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Forecasting volatility in the Chinese stock market under model uncertainty

Yong Li [a], Wei-Ping Huang [b], Jie Zhang [c,*]

[a] Hanqing Advanced Institute of Economics and Finance, Renmin University of China, Beijing 100872, China
[b] China Investment Securities, Shenzhen 518048, China
[c] Institute of China's Economic Reform & Development, Renmin University of China, Beijing 100872, China

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ABSTRACT

Volatility forecasting is an important issue in empirical finance. In this paper, the main purpose is to apply the model averaging techniques to reduce volatility model uncertainty and improve volatility forecasting. Six GARCH-type models are considered as candidate models for model averaging. As to the Chinese stock market, the largest emerging market in the world, the empirical study shows that forecast combination using model averaging can be a better approach than the individual forecasts.

1. Introduction

Accurate volatility forecasting is one of the key tasks in empirical finance, such as, investment, security valuation, risk management, and monetary policy. Consequently, in the past two decades, forecasting volatility in financial markets has attracted growing attention by academics and practitioners. Engle (1982) first proposed the so-called Autoregressive Conditional Heteroscedasticity (ARCH) model for modeling the asset volatility. A generalization of ARCH, GARCH, was developed by Bollerslev (1986). After that, many general extensions of these fundamental models have been developed, see Francq and Zakoian (2010) for an excellent overview. An excellent review about volatility forecasting using these volatility models was recently reported by Poon and Granger (2003).

While the use of models has undeniably led to a better measurement of volatility, it has in turn, given rise to a new problem, "model risk" or "model uncertainty," which is linked to the uncertainty of the choice of the volatility model itself. The literature revealed that discarding model uncertainty can create a large utility or wealth loss (Avramov, 2002; Rapach et al., 2009). However, with ignoring model uncertainty, most empirical studies on volatility forecasting focused on choosing the best model among the candidate models where the techniques ranging from in-sample criteria through out-of-sample criteria, such as AIC, BIC, were used.

In this paper, instead of choosing the best model, we use the model averaging technique to deal with model uncertainty. Several volatility models are considered to be appropriate candidates for model averaging. Recognizing that numerous empirical studies addressed international stock market volatility, but few focused on the emerging stock markets, we apply the model averaging technique to Chinese stock market. To the best of our knowledge, this is the first study to explore the model averaging technique to forecast Chinese stock market volatility under model uncertainty. This study attempts to enrich the existing literature by investigating the case of China, the largest transitional economy in the world, which has a unique market structure—particularly in the dominance of individual investors over institutional investors in the stock market (Ng and Wu, 2007).

The remainder of this paper is organized as follows. Section 2 describes the data and model averaging approach. Section 3 relates the empirical results and forecasting valuation. Finally, conclusions and discussions are included in Section 4.

2. Data and methodology

2.1. Data

China has two stock exchanges, the Shanghai Stock Exchange and the Shenzhen Stock Exchange, which were established on December 19, 1990 and July 3, 1991, respectively. Large companies mainly go public at the Shanghai Stock Exchange, while mid-sized and small companies at the Shenzhen Stock Exchange. As one of the largest emerging markets in the world, the Chinese stock market, (the sum of Shanghai

* Corresponding author.
E-mail address: zhangjie0402@ruc.edu.cn (J. Zhang).

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and Shenzhen stock exchanges), had 2063 listed companies by the end of 2010, and the market value run up to 30,520 billion yuan.[1]

In China, the China Securities Regulatory Commission (SCRC) approves the companies which want to list on the Exchanges, with the Exchange itself regulating the trading. Moreover, investors are required to maintain a capital account with a security dealer and can only trade under the limit of their capital. Margin trading and short sales are prohibited. During the period from May 21, 1992 through December 15, 1996, the stock market trading system was significantly modified, as its price-ceiling was abolished and stock price was determined by the force of demand and supply.[2] On December 16, 1996, the Shanghai and Shenzhen Stock Exchanges put the 10% limit-up and limit-down pricing system. The change of trading system can lead to a structure change in the financial series of stock return data. Hence, if the data of the period from 1992 to 1996 is included, the volatility will be overestimated. Furthermore, most large and high-quality companies were listed in Shanghai Stock Exchanges. Thus, in this paper, we only consider the data of Shanghai Composite Index after 1996 to be analyzed.

