence of the speculation ratio, are presented. $Ratio_t^{Hedge}$ stands for the computed absolute value of the hedging ratio and captures hedging activity. The error distribution is GED. *,**,*** denote statistical significance at the 10, 5, and 1 percent level, respectively.

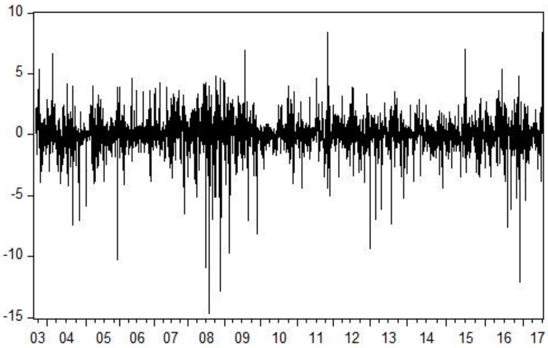
Table 7: Granger Causality Tests

Null Hypothesis	Obs.	Lags	F-Statistic	Prob.
Soybean Meal				
$Ratio_t^{Spec}$ does not Granger cause conditional volatility	3135	4	6.782^{***}	0.000
Conditional volatility does not Granger cause $Ratio_t^{Spec}$			4.363^{***}	0.002
$AbRatio_t^{Hedge}$ does not Granger cause conditional volatility	3137	2	4.222^{**}	0.015
Conditional volatility does not Granger cause $AbRatio_t^{Hedge}$			3.585^{**}	0.028
Soybean Oil				
$Ratio_t^{Spec}$ does not Granger cause conditional volatility	2057	6	6.993^{***}	0.000
Conditional volatility does not Granger cause $Ratio_t^{Spec}$			6.142^{***}	0.000
$AbRatio_t^{Hedge}$ does not Granger cause conditional volatility	2062	1	51.033^{***}	0.000
Conditional volatility does not Granger cause $AbRatio_t^{Hedge}$			0.131	0.718
Soybeans				
$Ratio_t^{Spec}$ does not Granger cause conditional volatility	3138	3	13.773^{***}	0.000
Conditional volatility does not Granger cause $Ratio_t^{Spec}$			4.817^{***}	0.003
$AbRatio_t^{Hedge}$ does not Granger cause conditional volatility	3140	1	24.080^{***}	0.000
Conditional volatility does not Granger cause $AbRatio_t^{Hedge}$			6.463^{**}	0.011
Palm Oil				
$Ratio_t^{Spec}$ does not Granger cause conditional volatility	1328	4	0.839	0.501
Conditional volatility does not Granger cause $Ratio_t^{Spec}$			3.821^{***}	0.004
$AbRatio_t^{Hedge}$ does not Granger cause conditional volatility	1330	2	36.905^{***}	0.000
Conditional volatility does not Granger cause $AbRatio_t^{Hedge}$			4.741^{***}	0.009
Corn				
$Ratio_t^{Spec}$ does not Granger cause conditional volatility	2807	3	0.633	0.593
Conditional volatility does not Granger cause $Ratio_t^{Spec}$			0.451	0.716
$AbRatio_t^{Hedge}$ does not Granger cause conditional volatility	2806	4	0.626	0.644
Conditional volatility does not Granger cause $AbRatio_t^{Hedge}$			0.518	0.723
Sugar				
$Ratio_t^{Spec}$ does not Granger cause conditional volatility	2734	4	9.894^{***}	0.000
Conditional volatility does not Granger cause $Ratio_t^{Spec}$			3.414^{***}	0.009
$AbRatio_t^{Hedge}$ does not Granger cause conditional volatility	2737	1	22.464^{***}	0.000
Conditional volatility does not Granger cause $AbRatio_t^{Hedge}$			1.669	0.197
Rapeseed Oil				
$Ratio_t^{Spec}$ does not Granger cause conditional volatility	737	2	6.473^{***}	0.002
Conditional volatility does not Granger cause $Ratio_t^{Spec}$			0.798	0.451

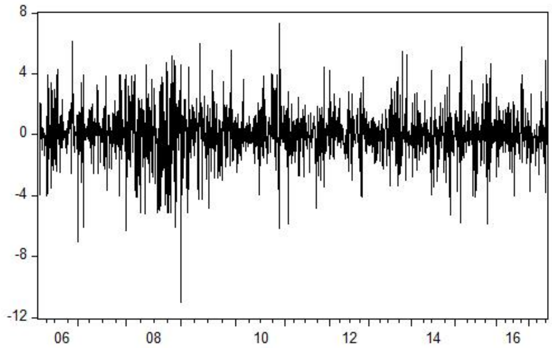
$AbRatio_t^{Hedge}$ does not Granger cause conditional volatility	738	1	2.168	0.141
Conditional volatility does not Granger cause $AbRatio_t^{Hedge}$			0.156	0.693
Cotton				
$Ratio_t^{Spec}$ does not Granger cause conditional volatility	3040	3	13.226***	0.000
Conditional volatility does not Granger cause $Ratio_t^{Spec}$			7.135***	0.000
$AbRatio_t^{Hedge}$ does not Granger cause conditional volatility	3040	3	0.626	0.598
Conditional volatility does not Granger cause $AbRatio_t^{Hedge}$			4.330***	0.005

Notes: Impulse response functions are displayed along with corresponding plus and minus 2 standard error bands (dashed lines), used to determine statistical significance. The impulse response functions show responses to Cholesky one standard deviation innovations. The horizontal axis shows the number of days after the shock.

