



Volatility forecasting using high frequency data: The role of after-hours information and leverage effects

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ARTICLE INFO

Keywords:

Non-ferrous metals futures
Volatility forecasting
After-hours information
Leverage effects
Volatility clustering

ABSTRACT

This investigation extends the HAR model to include the role of after-hours information and leverage effects to forecast daily volatility of the Chinese non-ferrous metals futures market. Furthermore, volatility clustering in the residuals of the volatility model is investigated. In addition to the usual leverage effects, the findings indicated new insights into additional leverage effects, which are captured by negative overnight returns and negative lunch-break returns. Moreover, after-hours information has a highly in-sample explanatory and there is no risk–return trade-off in the Chinese non-ferrous metals futures market. One-step ahead forecasts are investigated and the results indicated that the introduction of after-hours information and leverage effects in the HAR model exhibit better predictive power. Finally, the results are robust for various sampling frequencies. Our findings have important significance for investors and policy makers and will elucidate further research directions.

1. Introduction

With the development of China's economy in recent years, the demand for non-ferrous metal commodities, such as copper and aluminum, has greatly increased, as they are significant sources of raw materials for industry. Correspondingly, the price of these commodities has had a large impact on the extraction, processing, and manufacturing sectors. However, the increase of uncertainty factors, such as the exchange rate, import and export policies, and the existence of speculators, has lead to great fluctuations in the price of non-ferrous metals. This makes volatility modeling and forecasting of the Chinese non-ferrous metals futures market very significant, as it can assist investors in making portfolio allocation decisions and affect value-at-risk management decisions made by financial traders.

Most literatures on forecasting the volatility of metal futures market applied GARCH-type models which were sampled at daily to monthly frequencies (Aroui et al., 2013; Li and Li, 2015; Watkins and McAleer, 2008). Other volatility forecasting models commonly used to forecast the future volatility of the financial markets are stochastic volatility (SV)-type models (Baum and Zerilli, 2016; Larsson and Nossman, 2011), autoregressive (AR) models (Sadorsky and McKenzie, 2008), ARMA models (Xu and Ouenniche, 2012), and the jump-diffusion models (Askari and Krichene, 2008). However, all these models used low-frequency transaction data and can not accurately measure the

whole-day volatility information. Therefore, they all have their own defects. Using the high-frequency data, Andersen and Bollerslev (1998) first proposed the realized volatility (RV) as the more accurate measure of the integrated variances. Andersen et al. (2003), Andersen et al. (2004) found that simple reduced form models with realized volatility (RV) is significantly better than the popular GARCH and stochastic volatility (SV) models on forecasting future volatility in the financial markets. Corsi (2009) developed the heterogeneous autoregressive (HAR) model of realized volatility and found that the predictive power of HAR model strongly outperforms the GARCH and the ARFIMA-RV models. Therefore, HAR models are receiving more attention from investors. In a majority of the literature, these models used intra-day data that had been observed during normal trading hours. However, the overnight return data collected during break hours is also very important for volatility estimation and forecasting and this information directly affects investor risk. In addition, Wang et al. (2015) demonstrated that lunch-break information may have a large long-run impact on the volatility of the Chinese non-ferrous metals futures market. Therefore, this investigation contributes to the study of this issue by considering the role of after-hours information. In addition, the volatility clustering inherent in the residuals of the HAR models, which is considered in the work of Corsi et al. (2008), Todorova (2015), and Ciarreta and Zarraga (2016), is investigated. We test whether modeling the conditional heteroskedasticity of the realized volatility innovations

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can improve forecasting performance. The focus of this study is to investigate the role of after-hours information, volatility of realized volatility and asymmetry in the non-ferrous metals futures market.

Our research is motivated by the work of Wang et al. (2015), who extended the HAR-RV model to enable it to forecast volatility by considering the role of lunch-break returns, overnight returns, trading volume, and leverage effects. However, the paper did not account for the volatility of realized volatility, which was considered in Corsi et al. (2008), and this aspect is considered to be one of the innovations in this investigation. Therefore, we extend the HAR model by incorporating a GARCH specification to forecast the volatility of Chinese non-ferrous metals futures. This investigation is also related to the recent work of Todorova (2015), who captured the dynamics of realized volatility and leverage effects and constructed the HAR-L-GARCH model to analyze the volatility of the London Metals Exchange (LME) non-ferrous metal market. However, in contrast to the present work, Todorova (2015) made no attempt to consider the impact of after-hours information and the additional asymmetry effects with respect to overnight returns and lunch-break returns.

