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# Forecasting copper futures volatility under model uncertainty

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ABSTRACT

In practice, volatility forecasting under model uncertainty is an important issue. In this paper, the main purpose is to apply the model averaging techniques to reduce volatility model uncertainty and improve volatility forecasting. for the copper futures. Then, various loss functions are employed to assess the forecasting performance. The empirical study results show that the model averaging methods can significantly reduce the uncertainty of forecast. Furthermore, the OLS time-varying weighted model averaging method can achieve the smallest forecasting error and significantly reduce the over-prediction percentage.



## 1. Introduction

Copper is one of the most important industrial metals as well as iron and aluminum. Similar to crude oil, gold and other commodity markets, the future market is the mainly pricing and trading market for copper. Copper futures price has a marked impact on gold and other precious metals' prices (see, Morales and Andreosso-O'Callaghan (2011)). It is a key input for macroeconomic models and option pricing formulas. Market participants can predict and manage their exposure to risk with accurately forecasting its volatility.

London Metal Exchange (LME) is the biggest futures exchange for copper and handles more than 90% of the world trades. Since 2008, commodities especially copper futures' price experienced unexpected fluctuation affected by international financial crisis and European debt crisis. In January 2014, the price of LME three-month copper futures contract raised a high level around \$7460, but it sharply dropped to \$6320 two months later. Then in January 2015, copper futures' price went down to \$5339 and fleetly rised to \$6400 at the beginning of May. The high fluctuation of copper futures' price highlights the significance of volatility forecast. Hence it is of great importance to investigate the volatility of copper futures.

GARCH-type models are the most important and commonly used models in studying volatility. They can effectively describe the time-series fluctuation in volatility. Based on Engle (1982)'s ARCH (Autoregressive Conditional Heteroskedasticity) and Bollerslev (1986)'s GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, various of GARCH-type models are proposed, such as EGARCH, GJR-GARCH, NAGARCH, FIGARCH etc. Those models are frequently used in the volatility forecast studies of exchange market (Bollerslev, 1990; West and Cho, 1995; Wright, 2008), bond market (Bali, 2000), option market (Noh et al., 1994; Christensen and Prabhala, 1998) and stock market (Engle, 1990; Lamoureux and Lastrapes, 1990; Ding et al., 1993; Engle and Ng, 1993; Hamilton and Susmel, 1994; Gallo and Pacini, 1998; Li et al., 2013).

A large proportion of volatility studies focus on the stock market and confirm that GARCH-type models can model the stocks' volatilities variation. During recent years, there has a significant rise in the interest of modeling futures market's volatility. Similar to stock market and exchange market, volatility in futures market also behaves the characteristics of persistence, clustering and conditional heteroskedasticity. There are also numerous literatures on volatility forecast in crude oil futures market (see, Rafiq et al. (2009), Wei et al. (2010), Chang et al. (2011) and Wang and Wu (2012)), carbon futures market (Byun and Cho, 2013), precious metals futures market (Tully and Lucey, 2007; Batten et al., 2010; Shafiee and Topal; 2010), industrial metals furures market (Watkins and McAleer, 2008). Those studies show that

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GARCH-class models can effectively capture these futures market's volatility variation. Existing literatures on copper futures volatility mainly focus on the methods of measuring the volatility and estimating the spillover effect for different markets (see, Lien and Yang (2006) and Fung and Tse (2010)). Bracker and Smith (1999) found that copper futures returns were characterized by negative skewness and excess kurtosis. They employed five models, including random walk model (RW), GARCH, EGARCH, AGARCH and GJR-GARCH to capture the copper futures' volatility and found GARCH and EGARCH showed superior performance. However, market participants are also interested in out-of-sample forecasting ability since this is helpful to predict the future risk. Smith and Bracker (2003) studied the out-of-sample volatility forecasting ability with GARCH-type models in copper futures market. The results showed that GARCH, EGARCH and AGARCH are all superior to random walk model.

However, there are lots of challenges for individual model's forecasting since it ignores “model risk” or “model uncertainty”, which is linked to the uncertainty of the choice of the volatility model itself. Welch and Goyal (2008) found that numerous economic variables with in-sample predictive ability for the equity premium fail to deliver consistent out-of-sample forecasting gains. The literatures document that discarding model uncertainty can create a large utility or wealth loss (Avramov, 2002; Rapach et al., 2009; Li et al., 2013). However, without considering model uncertainty, most empirical studies on volatility forecasting focus on choosing the best model among the candidate models based on AIC and BIC critera.