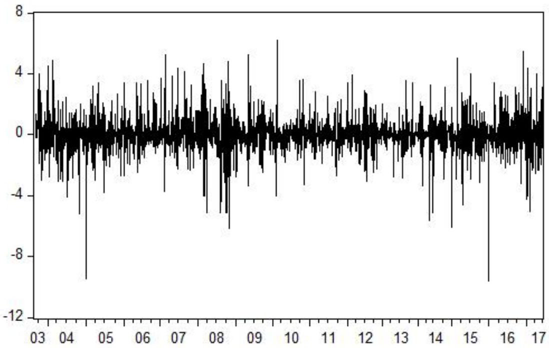
Figure 1: Log Returns



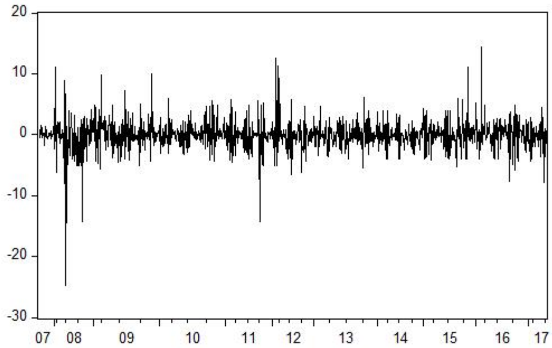
(a) Soybean Meal



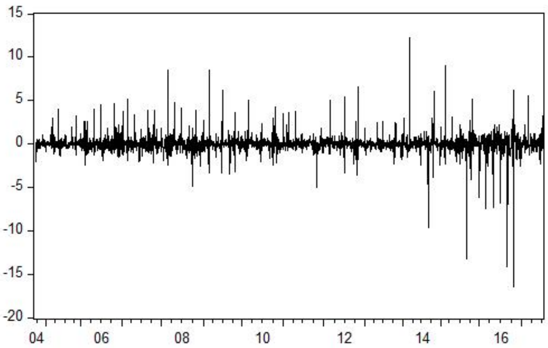
(b) Soybean Oil



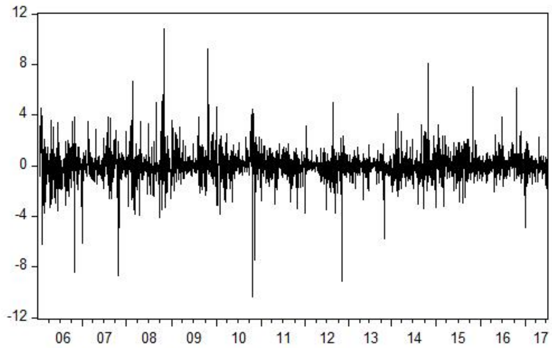
(c) Soybeans



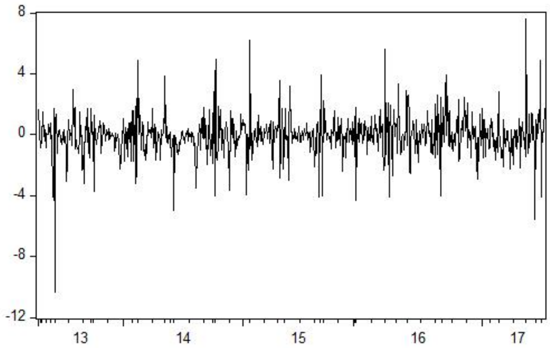
(d) Palm Oil



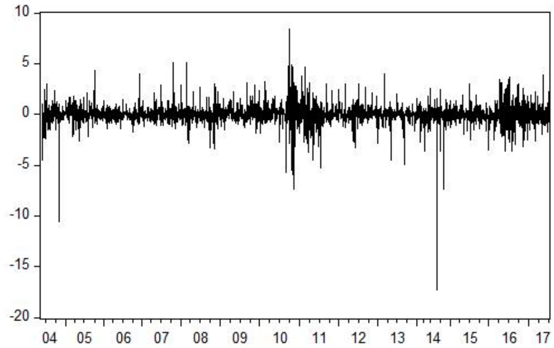
(e) Corn



(f) Sugar

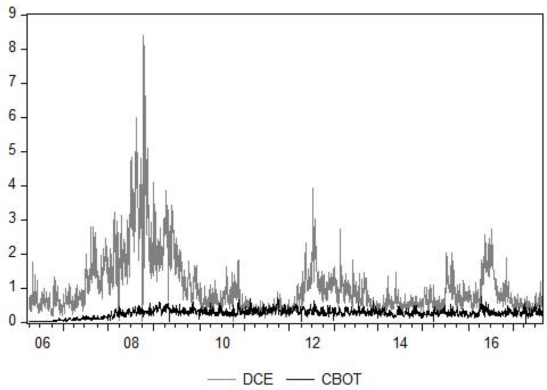


(g) Rapeseed Oil

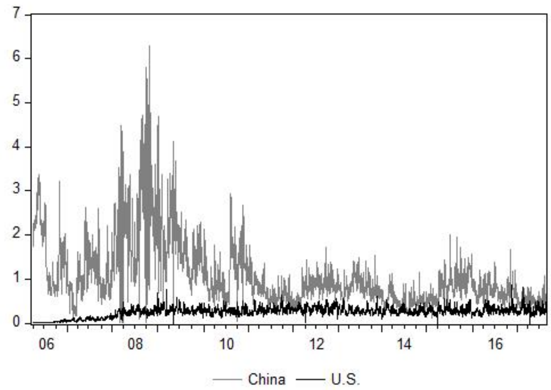


(h) Cotton

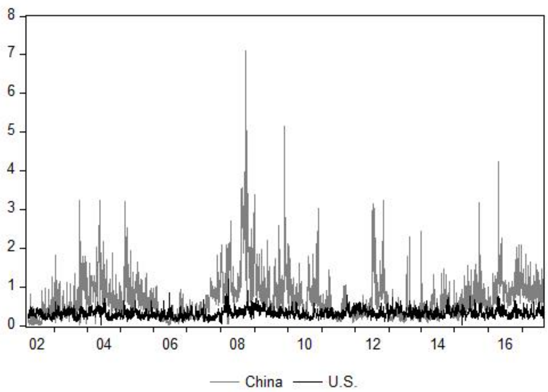
