Relationship between returns volatility and trading activity: Evidence from Chinese non-ferrous metals futures market

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Abstract

As one of the largest non-ferrous metals futures trading markets, Chinese non-ferrous metals futures market plays an important part in the world. However, research based on Chinese futures market of the price-volume relation is rather sparse. This paper studies the relation between returns volatility and trading activity of copper and aluminum futures in Chinese non-ferrous metals futures market on the basis of mixture distribution hypothesis. In addition, we divide the daily volatility of futures market into overnight volatility and trading volatility to distinguish between international market and local market. To discriminate between the impact of the market trends and of innovation on returns volatility, we also divide trading activity into expected and unexpected part on the basis of Gallant et al. and Bessembinder et al. The results show that the returns volatility increases when the trading is frequent, whereas it decreases when open interest increases. Furthermore, the trading activity and international market have a greater influence on aluminum futures than on copper futures.

Keywords: Chinese non-ferrous metals futures, returns volatility, trading activity, mixture distribution hypothesis

1. Introduction

It’s widely documented that trading activity plays an important role in returns volatility of financial market. This finding makes us possible to estimate returns volatility through measuring the intensity of trading activity. Trading activity reflects market information that motivated by all kinds of economic activities and market news. This leads to aggregate the changes of the expected market returns. Because of this, we are able to estimate returns volatility via a quantitative determination of trading activity.

Both of trading volume and open interest are important indicators of trading activity in futures market, which is motivated by market information. According to mixture distribution hypothesis (MDH), trading volume and open interest are supposed to reflect the information of futures market, and this kind of relation establishes a connection among trading volume, open interest and returns volatility [1-3]. On the view of Admati and Pfleiderer [4], the returns volatility-trading volume relation is variable, and trading volume is determined by the quantity of market trader who drives the market price. As a result, with the increasing of market traders, there is a rising trend of trading volume in a long term. In addition, trading volume series and open interest series contain both linear time trend, which reflects the daily change of trading volume and open interest that aren’t motivated by innovation, and non-linear time trend, which reflects the change of trading volume and open interest that are motivated by innovation.

As the largest emerging market, China’s consumption on non-ferrous metals is quite large every year. However, non-ferrous metals futures market has been established only for more than 15 years in China. In the process of liberalization, international market as well as local market makes a great impact on Chinese non-ferrous metals futures market. And MDH is always used to study this kind of impact. Although there are some related researches, the dynamic relationship among open interest, trading volume and returns volatility has not been adequately explored in emerging markets, especially in Chinese non-ferrous metals futures market.

Therefore, this paper represents an extension of the finance literature by studying the relationship between trading activity and returns volatility of Chinese non-ferrous metals futures market. To distinguish international market and local market, we divide daily volatility (close-to-close returns volatility) into trading volatility (open-to-close returns volatility) and overnight volatility (close-to-
open returns volatility). Additionally, we also divide trading activity into expected and unexpected part to discriminate between the impact of the market trends and of innovation on returns volatility.

2. Literature review

A large number of empirical studies prove there is a relation between trading volume and returns volatility. Mixture Distribution Hypothesis applied by Clark suggests that returns volatility is positively related to trading volume. Many people have done further studies on the basis of Clark. Tauchen and Pits [5] build a model of bivariate MDH to explain the relationship between the returns volatility and the trading volume in the speculative markets. In consideration of the limitation about the standard bivariate mixture model, Liesenfeld [2] develops the Generalized Mixture Model, which improves to explain the returns volatility by the standard bivariate mixture model. Based on Glosten and Milgrom [6], Andersen [7] proposes a hypothesis which is named Modify MDH. Bhar and Hamori [8] explain the dynamic relationship between returns volatility and trading volume in crude oil futures market, and find that the higher order lagged returns can affect trading volume. Sabri [9] uses monthly returns on emerging market indexes spanning five regions between 1997 and 2000 to find that stock price changes are most closely positively correlated with the stock trading volume and the exchange rate. Alizadeh [10] investigates the price volatility and trading volume relationship in the FFA market, and found that FFA price changes have a positive impact on trading volume. Using non-parametric tests, Wai [11] assess the dynamic implications of MDH. Using state-space methods, Fleming, Kirby and Ostdiek [3] investigate the relation among trading volume, volatility, and ARCH effects within a MDH framework.