Comparing with model selection, model averaging methods can achieve more stable performance in forecasting. Rapach et al. (2009) provided empirical explanations for the benefits of model averaging: (i)combining forecasts incorporated information from numerous models while substantially reducing forecast error; (ii) combination forecasts were linked to the real economy. Bates and Granger (1969) proposed the idea of model averaging, then various of model averaging methods were proposed, such as simple averaging method, trimmean averaging method, median averaging method, smoothed AIC(BIC) method, Bayesian averaging method, linear combination averaging method, etc, see Granger and Ramanathan (1984), Clements and Hendry, (1998), Hjort and Claeskens (2003) and their reference therein. On the basis of the empirical analysis, it has been documented that the model averaging methods can achieve superior performance than the individual model forecasting, see Avramov (2002), Rapach et al. (2009) and Li et al. (2013).

In this paper, we employ the model averaging methods for forecasting the copper futures' volatility and use various kinds of loss functions to assess the forecasting performance. To the best of our knowledge, this is the first study to explore the model averaging techniques to forecast industrial metals market's volatility under model uncertainty. The core thought of model averaging is that the weighted combination of forecasting models decreases the model uncertainty and improves forecasting accuracy. Model averaging method may not necessarily behave the best in all forecasts, but it could lower the risk of getting extreme value.

The paper is organized as follows: Section 2 provides a description of GARCH models, model averaging methods as well as loss functions employed in this paper. Section 3 presents the data and the empirical analysis. Section 4 shows the empirical results of in-sample estimation and out-of-sample forecasting. Section 5 summarizes this paper.

## 2. Methodology

### 2.1. GARCH models

#### 2.1.1. Linear models

The volatilities of financial assets' returns usually show the characteristics of volatility-clustering, conditional heteroskedasticity and long memory and persistence. ARCH and GARCH-type model can effectively model the variation of the volatilities. Engle (1982) proposed the ARCH model. ARCH(p) can be described as follows:

$$x_t = \mu_t + \varepsilon_t, \tag{1}$$

Where,

$$\varepsilon_t = \sqrt{h_t}\eta_t, \tag{2}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2, \tag{3}$$

$\mu_t$ denotes the conditional mean and $h_t$ is the conditional variance with the sufficient conditions $\omega > 0, \alpha_i > 0$. $\eta_t \sim i.\ i.\ dN(0, 1)$ and $\varepsilon_t | I_{t-1} \sim i.\ i.\ dN(0, h_t)$. But ARCH model usually needs a large lag length p for better fitting. Following Engle's seminal work, Bollerslev (1986) generalized the ARCH model into GARCH model. The specification for the conditional variance of GARCH(p,q) model can be described as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}, \tag{4}$$

The parameters should be nonnegative and the additional necessary and sufficient condition for stationary is:

$$\sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i < 1 \tag{5}$$

#### 2.1.2. Nonlinear models

It is well-known that the fluctuations of financial assets' returns are asymmetric in bull and bear markets, i.e., the leverage effect (Chevallier, 2009, 2011). Hence, Nelson (1991) proposed the exponential GARCH model (EGARCH) to incorporate the leverage effect. The specification for the conditional variance of EGARCH(p, q) model can be described as follows:

$$\ln h_t = \omega + \sum_{i=1}^{p} (\alpha_i(|\eta_{t-i}| - E|\eta_{t-i}|) + \gamma_i \eta_{t-i}) + \sum_{i=1}^{q} \beta_i \ln h_{t-i} \tag{6}$$

Since the conditional variance $h_t$ is the exponential form, there is no restriction on $\alpha_i$ and $\beta_i$, $\alpha_i(|\eta_{t-i}| - E|\eta_{t-i}|)$ shows that the conditional variance $h_t$ is influenced by the absolute value of $\eta_t$, $\gamma_i \eta_{t-i}$ shows that $h_t$ is also determined by $\eta_{t-i}$'s positive or negative sign. If $\gamma \neq 0$, there exists asymmetric effect for negative and positive shocks to returns. Generally, $\gamma < 0$, the impact of negative shocks is greater than positive shock.

Another popular model to capture the asymmetric effect of volatility is GJR-GARCH (also called the threshold GARCH) proposed by Glosten et al. (1993) and Zakoian (1994) independently. The conditional variance can be described as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i I(\varepsilon_{t-i} < 0) \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}, \tag{7}$$

Where, $I(\cdot)$ is an indicator function of $\varepsilon$,