Figure 2: Speculation Ratios



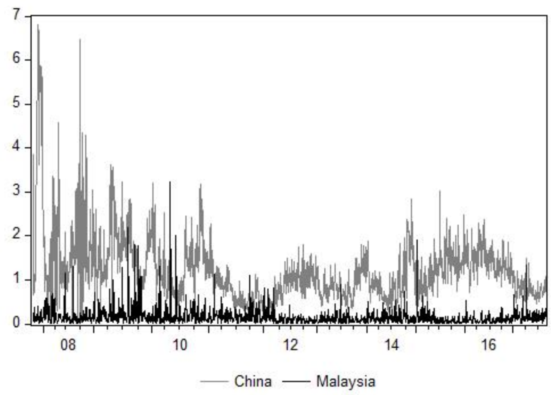
(a) Soybean Meal



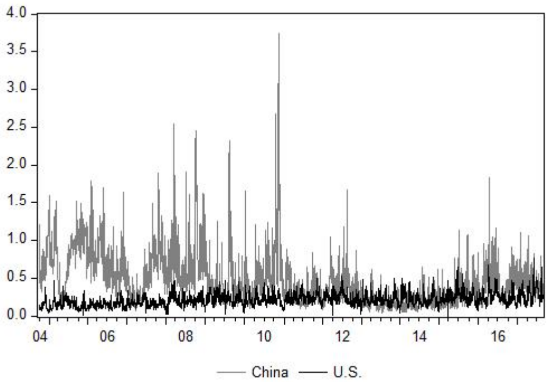
(b) Soybean Oil



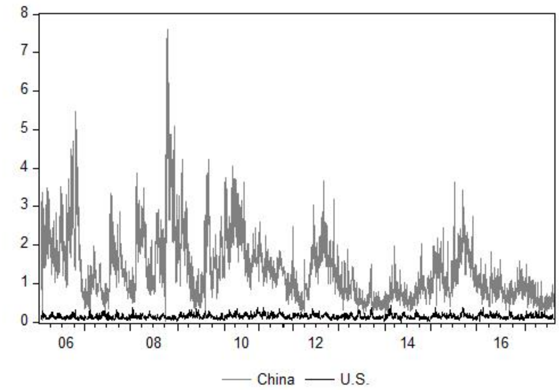
(c) Soybeans



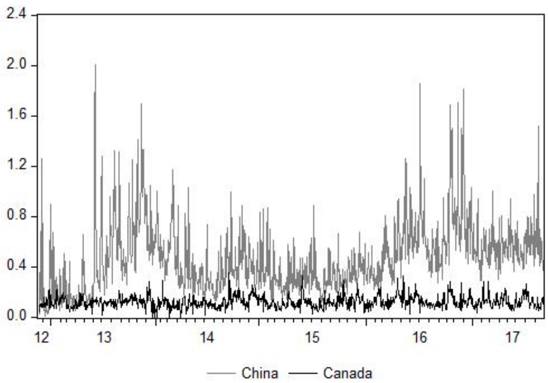
(d) Palm Oil



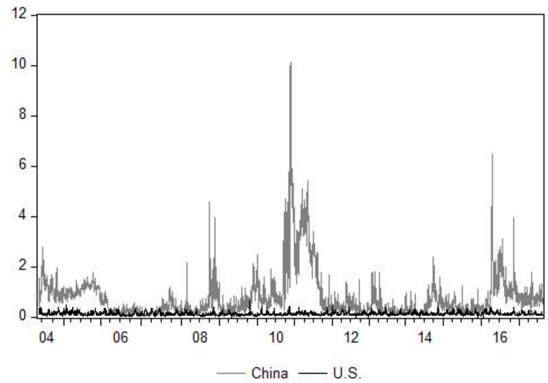
(e) Corn



(f) Sugar

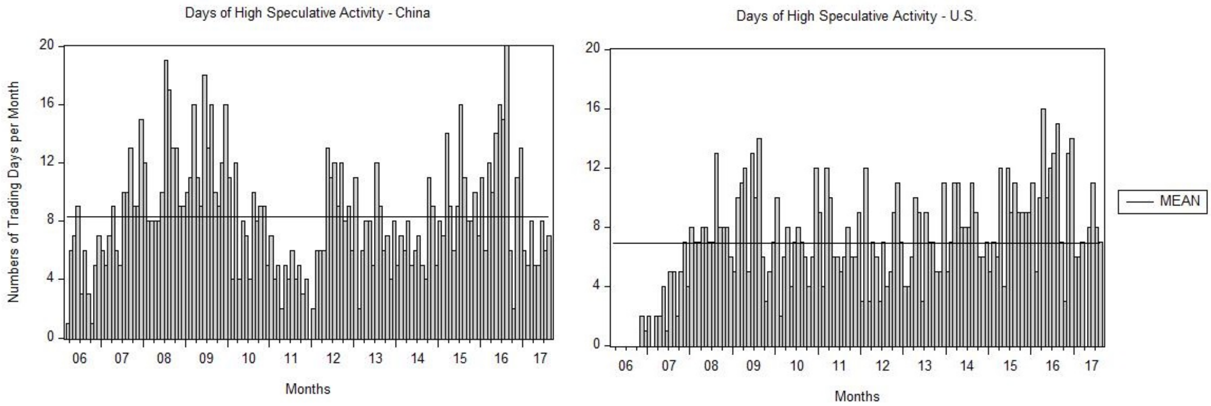


(g) Rapeseed Oil

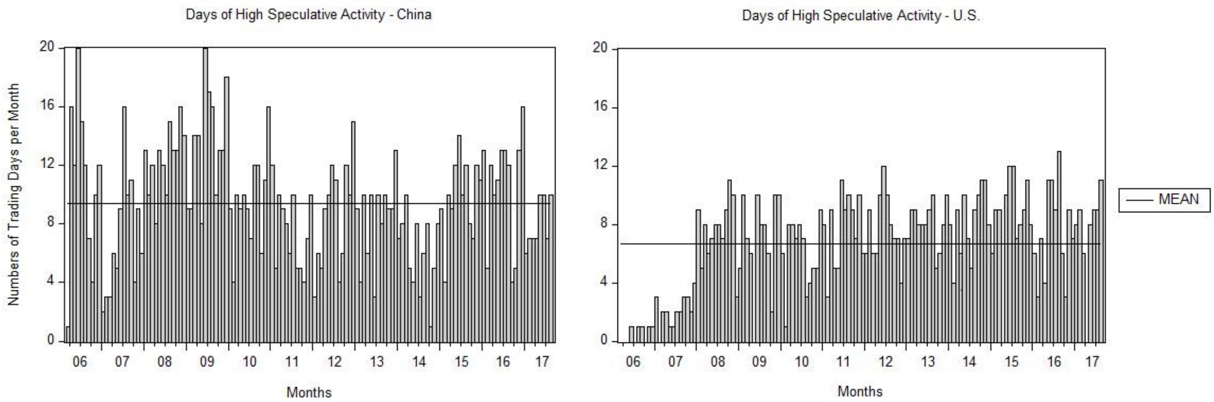


(h) Cotton

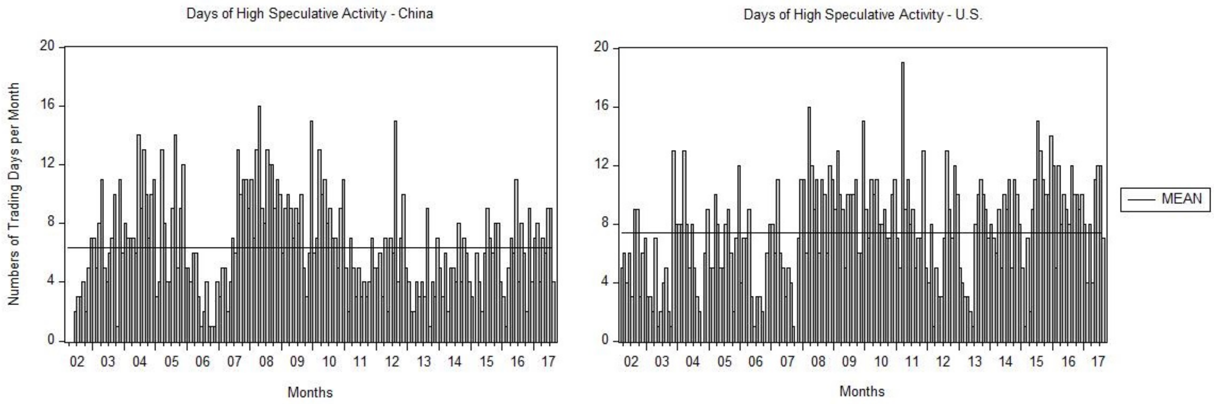
Figure 3: Hedging Ratios between [-0.025, 0.025]



