Speculation and Volatility - A Time-Varying Approach applied on Chinese Commodity Futures Markets

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Abstract There is an ongoing discussion and a lot of empirical investigations on, whether or not, speculative behavior increases volatility on commodity markets. However, little investigation is done for the Chinese market, mostly due to a missing standard measure for speculative behavior. Additionally, the studies that were undertaken, were carried out under the assumption that potential effects are constant over a long period of time. We address both shortcomings and empirically investigate the time-varying influence of speculative activity on returns volatility in Chinese futures markets for commodities. To measure speculative activity a speculation ratio, defined as trading volume divided by open interest, is used. We sequentially apply two time-varying VAR models with stochastic volatility to six heavily traded metal and agricultural contracts to show how the relationship between returns volatility and the speculation ratio evolves over time. We analyze Granger causality as well as impulse responses. Eventually, we find no evidence for an effect from speculation on volatility. On the contrary, for most commodities, return volatility seems to amplify speculative behavior.

Keywords Speculators · Derivatives · Commodity markets · China · Time-varying VAR

JEL Classification: C11 · G10 · G14 · G15 · Q02
1 Introduction

Over the past decade, Chinese commodity futures markets have extremely rapidly grown in size. Especially in the first half of 2016, the overall market activity has exploded and trading volume has reached unprecedented dimensions. Trading activity of the steel rebar contract on the Shanghai Futures Exchange (SHFE) impressively illustrates this development. On April 21, 2016, alone, its trading volume amounted to US$93 billion, thereby exceeding total overall trading volume of both the entire Shanghai and Shenzhen stock exchanges. The Shanghai rebar contract is now the third most traded futures contract in the world (Liao et al. 2016). However, analyzes of historical market data for Chinese commodity futures contracts indicate that, in 2016, overall open interest on these markets have surged to a much lesser extent than trading volume. Since market trading volume mostly captures speculators activity, while open interest mirrors hedging activity, this trend most likely implies that short term speculators have traded in these markets rather than hedgers.

In China, but also worldwide, commodity futures exhibited increasing returns volatility since 2000, with soaring price spikes in 2007 and 2011 and price crashes between mid 2007 and 2008. In line with the ongoing financialization of commodity futures markets, these events have encouraged an extended academic as well as a heated public debate about the role of speculators on futures markets. A large number of empirical studies have analysed, whether or not, speculative activity increases volatility on US commodity futures markets. Overall, these studies tend to find stabilizing effects of speculation. Studies by Till (2009) and Sanders et al. (2008) conclude that long-short speculators are not to blame for the excessive price impact in 2007-2008 because the rise in speculation was only a response to a rise in hedging demand. Brunetti et al. (2016) use Granger causality tests to analyze 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. Miffre & Brooks (2013) also investigate the influence of long-short speculators and conclude that speculators have no significant impact on volatility or cross-market correlation. The stabilizing hypothesis is quite reasonable since speculation provides market liquidity, helps hedgers to find a matching counterparty to transfer risks, improves price discovery and therefore stabilizes prices.

However, all of these studies above concentrate on markets in the US and there is only little research on speculation in commodity futures markets in China. Other than markets in the US, Chinese commodity futures markets appear to be characterized by extremely speculative trading behavior, where presumably speculative activity often exceeds hedging demand. Due to the growing global importance and the trading characteristics of Chinese commodity futures markets, we think it is of particular interest to investigate the role of speculation on these markets. For this reason, we empirically examine whether speculative activity in Chinese futures markets for commodities destabilizes futures returns.
Since there is no database that provides information about the type of traders (hedgers or speculators) active on these markets, we use a ratio that combines trading volume and open interest to capture speculation. This speculation ratio was first proposed by Garcia et al. (1986) and measures the relative dominance of speculative activity in contrast to hedging activity on a particular market. The extant literature on commodity futures concurs that speculators mostly impact on trading volume as they enter and exit a market during one trading day, while trying to avoid holding positions over night. Open interest, in turn, is mostly held by hedgers, which hedge the risks of their underlying positions for longer periods (Rutledge (1979), Leuthold (1983), Besssembinder & Seguin (1993)). Following this string of arguments, trading volume in daily data mostly captures speculators activity, while open interest mirrors hedging activity.

We sequentially apply two time-varying vector autoregression (VAR) models with stochastic volatility to analyze the dynamic relationship between the speculation ratio and returns volatility in six different Chinese commodity futures markets. With the first model we describe the joint dynamics of the investigated commodity futures returns and filter their volatility time series. In the second step we estimate the dynamics of volatility and speculation measure to analyze its’ dependencies. In most of the extant studies evaluating the effect of speculative activity on derivative markets, the estimated parameters are assumed to be constant over time. In contrast, we allow the coefficients to evolve over time. Our results indicate that speculative activity is driven by volatility. A high volatility attracts speculators attentions and leads to more speculative trading.