Previous studies focused primarily on mature futures markets, such as the London Metals Exchange (LME) and the Chicago Mercantile Exchange (CME), rather than emerging markets. In contrast, this investigation explores the Shanghai Futures Exchange (SHFE), which represents a typical Chinese commodity futures market and has been the most dramatically expanding market in the world during the past three decades. In fact, the trading volume of the SHFE in 2013 was 624 million hands and the SHFE rose to the top spot once again in terms of trading volume after three years, according to the volume ranking list developed by the global commodity futures exchange in 2013. The 2013 vol of the SHFE increased by 80% from the previous year. According to data from the World Federation of Exchanges (WFE), the 2015 trading volume growth rate of China's commodities exchanges was the first in the global market. The volume of commodity contract trades in the SHFE soared to more than 1 billion copies and increased by 25% in 2015. The trading volume of the CME in 2015, by contrast, grew by only 17%, while the LME trading volume fell by 4%. This paper focuses on copper and aluminum futures traded on the Shanghai Futures Exchange (SHFE) in China, because they are the most actively traded commodity futures in China. For example, in 2013, the trading volume of copper futures on the SHFE was 33,460 billion RMB Yuan (approximately US \$5577 billion), which accounted for 27.69% of the total futures trading volume on the SHFE, and was 3 times the trading volume of copper futures on the LME (Liu and An, 2014).¹ The volume growth in the China Commodity Exchange in recent years has dwarfed other competitors such as LME and CME. Furthermore, the SHFE copper futures price was lifted to the status of one of the authoritative quotes provided by the three major pricing centers of the global copper market. However, Chinese futures markets are still relatively immature, less information efficiency, more volatile, and less liquid than mature futures markets (Liu and An, 2014). Compared with the LME or the CME in US and European markets, the SHFE displays strong regional characteristics and has significant structural and institutional distinctions and, therefore, exhibits unique volatility and risk characteristics. Thus, from an empirical perspective, the SHFE is an interesting case for research.

This investigation makes several contributions to the existing literature. First, in contrast to stock and energy markets, volatility forecasting in non-ferrous metals futures is considerably limited. Although non-ferrous metal commodities play a very significant role in national economies, there exists only 45 refereed publications from 1980 to 2002 concerning the price of industrial metals (Watkins and Mcaleer, 2004). Moreover, this investigation covers the period from July 1, 2010 to December 1, 2015, and hence may be more significant for volatility

forecasting, considering the most recent history of the non-ferrous metals futures market.

This investigation also considers the role of after-hours information on volatility forecasting by introducing (negative) overnight returns and (negative) lunch-break returns. Then we test whether after-hours information during non-trading hours has a significant impact on future volatility in the Chinese non-ferrous metals futures market. Moreover additional leverage effects, which are captured by the negative lunch-break returns and negative overnight returns, are investigated, in addition to the traditional leverage effects. Following Corsi et al. (2008) and Todorova (2015), we account for the volatility of realized volatility by including a GARCH specification. This innovation considers the fact that the residuals of the HAR model reveal significant conditional heteroskedasticity and volatility clustering.

Although the HAR model is broadly used in stock and energy markets, research that applies the model to forecast industrial metal volatility is relatively scarce. Most volatility forecasts for metal markets apply GARCH-type models and are based on daily or monthly frequencies. The most recent study by Li and Li (2015) applied GARCH models to forecast copper futures volatility under model uncertainty. Bentes (2015) employed three volatility models of the GARCH family to examine the volatility behavior of gold returns. In contrast, we employ the HAR model, based on intraday data, to forecast the volatility of copper and aluminum futures, which is much more accurate than the GARCH model based solely on daily or monthly frequencies (Wen et al., 2016). The HAR model, first proposed by Corsi (2004), can capture the long-memory feature of realized volatility. The long-memory pattern is captured by aggregating the volatility over different periods; that is, daily for short-term traders, weekly for medium-term, and monthly for long-term.

The rest of this investigation is arranged as follows: Section 2 provides the volatility estimation, the data, and the summary statistics. Section 3 describes the volatility models. In Section 4, the results of in-sample analysis of the extended HAR-LA and HAR-LA-GARCH models are given. Section 5 evaluates the out-of-sample forecasting performances of extended HAR models. In Section 6, we present the robustness test. Finally, the conclusions are discussed in Section 7.

2. Volatility estimation and data

An appropriate volatility measure series is important for high-frequency volatility forecasting. Realized volatility is widely used as an appropriate realized measure in many papers. However, realized volatility only reflects volatility during trading hours, while ignoring the overnight information produced during non-trading hours. Therefore, a more proper proxy for daily volatility is required for forecasting accuracy.

2.1. Intraday integrated variance estimation

In the course of exploring the volatility of non-ferrous metals futures, we used realized volatility as the measure of daily quadratic variation. By dividing a trading day into M periods of time, the resultant continuous intraday returns based on intraday metals futures' quotations, $p_{t,j/M}$, can be written as:

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

with the first index t denoting the day of observation $t = 1, 2, \dots, T$. The realized volatility, which is estimated by the sum of squared intraday returns:

$$RV_t = \sum_{j=1}^M r_{t,j}^2 \quad (2)$$

The realized volatility can be used as an estimator of intraday integrated variance. However, both the data frequency and market

¹ Sources: www.shfe.com.cn and www.dce.com.cn.

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