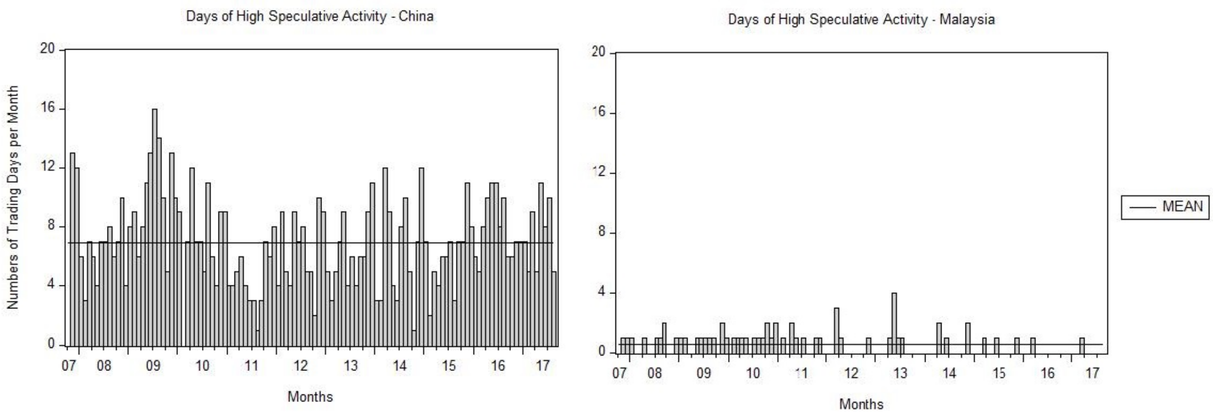
(a) Soybean Meal



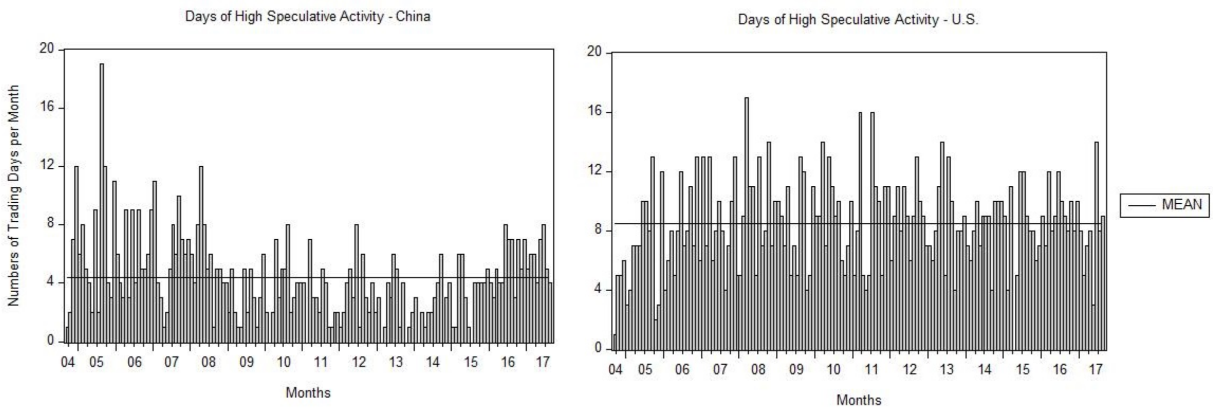
(b) Soybean Oil



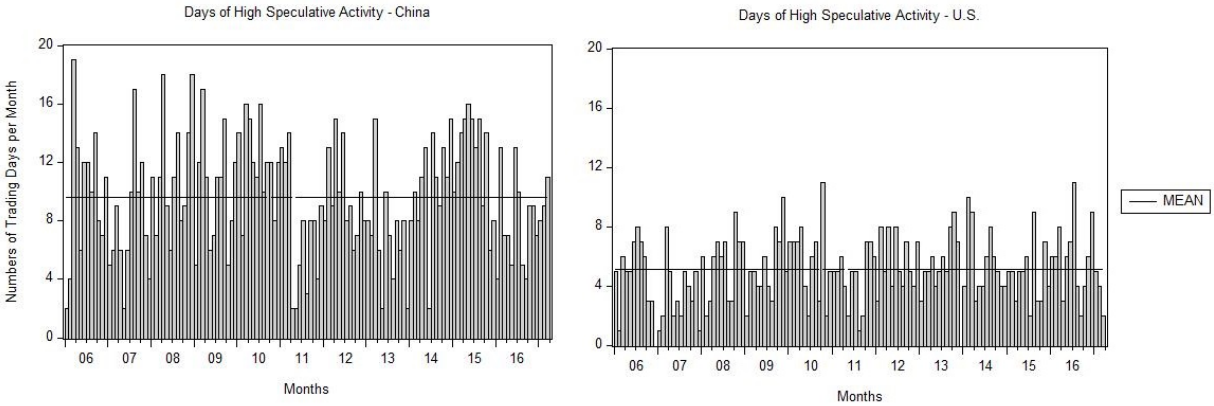
(c) Soybeans



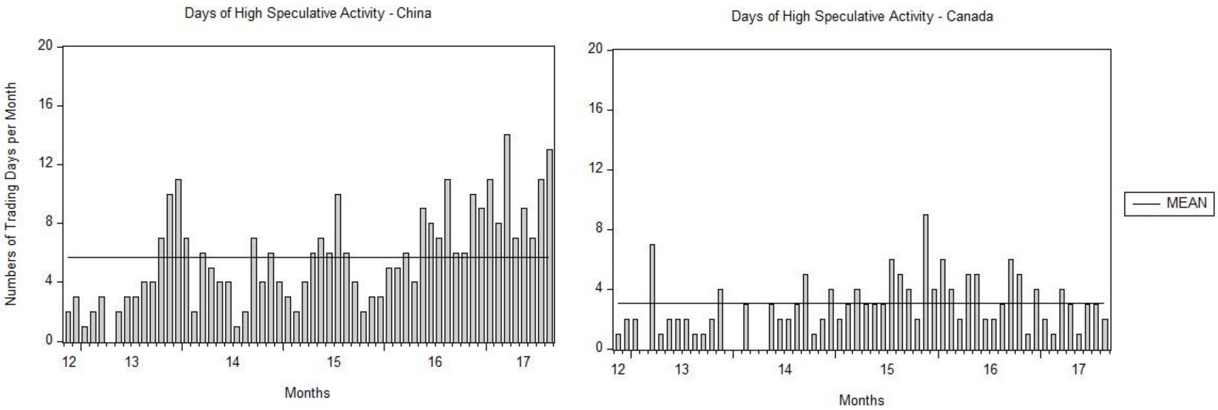
(d) Palm Oil



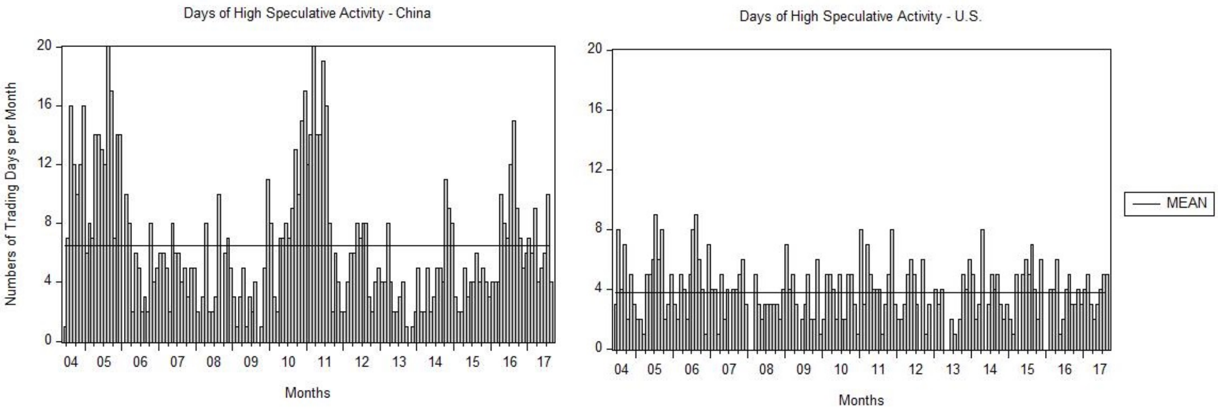
(e) Corn



(f) Sugar



(g) Rapeseed Oil



(h) Cotton

Table 8: Variance Decomposition

Speculation Ratio

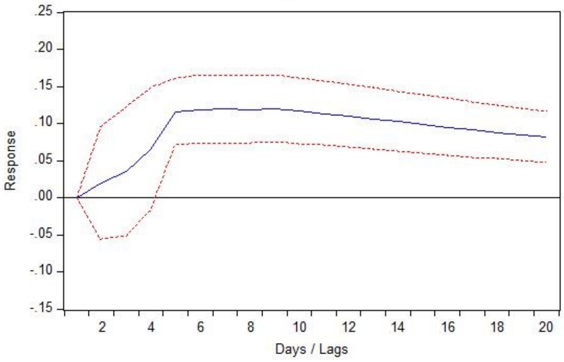
		Soybean Meal		Soybean Oil		Soybeans		Palm Oil		Corn		Sugar		Rapeseed Oil		Cotton	
Expl.V.	Day	Vol.	R_t^S	Vol.	R_t^S	Vol.	R_t^S	Vol.	R_t^S	Vol.	R_t^S	Vol.	R_t^S	Vol.	R_t^S	Vol.	R_t^S
Vol.	1	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00
	5	99.74	0.26	99.79	0.21	98.46	1.54	99.92	0.08	99.95	0.05	99.15	0.85	98.72	1.28	99.62	0.38