The remainder of this paper is structured as follows: Section 2 introduces the speculation measure and its computation. Section 3 presents the data used and the econometric methodology employed, Section 4 outlines our empirical results. Section 5 summarizes and concludes.

### 2 Speculation Measure

We aim at investigating the influence of speculative activity on returns volatility over time. As the relative dominance of speculators compared to hedgers on a market changes over time, their impact on volatility is most likely to be time varying as well. To examine the character of daily trading activities, we compute a ratio, that combines daily measures of trading volume and open interest. All trades of a particular contract executed during a day are captured by the daily trading volume. In turn, open interest describes all positions of that very contract that are still open at the end of that trading day. In this context, open simply means that the position has neither been equalized by an opposite futures position, nor been fulfilled by the physical delivery of the commodity or by cash settlement.

The speculation ratio is defined as daily trading volume ($TV_t$) divided by end-of-day open interest ($OT_t$):
TVAR approach to speculation

\[ \text{Ratio}_{t}^{\text{Spec}} = \frac{T_{V_{t}}}{O_{I_{t}}} \] (1)

It therefore measures the relative dominance of speculative activity in the contract analyzed 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.

This speculation ratio reflects the assumption that hedgers hold their positions for longer periods due to their underlying positions, whereas speculators mainly try to avoid holding their positions over night. Based on their different trading behaviour, speculators and hedgers influence the amount of trading volume and open interest in very different ways. 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 (Rutledge (1979), Leuthold (1983), Bessembinder & Seguin (1993)).

Obviously, the ratio’s ability to measure the dominance of speculative activity depends on the assumption that hedgers and speculators hold their trading positions for different time periods. There is empirical evidence that seems to approve the assumption that hedgers tend to hold their position for longer periods than speculators (Ederington & Lee (2002), Wiley & Daigler (1998)). However, we are convinced that especially for Chinese commodity futures markets the assumptions about the different trading behaviors are realistic. A report published by Citigroup Research, which has analyzed the composition of traders active on China’s commodity markets in 2016, indicates that most speculative trades have been conducted through high-frequency transactions, with average tenure of each contract reportedly lower than four hours (Liao et al. 2016).

Based on the speculation ratio (1), we are able to investigate the role of short term speculators on commodity futures markets. A few empirical studies use this measure to explore short term speculation in US commodity futures markets. Streeter and Tomek (1992) find a positive influence of the speculation ratio on returns volatility for soybeans. Robles et al. (2009) report that speculation Granger causes futures prices in the markets for wheat and rice.

More recently, Chan et al. (2015) examine the role of speculators on oil futures markets. They proxy speculative activity by using the speculation ratio and conclude that the oil futures market is dominated by uniformed speculators in the post-financialization period.\(^1\) Lucia et al. (2015) apply the speculation ratio to explore the relative importance of speculative activity versus hedging activity in the European carbon futures market. They outline the different dynamics of speculative behavior during three phases of the European Union Emission Trading Scheme.

\(^1\) The speculation ratio has not only been used to investigate commodity markets. Chaturath et al. (1996), for instance, apply it to examine the impact of speculation on the volatility of exchange rates.
3 Data and Methodology

3.1 Data

In order to investigate the time-varying behavior of speculative activity on Chinese commodity futures markets, we analyze daily data for four agricultural and two metal contracts. In particular, we examine contracts for soybeans and corn, traded on the Dalian Commodity Exchange (DCE), cotton and sugar contracts, traded on the Zhengzhou Commodity Exchange (ZCE) and contracts for copper and steel rebar, traded on the Shanghai Futures Exchange.

For all six contracts, we obtain time series data of daily settlement prices, trading volume and open interest from Thomson Reuters Datastream. Prices of contracts are quoted in Chinese Yuan Renminbi per 10 metric ton (MT), daily trading volume represents the number of contracts traded during a day and open interest is the number of contracts outstanding at the end of each trading day.

Summary statistics for the speculation ratio and returns are reported in Table 1. It displays the mean, maximum, minimum, standard deviation, skewness, kurtosis and the number of observations for all commodities examined. Sugar and steel show with 1.40 and 1.41 the highest mean of the speculation ratio. Corn shows the lowest mean with 0.44. Indicated by the distance of the extreme values (maximum and minimum) as well as by the standard deviation, the speculation ratio for cotton seems to be the most volatile. The mean values of the returns are close to zero for all contracts. According to the standard deviation, the market for cooper reveals the highest volatility. Skewness and kurtosis parameters indicate that none of the six time series follow a normal distribution.

Figures 6 and 7 show price time series and the calculated speculation ratio for the six commodity contracts examined.

