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Volatility forecasting in Chinese nonferrous metals futures market

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Abstract: This paper seeks to model and forecast the Chinese nonferrous metals futures market volatility and allows new insights into the time-varying volatility of realized volatility and leverage effects using high-frequency data. The LHAR-CJ model is extended and the empirical research on copper and aluminum futures in Shanghai Futures Exchange suggests the dynamic dependencies and time-varying volatility of realized volatility, which are captured by long memory HAR-GARCH model. Besides, the findings also show the significant weekly leverage effects in Chinese nonferrous metals futures market volatility. Finally, in-sample and out-of-sample forecasts are investigated, and the results show that the LHAR-CJ-G model, considering time-varying volatility of realized volatility and leverage effects, effectively improves the explanatory power as well as out-of sample predictive performance.

Key words: volatility forecasting; leverage effect; time-varying volatility; nonferrous metals futures; high-frequency data

1 Introduction

Nonferrous metal commodities play a very significant role in national economies, since they are more and more demanded by other types of market participants and their prices have an impact on the extraction, processing and manufacturing sectors. For example, aluminum is an energy-intensive commodity and copper is a base metal, and they all have major role in industrial production and manufacturing. However, nonferrous metals prices are easily influenced by speculators, especially in our recent emerging economies. The increase of uncertain factors such as the change of exchange rates, import and export policies and the fund's trading direction will bring about great fluctuations to the price of nonferrous metals. Volatility forecasting can help investors make decisions for portfolio allocation and value at risk management for financial traders. Hence, it is of great importance to improve volatility modeling and forecasting in nonferrous metals futures market.

Although the volatility forecasting in stock and energy markets attracts considerable attention of the empirical and theoretical research, relatively little is considered in base (or industrial) metals commodities. The study of metal price is considerably limited and there exist only 45 refereed publications over the period from 1980 to 2002 [1]. In the recent years, the literatures about metals commodities mainly focus on several aspects: volatility properties [2−5], the spillover effect for different markets [6−11] and the information flows between precious metals futures markets [12,13]. Besides, some researchers are trying to analyze the behavioral influences in nonferrous metal prices [14], the impact of speculation [15−17], the price−volume correlation [18] and the role of outliers and oil price shocks on volatility of metal prices [19,20].

As we all know, the impetuous development of Chinese economy triggers high dynamics in the nonferrous metals futures market, which in turn makes the understanding of the time-varying volatility of realized volatility an increasingly important issue. However, none of the above mentioned issues is concerned with the time-varying volatility of realized

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volatility other than TODOROVA [4]. In addition, most researches discussed above do not consider the leverage effects of nonferrous metals futures market, which are very important for policy makers and investors. The time-varying volatility of realized volatility and leverage effects in nonferrous metals futures market will be our focus in this work.

Several contributions are made to the existing literature. Firstly, in contrast to energy and precious metals commodities, volatility forecasting in nonferrous metals futures market is less studied, while nonferrous metals commodities play a very significant role in national economies. Secondly, in contrast to the LHAR-CJ model proposed by CORSI and RENO [21], we go one step further and account for the conditional heteroscedasticity of residual and volatility clustering by incorporating a GARCH specification. The idea is similar to the work of CORSI et al [22] and ANDERSEN et al [23]. Finally, the sample covers the period from July 1, 2010 to July 1, 2015 and hence may be more significant in volatility forecasting in the light of most recent nonferrous metals futures market history.

2 Volatility estimation and jump detection test statistics

2.1 Volatility estimation

Realized volatility (RV), proposed by ANDERSEN and BOLLERSLEV [24], is an estimation of volatility based on intraday data. It is defined as the sum of squares of daily return. A trading day is divided into M time periods, and then the discrete-time within-day geometric return can be written as

$$r_{t,j}=100(p_{t,j/M}-p_{t,(j-1)/M})\quad (j=1,\ 2,\ 3,\ \cdots,\ M) \tag{1}$$

where $p_{t,j/M}$ is the jth closing price of the trading day t, M refers to the number of intraday equally return observations over the trading day, which depends on the sampling frequency.

Considering the effect of overnight return on realized volatility, the squared overnight return is added to the realized volatility to forecast the course of daily volatility in Chinese nonferrous metals futures market like BLAIR et al [25] and GONG et al [26]. Therefore, the RV of trading day t (RV_t) in this paper can be given as

$$RV_t=\sum_{j=1}^{M}r_{t,j}^2+r_{t,n}^2 \tag{2}$$

where $r_{t,n}^2$ is the squared overnight return, which reflects the overnight logarithmic price change from day t−1 to day t.

2.2 Jump detection test statistics

According to the conclusions of BARNDORFF-NIELSEN and SHEPHARD [27,28], the price volatility of financial asset is not continuous due to the influence of information shock on the market and the investors' behavior. In order to separate the continuous variation and jump variation in RV, the realized bipower variation method and jump test statistics are used. The realized bipower variation (RBV) which is the consistent estimator of integrated volatility, is defined as

$$RBV_t=\mu_1^{-2}\left(\frac{M}{M-2}\right)\sum_{j=3}^{M}\left|r_{t,j-2}\right|\left|r_{t,j}\right| \xrightarrow[M\to\infty]{p} \int_{t-1}^{t}\sigma^2(\tau)\,\mathrm{d}\tau \tag{3}$$

where $\mu_1=\sqrt{2/\pi}$ is the excepted absolute value of a standard normal random variable and $\dfrac{M}{M-2}$ is the amendment to sample capacity. According to the research of BARNDORFF-NIELSEN and SHEPHARD [27,28], the difference between $RV_t(M)$ and $RBV_t(M)$ converge in probability to the discontinuous jump variation as the sampling frequency goes to infinity.

$$RV_t(M)-RBV_t(M)\xrightarrow[M\to\infty]{p}J_t \tag{4}$$

In order to select statistically significant jumps from the discontinuous jump variation, the jump test statistics Z_t, proposed by HUANG and TAUCHEN [29], is adopted. The expression of test statistics Z_t is defined by

$$Z_t=\frac{(RV_t-RBV_t)/RV_t}{\sqrt{\left(\left(\frac{\pi}{2}\right)^2+\pi-5\right)\frac{1}{M}\max\left(1,\frac{RQV_t}{RBV_t^2}\right)}}\to N(0,1) \tag{5}$$

where RQV_t is an estimator of forth-power variation, which is defined by

$$RQV_t=M\mu_{4/3}^{-3}\left(\frac{M}{M-4}\right)\sum_{j=5}^{M}\left|r_{t,j-4}\right|^{4/3}\left|r_{t,j-2}\right|^{4/3}\left|r_{t,j}\right|^{4/3} \tag{6}$$

According to ANDERSEN et al [30], RBV_t is not a robust estimator to test the discontinuous jump variation since it is greatly influenced by sampling frequency. Due to the impact of factors like microstructure noise of the market, the estimate value of RBV_t cannot even converge to integrated volatility with the increase of sampling frequency. ANDERSEN et al [30] proposed $MedRV_t$ as the robust estimator instead of RBV_t. $MedRV_t$ is defined as

$$MedRV_t=\frac{\pi}{6-4\sqrt{3}+\pi}\cdot\left(\frac{M}{M-2}\right)\sum_{j=2}^{M-1}Med\left(\left|r_{t,j-1}\right|,\left|r_{t,j}\right|,\left|r_{t,j+1}\right|\right)^2 \tag{7}$$