	10	98.81	1.19	98.74	1.26	96.39	3.61	99.91	0.09	99.93	0.07	96.52	3.48	98.66	1.34	98.45	1.55
	15	98.08	1.92	97.12	2.88	95.37	4.63	99.89	0.11	99.92	0.08	93.57	6.43	98.65	1.35	97.34	2.66
	20	97.58	2.42	95.81	4.19	94.95	5.05	99.88	0.12	99.92	0.08	91.08	8.92	98.65	1.35	96.50	3.50
R_t^S	1	0.93	99.07	2.26	97.74	0.76	99.24	0.08	99.92	0.00	100.00	0.25	99.75	0.95	99.05	1.22	98.78
	5	1.96	98.04	4.51	95.49	2.07	97.93	0.64	99.36	0.02	99.98	1.24	98.76	0.58	99.42	3.71	96.29
	10	2.77	97.23	5.02	94.98	2.76	97.24	0.54	99.46	0.02	99.98	2.12	97.88	0.54	99.46	5.05	94.95
	15	3.15	96.85	5.69	94.31	3.02	96.98	0.50	99.50	0.02	99.98	2.82	97.18	0.53	99.47	5.67	94.33
	20	3.35	96.65	6.14	93.86	3.12	96.88	0.48	99.52	0.02	99.98	3.33	96.67	0.53	99.47	6.00	94.00