The theoretical relationship between volatility and trading volume has generally been explained using the information-flow paradigm [5] and the market-microstructure paradigm [12]. The use of ARCH/GARCH model in MDH is also an important method on studying the returns volatility. The relationship between MDH and GARCH was first concerned by Diebold [13]. Gallant [14] shows that returns volatility depends on the conditional variance of explanatory variables which can cause the GARCH effects. Lamoureux and Lastrapes [15, 16] build a GARCH model based on MDH by using trading volume to represent the information reaches the market. Since then, people begin to concentrate on the relationship among returns volatility, trading volume and GARCH effects clearer [1, 19-21]. However, some studies hold the opposite idea, such as the study on DJIA by Darrata, Rahmanb and Zhong [22], study on Irish stock exchange by Lucey [23], as well as Anea and Ureche-Rangaub [24].

Although a certain quantity of research on the relationship between volatility and trading volume of financial market has been carried out, there is a dearth in China. Besides, the majority of studies which concern on MDH always make the relationship between trading volume and price as a whole, few differentiate between trading hours and non-trading hours. This paper tries to make a complement of the literature on the two points.

3. Research method

3.1. Expected and unexpected trading activity estimator

Both of the predictable and unpredictable trading activity can influence the market price by making an impact on the market trading activity which can cause returns volatility. Considering there are linear time trend and non-linear time trend in both of the trading volume series and open interest series, we eliminate the trend using the method proposed by Gallant et al. [14].

Step 1. Taking the logarithm of the original time series data:

\[ G_i^t = \log(G_i) \]  \hspace{1cm} (1)

Step 2. Making a regression of \( G_i^t \):

\[ G_i^t = c_0 + c_1t + c_2t^2 + \mu_i \]  \hspace{1cm} (2)

Where \( G_i \) is original time series, \( G_i^t \) is the natural logarithm of \( G_i \), \( t \) represents a linear time trend, and \( t^2 \) represents a non-linear time trend, \( \mu \) is the trading volume which excludes time trend.
We use $G'_i$ represent $\mu$ and divide $G'_i$ into a predictable part and an unpredictable part by ARMA model.

Step 3. Making a regression of $G'_i$ by ARMA model:

$$G'_i = \sum_{i=1}^{m} a_i G'_{i-1} + \sum_{j=1}^{n} b_j G'^*_{r-j} + c \quad (3)$$

Where $\sum_{i=1}^{m} a_i G'_{i-1}$ is the predictable part of $G'_i$, $\sum_{j=1}^{n} b_j G'^*_{r-j}$ is the unpredictable part of $G'_i$, and $c$ is a constant. So we get the expected and unexpected trading activity estimator which is the predictable and unpredictable part of $G'_i$, respectively.

### 3.2. Econometric methodology

The GARCH model is used to study the volatility effects frequently. Lamoureux and Lastrapes [15, 16] develop a GARCH model based on MDH, and find that the market information represented by trading volume can weaken the GARCH effects on the assumption of serial correlation between the trading activity and returns volatility. This model is given by,

$$r_t = a + r_{t-1} + \epsilon_t \quad (4)$$

$$\epsilon_t | (V_t, \epsilon_{t-1}, \epsilon_{t-2}, ...) \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1} + \beta_1 h_{t-1} + \gamma V_t \quad (4a)$$

Where $r_t$ is the returns of period $t$, $V_t$ is the trading volume of period $t$, $\alpha_1$ shows the ARCH effects of model, $\beta_1$ shows the GARCH effects, and $(\alpha_1 + \beta_1)$ is the volatility persistence of GARCH, which the closer $(\alpha_1 + \beta_1)$ to 1, the longer returns volatility persistence.

Building the GARCH model on the basis of MDH, we study how the trading activity influences the returns volatility. And we also divide both of the trading volume and open interest into two parts, one is expected part, another one is unexpected part. Expected part reflects the trend of returns volatility, while unexpected part can cause the unexpected returns volatility.

$$r_t = a_0 + r_{t-1} + \epsilon_t \quad (5)$$

$$\epsilon_t | (V_{Exp}, V_{Une}, O_{Exp}, O_{Une}, S, \epsilon_{t-1}, \epsilon_{t-2}, ...) \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1} + \beta_1 h_{t-1} + \gamma_1 V_{Exp} + \gamma_2 V_{Une} + \gamma_3 O_{Exp} + \gamma_4 O_{Une} \quad (5a)$$

where $V_{Exp_t}$, $V_{Une_t}$ is the expected and unexpected trading volume of period $t$, respectively. $O_{Exp_t}$ is the expected open interest of period $t$, and $O_{Une_t}$ is the unexpected open interest. $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ shows the impact of $V_{Exp_t}$, $V_{Une_t}$, $O_{Exp_t}$, $O_{Une_t}$ on $h_t$ respectively.