3.2 Methodology

We aim at describing the dynamics of daily commodity futures price returns, derive an underlying volatility process and analyze its interdependence with speculation. Departing from economic intuition, it seems highly implausible that either the dynamics of the returns, the volatility, or its dependence on speculation activity are constant over the long observation period. This is a threat to the validity of all models with constant parameters. Thus, confidence intervals and test results rely on the assumption of constant parameters. Significance statements and evidence for or against the influence of speculation on volatility become unreliable. Therefore, we use a flexible framework that

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2 In a Monte-Carlo simulation the authors could show that a model with time-varying parameters and stochastic volatility could create a time series that implies significant counterfactual results when estimated with an AR-GARCH model as in Bohl et al. (2016).
allows all parameters that govern the dynamics and the volatility to vary stochastically over time.

In particular, we apply a two step procedure, in which each step implements a time-varying parameter VAR model with stochastic volatility of the form

\[ y_t = c_t + B_t y_{t-1} + A_{t-1}^1 \Sigma_t \epsilon_t \]  
\[ B_t = B_{t-1} + \nu_t \]  
\[ \alpha_t = \alpha_{t-1} + \xi_t \]  
\[ \log(\sigma_t) = \log(\sigma_{t-1}) + \eta_t, \]

with intercept \( c_t \), coefficient matrix \( B_t \), both time varying; \( A_t \) is a lower triangular matrix (with ones on the main diagonal), whose free elements are stacked in \( \alpha_t \) and \( \Sigma_t \) as a diagonal matrix with positive elements \( \sigma_t \) on the diagonal. \( \{\epsilon_t, \nu_t, \xi_t, \eta_t\} \) are mean zero, homoskedastic and mutually independent Gaussian random vectors of appropriate dimension, where the variance of \( \epsilon_t \) is set to one for identification reasons.

Conducting our first step, \( y_t \) denotes the multivariate time series of logarithmized commodity returns. We use the MCMC approach proposed by Primiceri (2005), respectively Del Negro & Primiceri (2015), and its implementation given in the R package bvarsv by Fabian Krueger to derive posteriors of the model parameters given the observed data. The approach provides a sample for the volatility \( \sigma_{i,t} \) for each commodity return \( i \) at time \( t \). The commodity-and time-point-wise mean of this sample is an estimator for the unobserved latent volatility process, denoted \( \bar{\sigma}_{i,t} \) in the following. \( \bar{\sigma}_{i,t} \) quantifies the degree of variation in prices of commodity futures.

To examine whether there exists a systematic relationship between this very variation and speculative activity, measured by the aforementioned ratios, we next use again the time-varying VAR model with stochastic volatility to describe the joint dynamics of the volatility and the speculation ratios of the various commodities. We obtain model equations of the form (2) for each commodity, where, in turn, \( y_t \) now represents a bivariate time series \( (\bar{\sigma}_{i,t}, r_{i,t})' \), where \( r_{i,t} \) denotes the time series of speculation ratios for commodity \( i \), \( i = 1, \ldots, n \). We denote this time series with \( z_{i,t} \) and add a superindex \( z \) to its parameters in the following.

Again, we use the aforementioned estimation procedure and implementation. Eventually, we obtain an estimate for the \( B_z^1 \)-matrix process which describes how the relationship between the lagged variables and the actual variables evolve over time. Here, we are particularly interested in those coefficients that can indicate a plausible Granger causal effect from speculative activity on returns volatility, and vice versa, i.e. \( B_{z,1,2,t} \), respectively \( B_{z,2,1,t} \).

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3 We set the thinning parameter to 100, use 50000 MCMC steps after dismissing the first 10000 steps as burn-in phase for both steps and set \( PQ \) between 300 and 3000 for the second step, which reduces the prior mean of \( \text{Var}(\nu_t) \) in comparison to the default value. The other (hyper)parameters are set to their default value, leading to an elicitation that implies not flat, but diffuse and uninformative priors. For details, we refer to the package manual and to Primiceri (2005), respectively Del Negro & Primiceri (2015), for very detailed prior discussions.
Lastly, our results can be used to provide impulse response diagrams visualizing the hypothetical effect of a shock in the speculation measure on volatility in the estimated model and vice versa.

4 Empirical Results

We use the described methodology on two settings. First, we use eleven years of data on soybeans, corn, copper, cotton and white sugar on futures returns and the speculation ratio. In the second version we add the time series for the steel contract and reduce the timespan to five years.\(^4\)

Our estimation results are summarized in the appendix. The filtered volatility process along with the speculation ratio, can be seen in Figure 3 and Figure 4. The co-movement is evident on the first sight.

