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Structural changes and volatility correlation in nonferrous metal market

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Abstract: The GARCH and DCC-GARCH models are used to study the volatility aggregation and dynamic relevance of China's three kinds of nonferrous metals (copper, aluminum and zinc) prices incorporating structural changes. The results show that copper, aluminum and zinc returns have many structure breaks points, and nonferrous metals have the great volatility risk during financial crisis. From the results of GARCH with and without structural changes, it is found that the volatility clustering of single nonferrous metal is overvalued when ignoring the structural mutation, and the return of aluminum is the most overvalued, indicating that aluminum market is more susceptible to external shock. Furthermore, it is also found that dynamic volatility correlation exists in the three prices of nonferrous metals, and the structural changes have no significant effect on the volatility correlation of the three nonferrous metals.

Key words: copper; zinc; aluminum; nonferrous metals price; structural changes; DCC-GARCH model; volatility dynamic correlation

1 Introduction

Nonferrous metals (such as copper, aluminum and zinc) play a crucial role in industrial production and economic activity. With the development of China's economy and commodity market, the demand for nonferrous metals grows rapidly, and the price dynamics of nonferrous metal markets are extremely volatile. As an important industrial raw material, the price volatility of nonferrous metals has an important influence on a country's nonferrous metals industry and the macro economy [1]. Thus, the research on volatility of nonferrous metals price has become a hot area [2].

The reason of the price volatility of nonferrous metals is concerned by a number of researches [3−5]. BOSCHI and PIERONI [6] studied the interaction between aluminum market and macroeconomic variables. The results showed that the aluminum metal prices are ultimately determined by the fundamentals of supply and demand. CHEN [7] researched the price data of nonferrous metals from 1900 to 2007, showing that the price volatility of nonferrous metals is mainly determined by the global macroeconomic factors during 1972 to 2007. CUMMINS et al [8] discussed the influence of behavior factors on the price volatility of nonferrous metals.

Additionally, the research on nonferrous metal price volatility spillover is concentrated [9,10]. XIARCHOS and FLETCHER [11] investigated the one-way relationship between metal and scrap metal. The study concluded that there exists information transfer in the scrap metal and the basic metal market in short term. TODOROVA et al [12] analyzed the volatility spillover effect between five kinds of nonferrous metals (aluminum, copper, lead, nickel and zinc) by using HAR models. YUE et al [13] used the VAR-DCC-GARCH model to explore the co-movement relationship between the price of China's nonferrous metals market and the price of LME in London. In summary, previous studies have indicated that the volatility of the price of nonferrous metals and the volatility spillover have attracted much attention of scholars, but there is still much issue.

Particularly, nonferrous metal prices have been subjected to frequent structural changes or regime shifts due to economic and geo-political events. WATKINS and MCALEER [14] predicted and simulated copper and aluminum futures price volatility by the AR(1)-GARCH(1,1) model. The results showed that the price fluctuations of nonferrous metals may be affected by the special events within the industry. Thus, considering

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structural changes in the prices is necessary when we study the volatility of nonferrous metal prices. In this paper, we use the iterative cumulative square and algorithm (ICSS algorithm, INCLAN and TIAO [15]) to identify the points of structural changes in the variance of nonferrous metals returns [16−18]. Furthermore, we evaluate the impact of structural changes on volatility cluster using a univariate GARCH model. And we use the DCC-GARCH model proposed by ENGEL [19] to measure the dynamic correlation between the volatility of the nonferrous metals price [20,21]. We construct the DCC-GARCH model with structural changes and without structural changes to measure the volatility correlation of nonferrous metal prices. In addition, the copper, aluminum and zinc are the most important nonferrous metal industry, and their prices are closely related to the global industrial output, so we use copper, aluminum and zinc as the object of our study in this paper.

2 Methodology

The dynamic conditional correlation GARCH model (DCC-GARCH) was proposed by ENGEL [19]. The model can not only study the volatility clustering of individual variables, but also analyze the strength of the relationship between the two variables. The model assumes that the return on assets at the t period follows a mean of 0, and the conditional multidimensional normal distribution of covariance matrix H_t:

$$\begin{cases} \boldsymbol{r}_t \,|\, \varphi_{t-1} \sim N(0, \boldsymbol{H}_t) \\ \boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t \end{cases} \tag{1}$$

where $\boldsymbol{r}_t$ is a k×1 vector, $\boldsymbol{H}_t$ is conditional covariance matrix, $\boldsymbol{D}_t$ is a k×k diagonal matrix which is composed of the time varying standard deviation $\sqrt{h_{i,t}}$ of the single variable GARCH model, and $\boldsymbol{R}_t$ is time varying correlation coefficient matrix. $\sqrt{h_{i,t}}$ can be obtained by the single variable GARCH model:

$$h_{it} = \omega_i + \sum_{p=1}^{p} \alpha_{i,p} r_{i,t-p}^2 + \sum_{q=1}^{q} \beta_{i,q} h_{it-1} \tag{2}$$

where ω_i is a constant, $\sum_{p=1}^{p} \alpha_{i,p} r_{i,t-p}^2$ is p order ARCH terms, $\sum_{q=1}^{q} \beta_{i,q} h_{it-1}$ is q order AR terms. ENGEL [19] suggested that the link of the asset volatilities can be expressed as the following dynamic correlation structure:

$$\boldsymbol{Q}_t = \left(1 - \sum_{m=1}^{M} \theta_{1m} - \sum_{n=1}^{N} \theta_{2n}\right) \bar{\boldsymbol{Q}} + \sum_{m=1}^{M} \theta_{1m} (\boldsymbol{\varepsilon}_{i-m} \boldsymbol{\varepsilon}_{j-m}) + \sum_{n=1}^{N} \theta_{2n} \boldsymbol{Q}_{t-n} \tag{3}$$

$$\boldsymbol{Q}_t^* = \begin{pmatrix} \sqrt{q_{11}} & 0 & 0 & \dots & 0 \\ 0 & \sqrt{q_{22}} & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & 0 \\ 0 & 0 & 0 & \dots & \sqrt{q_{kk}} \end{pmatrix} \tag{4}$$

$$\boldsymbol{R}_t = \boldsymbol{Q}_t^{*-1} \boldsymbol{Q}_t \boldsymbol{Q}_t^{*-1} \tag{5}$$

where $\boldsymbol{\varepsilon}_t = \boldsymbol{D}_t^{-1} \boldsymbol{r}_t$, $\boldsymbol{\varepsilon}_t \sim N(0, R_t)$; $\bar{\boldsymbol{Q}}_t$ is the unconditional covariance of $\boldsymbol{\varepsilon}_t$; θ_{1m} and θ_{2n} are estimation coefficients for dynamic conditional correlation models. If they are significantly not equal to 0, there is a dynamic conditional correlation coefficient among different assets. $\boldsymbol{Q}_t^*$ is a diagonal matrix of $\boldsymbol{Q}_t$ on the diagonal. The dynamic conditional correlation coefficient among different variables is expressed by the elements $\rho_{i,j,t} = q_{i,j,t} / \sqrt{q_{i,i,t} q_{j,j,t}}$ on R_t.

Following ENGEL's result [19], the DCC-GARCH model is divided into two steps. The first step is to estimate the univariate GARCH model, and the second step is to estimate the DCC model based on the first step. The likelihood function which estimates this model can be written in the following form:

$$L(\boldsymbol{\Theta}, \phi) = L_1(\boldsymbol{\Theta}) + L_2(\boldsymbol{\Theta}, \phi) \tag{6}$$

where Θ represents the estimated result of the conditional variance in the first step

$$L_1(\boldsymbol{\Theta}) = -\frac{1}{2} \sum_t (\boldsymbol{n} \ln(2\pi) + \ln|\boldsymbol{D}_t|^2 + \boldsymbol{e}_t' \boldsymbol{D}_t^{-2} \boldsymbol{e}_t) \tag{7}$$

And ϕ is the estimation of conditional correlation coefficient based on the first step estimation

$$L_2(\boldsymbol{\Theta}, \phi) = -\frac{1}{2} \sum_t (\ln|\boldsymbol{R}_t| + \varepsilon_t' \boldsymbol{R}_t^{-1} \varepsilon_t - \varepsilon_t' \varepsilon_t) \tag{8}$$

In order to construct the DCC-GARCH model with structural changes, we need to regard detect point mutation of ICSS algorithm as a dummy variable is introduced into the univariate GARCH model.

The univariate GARCH model can be written as

$$\begin{cases} \boldsymbol{r}_t = c + \lambda \boldsymbol{r}_{t-1} + \boldsymbol{e}_t, \ \boldsymbol{e}_t \,|\, I_{t-1} \sim N(0, h_t) \\ h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} \end{cases} \tag{9}$$

Then, the ICSS algorithm is used to detect the mutation point as dummy variable, which is introduced into the univariate GAHCH model, and gain the univariate GAHCH model with structural changes:

$$\begin{cases} \boldsymbol{r}_t = c + \lambda \boldsymbol{r}_{t-1} + e_t, e_t \,|\, I_{t-1} \sim N(0, h_t) \\ h_t = \omega + d_1 D_1 + \dots + d_n D_n + \alpha e_{t-1}^2 + \beta h_{t-1} \end{cases} \tag{10}$$

N mutation points are obtained by using the ICSS algorithm. The two-mutation point interval region is called the volatility regime, which can get the n+1 wave mechanism. In the first i+1, the virtual variable takes one,