Abs. Hedging Ratio

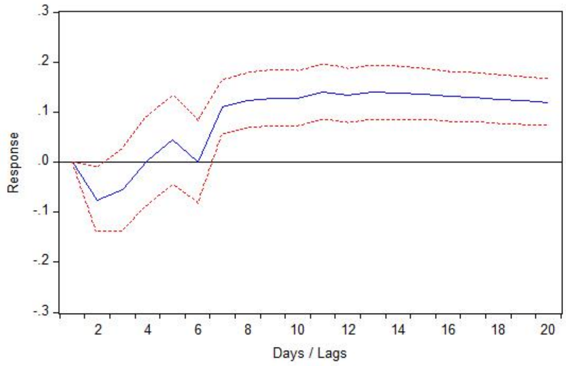
		Soybean Meal		Soybean Oil		Soybeans		Palm Oil		Corn		Sugar		Rapeseed Oil		Cotton	
Expl.V.	Day	Vol	R_t^H	Vol	R_t^H	Vol.	R_t^H	Vol.	R_t^H	Vol.	R_t^H	Vol.	R_t^H	Vol.	R_t^H	Vol.	R_t^H
Vol.	1	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00
	5	99.80	0.20	96.89	3.11	98.93	1.07	91.08	8.92	99.93	0.07	99.13	0.87	99.60	0.40	99.94	0.06
	10	99.80	0.20	96.53	3.47	98.85	1.15	89.86	10.14	99.93	0.07	98.99	1.01	99.58	0.42	99.87	0.13
	15	99.80	0.20	96.50	3.50	98.85	1.15	89.79	10.21	99.93	0.07	98.96	1.04	99.58	0.42	99.86	0.14
	20	99.80	0.20	96.50	3.50	98.85	1.15	89.79	10.21	99.93	0.07	98.95	1.05	99.58	0.42	99.86	0.14
R_t^H	1	0.04	99.96	0.18	99.82	0.10	99.90	0.03	99.97	0.06	99.94	0.01	99.99	0.03	99.97	0.10	99.90
	5	0.39	99.61	0.20	99.80	0.45	99.55	0.72	99.28	0.12	99.88	0.05	99.95	0.04	99.96	0.78	99.22
	10	0.43	99.57	0.20	99.80	0.48	99.52	0.90	99.10	0.15	99.85	0.08	99.92	0.04	99.96	1.13	98.87
	15	0.43	99.57	0.20	99.80	0.48	99.52	0.91	99.09	0.15	99.85	0.08	99.92	0.05	99.95	1.17	98.83
	20	0.43	99.57	0.20	99.80	0.48	99.52	0.91	99.09	0.15	99.85	0.09	99.91	0.05	99.95	1.18	98.82

Notes: Conditional volatility is denoted by Vol., speculation ratio by R_t^S, absolute value of the hedging ratio by R_t^H and explained variable by Expl.V..

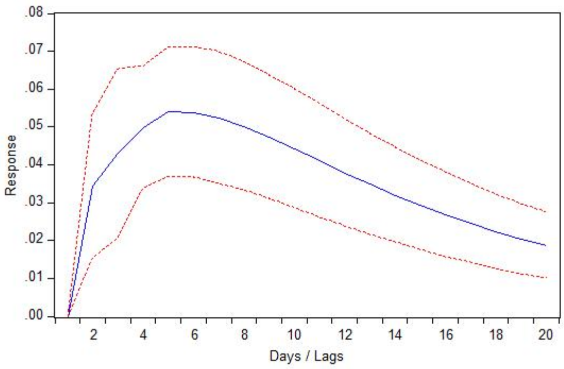
Figure 4: Impulse Response Functions - Response of Conditional Volatility to $Ratio_t^{Spec}$