### 4. Data and empirical research

#### 4.1. The data

This paper selects copper futures and aluminum futures which is the longest and largest non-ferrous metals futures in China as research objects. Existing research on the futures market has shown that, compared to the far contract, near contract is more active. So we select the copper and aluminum futures near contracts of Shanghai Futures Exchange from January 1, 2005 to August 31, 2012. In each near contract delivery month, we get a continuous sequence of futures contracts through continuous loop as a result of selecting the next to near contracts instead. And we remove the data which contain missing data to constitute two complete sets of time-series data. All data come from the China Stock Market & Accounting Research Database (CSMAR) and the Shanghai Metal Exchange (SHFE).
We divide daily volatility into trading volatility and overnight volatility, and estimate the returns volatility of the three. The daily volatility reflects the returns volatility from one day close to the next day close, trading volatility reflects the returns volatility from open to close in a trading day, and overnight volatility reflects the returns volatility from one day close to the next day open. In that way, trading volatility shows the influence of Chinese market on the returns volatility in Chinese non-ferrous metals futures market, while overnight volatility reflects the influence of international market on the returns volatility in Chinese non-ferrous metals futures market.

4.2. GARCH (1, 1) model without distinguishing expected and unexpected trading activity

The conditional volatility of non-ferrous metals futures returns is modeled by GARCH (1, 1) model, which is proposed by Lamoureux and Lastrapes [15, 16]. We also take open interest as exogenous variables. The GARCH (1, 1) model is given by,

\[ r_t = a + r_{t-1} + \varepsilon_t \]

(6)

\[ \varepsilon_t \mid (V_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) \sim N(0, h_t) \]

(6a)

\[ h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 h_{t-1} + \gamma \varepsilon_t + \gamma_a O_t \]

Where \( r_t \) is the returns, \( V_t \) is the trading volume, \( O_t \) is the open interest. \( \alpha_1 \) shows the ARCH effects of model, \( \beta_1 \) shows the GARCH effects, \( (\alpha_1 + \beta_1) \) is the volatility persistence of GARCH, \( \gamma \) shows the impact of \( V_t \) on \( h_t \), and \( \gamma_a \) reflects the impact of \( O_t \) on \( h_t \).

Table 1 shows the GARCH parameters estimate of copper futures, in which \( \text{Cu}_{\text{cc}} \) represents daily volatility of copper futures, \( \text{Cu}_{\text{oc}} \) represents trading volatility of copper futures, \( \text{Cu}_{\text{co}} \) represents overnight volatility of copper futures. Table 2 presents the GARCH parameters estimate of aluminum futures, in which \( \text{Al}_{\text{cc}} \) represents daily volatility of aluminum futures, \( \text{Al}_{\text{oc}} \) represents trading volatility of aluminum futures, \( \text{Al}_{\text{co}} \) represents overnight volatility of aluminum futures.

For the three returns volatility of both copper and aluminum futures, sum of ARCH and GARCH coefficient that reported by \( (\alpha_1 + \beta_1) \) is very high. This shows that Chinese non-ferrous metals futures market is high volatility persistent. ARCH coefficient of aluminum futures is nearly twice over copper futures, while GARCH coefficient of aluminum futures is less than copper futures. This indicates that the impact of innovation on aluminum futures market is higher than on copper futures market. It shows that compared to copper futures market, aluminum futures market is easily influenced by trading activity.

Dividing daily volatility into trading volatility and overnight volatility, we find that ARCH effects of returns on copper futures market change a little, while ARCH effects of returns on aluminum futures market reduce. And coefficient of ARCH effects on overnight volatility is higher than on trading volatility in copper futures market, but coefficient of ARCH effects on overnight volatility is lower than on trading volatility in aluminum futures market. This indicates that the impact of international market on copper and aluminum futures market is different. The impact of international market is higher than of local market in copper futures market, whereas the impact of international market is lower than of local market in aluminum futures market.

By estimating the effect of trading volume and open interest to returns volatility with GARCH (1, 1) model, we also find that trading volume results in a positive impact on returns volatility, while open interest results in a negative impact on returns volatility. It shows that futures market becomes instability when a large number of people are trading, and futures market becomes stable when people holding a quality of futures contract. As discussed above, the MDH is proved to be suitable for Chinese non-ferrous metals futures market.
4.3. GARCH (1, 1) model distinguishing expected and unexpected trading activity

Then, we divide trading volume and open interest into expected and unexpected parts. Using Eq. (5), we test three kind of returns volatility through GARCH (1, 1) model in which expected trading volume, unexpected trading volume and open interest are used as exogenous variables. As showed in Table 3 and Table 4, coefficients of unexpected trading activity(trading volume and open interest) is much higher than expected trading volume and open interest in all groups. This result suggests that it needs to consider the relationship between returns volatility and expected trading activity, or unexpected trading activity separately.
Table 4. Estimation for aluminum futures by distinguishing expected and unexpected trading activity