Both time series serve as the data basis for the second step. The second step now reveals whether this co-movement is driven by a Granger causal effect of speculative activity on returns volatility. Figure 5 and Figure 6 show the posterior medians of the different critical coefficients. There is not one commodity for both timespan where the confidence interval does not include zero. Hence, there is no significant effect from the speculation measure on volatility in the sense of Granger causality. On the contrary, the non-zero coefficients controlling the impact from volatility on speculative activity which are depicted in Figure 7 and Figure 8 suggest that, indeed, volatility is driving speculation.

Eventually, we provide impulse response diagrams for the response of a shock in volatility on speculation in Figure 9 and Figure 10. The impulse responses visualize the aforementioned dynamics. In the estimated model, a shock in volatility affects the speculation ratio considerably, while a shock in speculative activity has essentially no impact on volatility (not depicted).

5 Conclusion

Motivated by a sharp increase in speculative trading volume on Chinese commodity futures markets in the last years, we aim at investigating the dynamic relationship of speculative activity and returns volatility over time. To this end, we employ a speculation measure that combines volume and open interest data in a flexible framework to describe and analyze their co-movements with volatility of futures returns in the Chinese futures markets for soybean, corn, copper, cotton, sugar and steel.

Our preliminary empirical results suggest that there is no causal effect from speculative behaviour to the variation in futures returns. However, we find evidence that volatility drives speculative activity.

\(^4\) In particular, we investigate the years 2006-2016 and 2012 to 2016, respectively.
References


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Till, H. (2009), ‘Has there been excessive speculation in the u.s. oil futures markets? what can we (carefully) conclude from new cftc data?’.

6 Appendix

Table 1  Summary Statistic

<table>
<thead>
<tr>
<th>Speculation Ratio</th>
<th>Soybean</th>
<th>Corn</th>
<th>Copper</th>
<th>Cotton</th>
<th>Sugar</th>
<th>Steel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.6932</td>
<td>0.4363</td>
<td>0.9896</td>
<td>0.7555</td>
<td>1.3973</td>
<td>1.4133</td>
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<tr>
<td>Maximum</td>
<td>7.0993</td>
<td>3.7420</td>
<td>3.9482</td>
<td>10.1136</td>
<td>7.5940</td>
<td>7.6736</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.0150</td>
<td>0.0441</td>
<td>0.0016</td>
<td>0.0071</td>
<td>0.0273</td>
<td>0.1352</td>
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<tr>
<td>Std. Dev.</td>
<td>0.6041</td>
<td>0.3442</td>
<td>0.5326</td>
<td>1.0217</td>
<td>0.8920</td>
<td>0.8395</td>
</tr>
<tr>
<td>Skewness</td>
<td>2.7236</td>
<td>2.6014</td>
<td>1.4398</td>
<td>3.3436</td>
<td>1.6619</td>
<td>1.8560</td>
</tr>
<tr>
<td>Returns</td>
<td>Soybean</td>
<td>Corn</td>
<td>Copper</td>
<td>Cotton</td>
<td>Sugar</td>
<td>Steel</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0172</td>
<td>0.0095</td>
<td>-0.0016</td>
<td>-0.0013</td>
<td>0.0146</td>
<td>-0.0036</td>
</tr>
<tr>
<td>Maximum</td>
<td>6.1891</td>
<td>12.2418</td>
<td>5.9925</td>
<td>8.3768</td>
<td>10.7963</td>
<td>7.9182</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1.0230</td>
<td>1.0867</td>
<td>1.4958</td>
<td>1.0226</td>
<td>1.2130</td>
<td>1.2621</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.3688</td>
<td>-1.6892</td>
<td>-0.2726</td>
<td>-1.7774</td>
<td>-0.0676</td>
<td>0.4491</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>12.2336</td>
<td>60.2679</td>
<td>5.5362</td>
<td>41.5830</td>
<td>15.1726</td>
<td>8.8927</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>2655</td>
<td>2655</td>
<td>2655</td>
<td>1875</td>
<td>2655</td>
<td>2655</td>
</tr>
</tbody>
</table>
Fig. 1 Futures Prices
Fig. 2 Speculation Ratio
Fig. 3 Speculation Ratio and Volatility (11 years).
Fig. 4 Speculation Ratio and Volatility (5 years).
Fig. 5 $B_{1,2,t}$ posterior median and 95% credibility interval (11 years).
Fig. 6 $B_{1,2,t}$ posterior median and 95% credibility interval (5 years).
Fig. 7 $B_{2, t}$ posterior median and 95% credibility interval (11 years).
Fig. 8 $B_{2,1,t}^2$ posterior median and 95% credibility interval (5 years).
Fig. 9 Impulse Response Functions with 95% credibility interval (11 years).
Fig. 10  Impulse Response Functions 95% credibility interval (5 years).