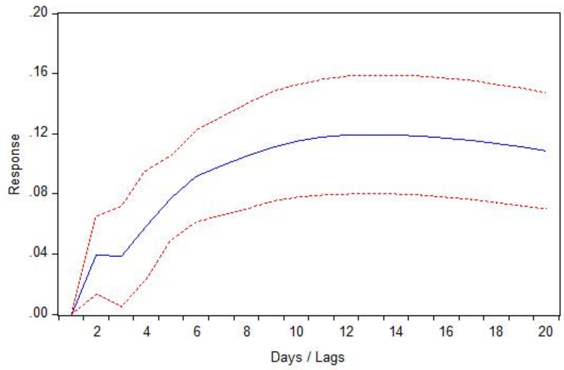
(a) Soybean Meal



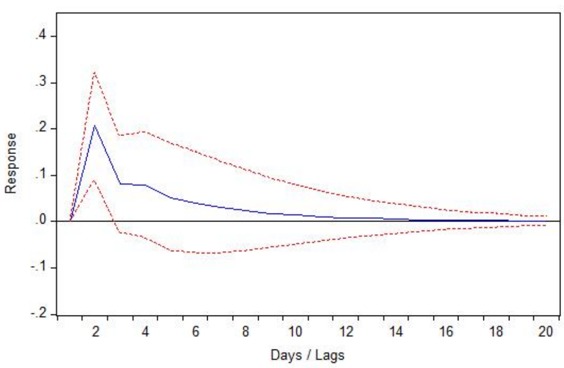
(b) Soybeans Oil



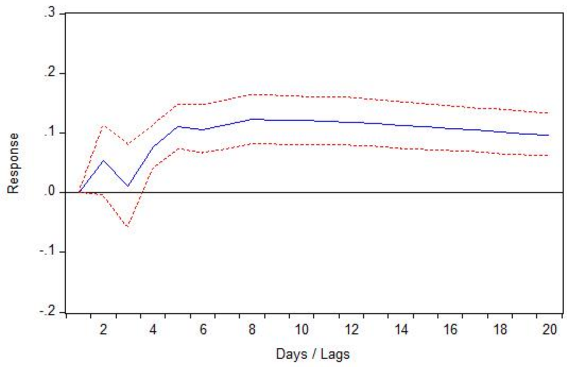
(c) Soybeans



(d) Sugar



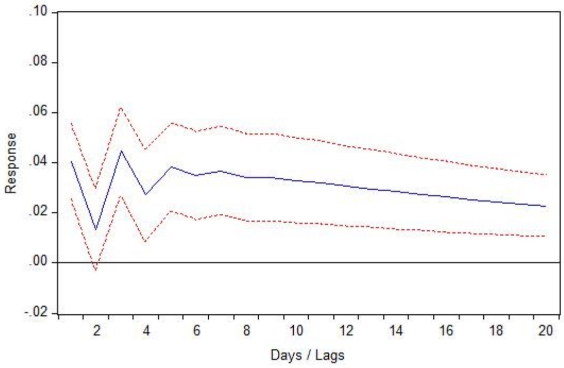
(e) Rapeseed Oil



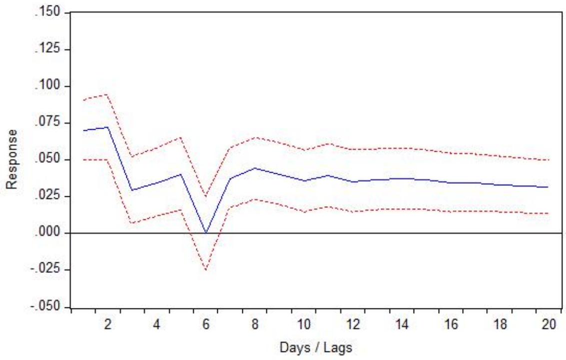
(f) Cotton

Notes: Impulse response functions are displayed along with corresponding plus and minus 2 standard error bands (dashed lines), used to determine statistical significance. The impulse response functions show responses to Cholesky one standard deviation innovations. The horizontal axis shows the number of days after the shock.

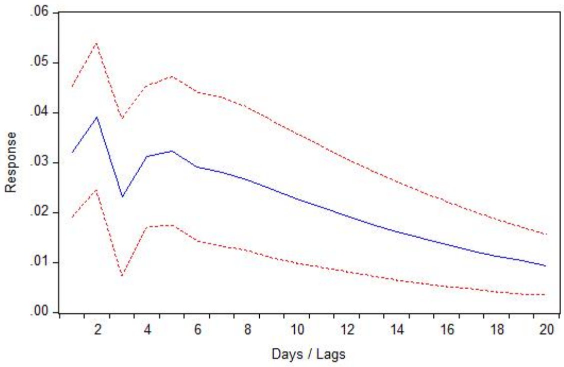
Figure 5: Impulse Response Functions - Response of $Ratio_t^{Spec}$ to Conditional Volatility



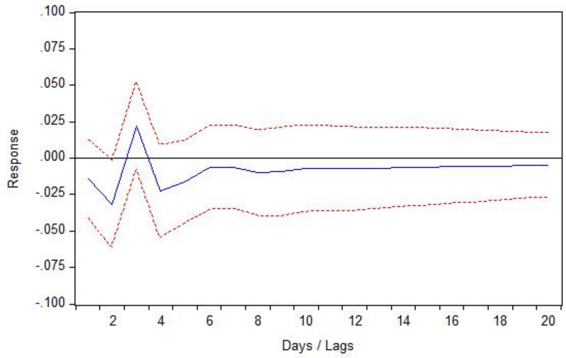
(a) Soybean Meal



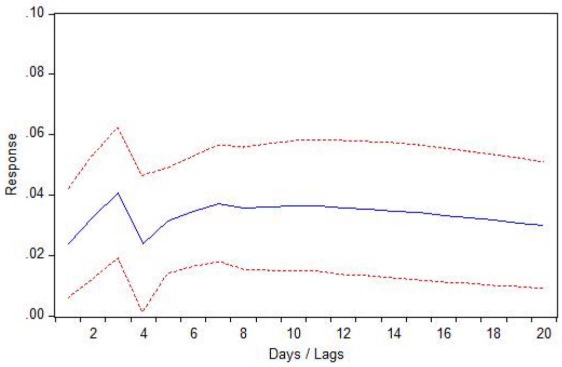
(b) Soybean Oil



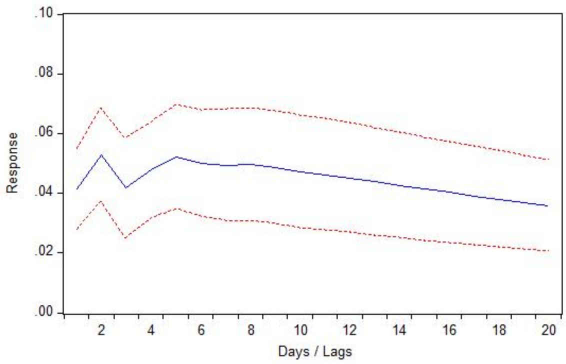
(c) Soybeans



(d) Palm Oil



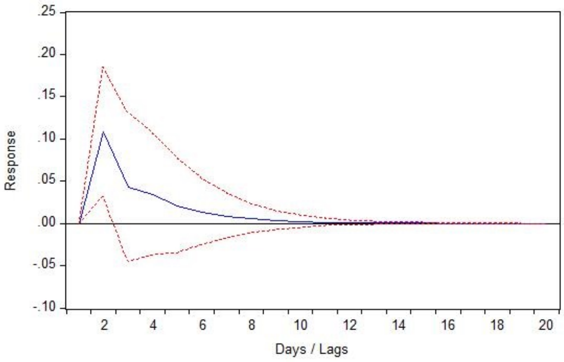
(e) Sugar



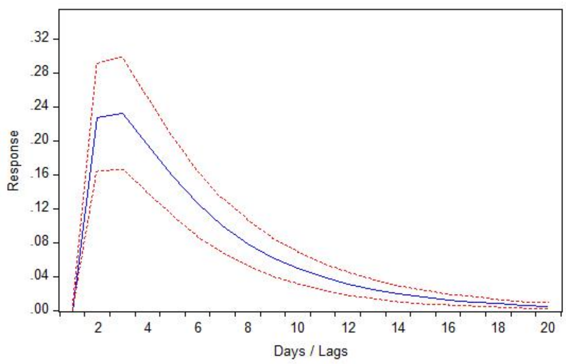
(f) Cotton

Notes: Impulse response functions are displayed along with corresponding plus and minus 2 standard error bands (dashed lines), used to determine statistical significance. The impulse response functions show responses to Cholesky one standard deviation innovations. The horizontal axis shows the number of days after the shock.