<table>
<thead>
<tr>
<th></th>
<th>( \alpha )</th>
<th>( \beta )</th>
<th>( \gamma )</th>
<th>( \alpha + \beta )</th>
<th>( \gamma )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.1825***</td>
<td>0.7530***</td>
<td>0.0132***</td>
<td>0.9355</td>
<td>0.0688***</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>(0.1137***</td>
<td>0.4981***</td>
<td>0.0914***</td>
<td>0.6118</td>
<td>0.1932***</td>
</tr>
<tr>
<td></td>
<td>0.0942***</td>
<td>0.9040***</td>
<td>-0.002*</td>
<td>-0.0058***</td>
<td>0.0299***</td>
</tr>
<tr>
<td>( \beta )</td>
<td>(0.1137***</td>
<td>(1.9549)</td>
<td>(19.0447)</td>
<td>(25.2141)</td>
<td>(18.6018)</td>
</tr>
<tr>
<td></td>
<td>0.1918***</td>
<td>0.7848***</td>
<td>0.0531***</td>
<td>0.0531***</td>
<td>0.0531***</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>(20.4998)</td>
<td>(88.6209)</td>
<td>(18.6018)</td>
<td>(18.6018)</td>
<td>(18.6018)</td>
</tr>
<tr>
<td></td>
<td>0.1134***</td>
<td>0.4987***</td>
<td>0.1886***</td>
<td>0.0066***</td>
<td>-0.4187***</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>(0.3928)</td>
<td>(3.2139)</td>
<td>(0.8462)</td>
<td>(0.8462)</td>
<td>(-4.3923)</td>
</tr>
<tr>
<td></td>
<td>0.1099***</td>
<td>0.8829***</td>
<td>0.0314***</td>
<td>-0.3598***</td>
<td>-0.4388***</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>(26.6303)</td>
<td>(294.910)</td>
<td>(20.9487)</td>
<td>(-5.2504)</td>
<td>(-16.8618)</td>
</tr>
</tbody>
</table>

***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. Numbers in () is Z-Statistic.

In copper futures market, the impact of trading volume on returns volatility is positive. In the daily volatility, the impact of unexpected trading volume on returns volatility is higher than expected trading volume. However, when we divide daily volatility into trading volatility and overnight volatility, the impact of unexpected and expected trading volume on returns volatility only has little difference. The impact of open interest on returns volatility is negative. In addition, the impact of unexpected open interest on returns volatility, is much higher than the impact of expected open interest. Therefore, unexpected trading activity has greater influence on returns volatility than expected trading activity, and compared to trading volume, open interest can better reflect unexpected trading activity.

In aluminum futures market, the impact of trading volume on returns volatility, including daily volatility, trading volatility, and overnight volatility, is still positive, and the impact of unexpected trading volume is higher than expected trading volume. Furthermore, the impact of open interest on returns volatility is still negative. In all groups, unexpected open interest has a greater impact on returns volatility than expected open interest. Therefore, compared to expected trading activity, unexpected trading activity has more influence on returns volatility in aluminum futures market. Trading volume and open interest can both reflect unexpected trading activity.

5. Conclusions

In this paper, MDH is tested through GARCH (1, 1) model in which volume and open interest are used as exogenous variables. In order to explain Chinese non-ferrous metals futures market from a more micro-level, we divide daily volatility into trading volatility and overnight volatility, and divide trading activity into expected and unexpected part. The conclusions are as follows.

1) We prove that MDH is applicable in Chinese non-ferrous metals futures market. The results show the impact of trading volume on returns volatility is positive, while the impact of open interest on returns volatility is negative. This means large numbers of market information will change the traders’ expectation of market price when more and more trading volume is created, in that way frequent trading activity bring increased fluctuations of returns volatility. As trading volume in copper futures market is more than aluminum futures market, impact of trading volume on returns volatility is higher in copper futures market. And traders are more willing to hold open interest when market is in a stable state, then a large number of positions can contribute to the sustainable of returns volatility.

2) Dividing daily volatility into trading volatility and overnight volatility, and estimating them respectively, we find that impact of trading activity on returns volatility is different among the three groups. It means that local market and international market can both play a significant role in Chinese non-ferrous metals futures market. And the impact of international market on aluminum futures market is much greater than copper futures market.

3) Comparing to aluminum futures market, copper futures market is less influenced by trading activity. When we divide trading activity into expected and unexpected part, we find that the impact of unexpected trading activity on copper futures market is smaller than aluminum futures market. This indicates that copper futures market is more stable than aluminum futures market.
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7. References