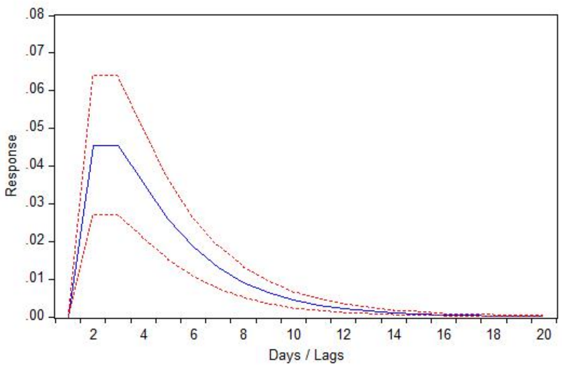
Figure 6: Impulse Response Functions - Response of Conditional Volatility to $Ratio_t^{AbHedge}$



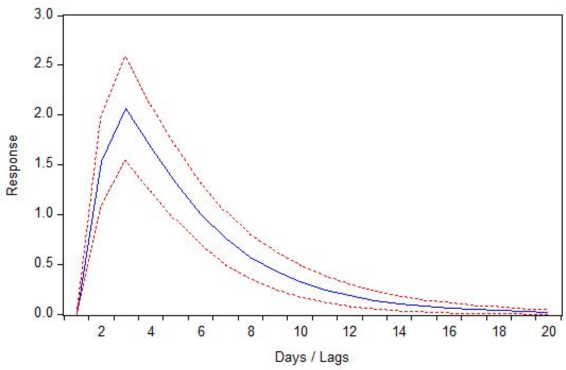
(a) Soybean Meal



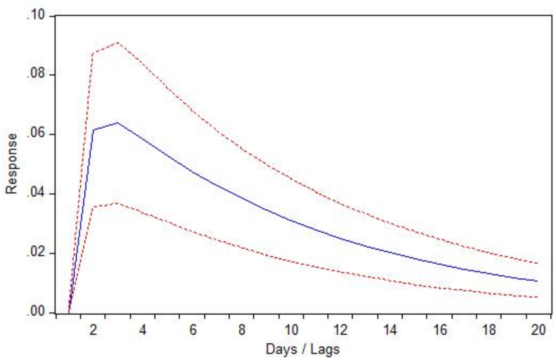
(b) Soybean Oil



(c) Soybeans



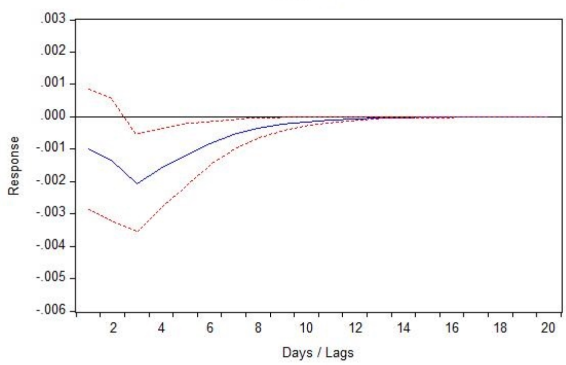
(d) Palm Oil



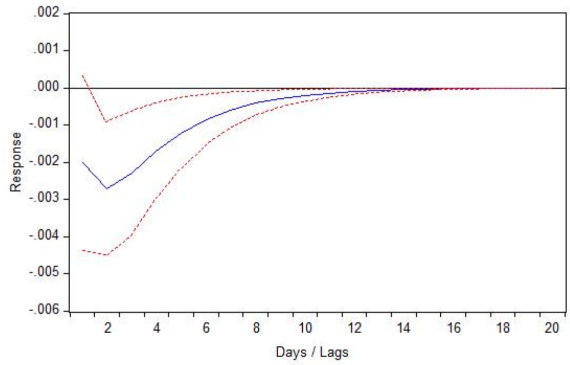
(e) Sugar

Notes: Impulse response functions are displayed along with corresponding plus and minus 2 standard error bands (dashed lines), used to determine statistical significance. The impulse response functions show responses to Cholesky one standard deviation innovations. The horizontal axis shows the number of days after the shock.

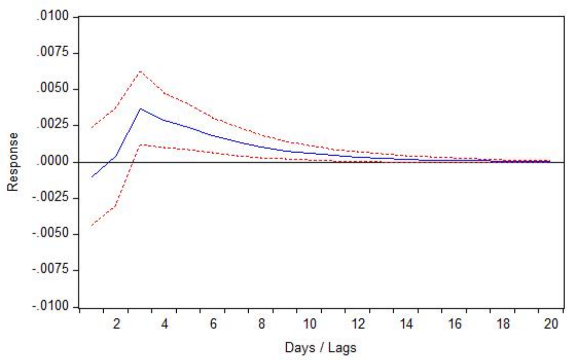
Figure 7: Impulse Response Functions - Response of $Ratio_t^{AbHedge}$ to Conditional Volatility



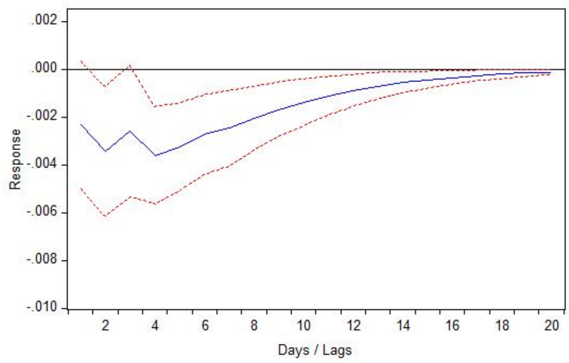
(a) Soybean Meal



(b) Soybeans



(c) Palm Oil



(d) Cotton

Notes: Impulse response functions are displayed along with corresponding plus and minus 2 standard error bands (dashed lines), used to determine statistical significance. The impulse response functions show responses to Cholesky one standard deviation innovations. The horizontal axis shows the number of days after the shock.