The raw data are daily stock price indexes (p_t) covering the period from January 2, 1997 to December 31, 2010, which makes a total of 3385 daily observations. The data come from Wind Financial database. Daily returns are identified as the first difference in the natural logarithm of the closing index value for two consecutive trading days, that is, $r_t = \ln(p_t/p_{t-1})$. According to Merton (1980) and Perry (1982), the realized volatility in a month can be simply calculated as the sum of squared daily returns in the corresponding month,

$$\sigma_T^2 = \sum_{t=1}^{N_t} r_t^2. \tag{1}$$

where N_t is the number of trading days in this month t.

Table 1 contains some summary statistics. We can find that the skewness is negative, which indicates the distribution is non-symmetric. Moreover, the large kurtosis suggests that the return series are leptokurtic (fat-tailed) and sharply peaked about the mean compared with the normal distribution. Additionally, the JB statistic rejects the null hypothesis of normal distribution.

2.2. Model averaging technique

The standard GARCH(1,1) model is often used to forecast the asset volatility. We model r_t as $r_t = \mu + \varepsilon_t$, assuming that the error (ε_t) is distributed as normal distribution with zero mean and variance σ_t^2. The GARCH(1,1) evaluates the positive and negative ε_t of the same magnitude equally, which is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2}$$

However, the GARCH model cannot explain asymmetry in the volatility. The EGARCH(1,1) and GJR-GARCH(1,1) models, conversely, allow asymmetry in the conditional volatility equation respectively given by:

$$\ln\left(\sigma_t^2\right) = \alpha_0 + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \lambda \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}}\right] + \beta \ln\left(\sigma_{t-1}^2\right) \tag{3}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 D_{t-1}^- + \beta \sigma_{t-1}^2 \tag{4}$$

where D_{t-1}^- is a dummy variable taking the value of 1 if $\varepsilon_{t-1} < 0$, and 0 otherwise. In addition, the return distribution is often shown as fatter tails (see the summary statistics in Table 1). Hence, the conditional normality in GARCH models can be replaced by t distributions. Thus, in this paper, we use the following six models for model averaging: GARCH(1,1), GARCH(1,1) − t, EGARCH(1,1), EGARCH(1,1) − t, GJR-GARCH(1,1), and GJR-GARCH(1,1) − t.

The data are divided into two parts: one is used as the training set to estimate the parameters, while the other is used to evaluate the forecasting effect. In order to evaluate the forecast effect, we consider three different choices of training sample. In the first case, the first 84 monthly observations (from January 1997 to December 2003) are used as training samples; in the second case, the first two-thirds (from January 1997 to April 2005), 112 monthly observations are used; in the third case, the first three quarters (from January 1997 to June 2006), 126 monthly observations, are used. We make the one-step-ahead forecast of the day's volatility, and then roll the sample forward one observation at a time, constructing a new one-step-ahead forecast at each stage. These out-of-sample forecasts of daily variance are summed up to obtain the monthly total volatility.

For our study, we use the model averaging strategies to generate the forecasts. The combination forecasts of $\hat{\sigma}_{c,t}^2$ at month t are weighted averages of the $N = 6$ individual forecasts given as follows:

$$\hat{\sigma}_{c,t}^2 = \sum_{i=1}^{N} \omega_{i,t} \hat{\sigma}_{i,t}^2 \tag{5}$$

where $\{\omega_{i,t}\}_{i=1}^N$ are the weights at month t. $\hat{\sigma}_{i,t}^2$ are the single forecasts of each individual model at month t. Five different averaging strategies are adopted to generate the forecasts as follows:

1) simple mean weight averaging: $\omega_{i,t} = {}^1/_N$ for $i = 1, \ldots, N$
2) median averaging: the median of $\left\{\hat{\sigma}_{i,t}^2\right\}_{i=1}^N$ is used
3) trimmed mean averaging: set $\omega_{i,t} = 0$ for the individual forecasts with the smallest and largest magnitudes and $\omega_{i,t} = {}^1/_{(N-2)}$ for the remaining individual forecasts
4) regression combination approach by Clements and Hendry (1998): the combination weights are derived from the following regression:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \hat{\sigma}_{1,t}^2 + \alpha_2 \hat{\sigma}_{2,t}^2 + \cdots + \alpha_N \hat{\sigma}_{N,t} + \xi_t \tag{6}$$

where σ_t^2 is the monthly realized volatility in Eq. (1) and $\hat{\sigma}_{i,t}^2$, $i = 1, 2, \ldots, N$ are N different forecasts of individual forecasts. The resulting combination forecast is then given by

$$\hat{\sigma}^2{}_{c,t} = \hat{\alpha}_0 + \hat{\alpha}_1 \hat{\sigma}^2{}_{1,t} + \hat{\alpha}_2 \hat{\sigma}^2{}_{2,t} + \cdots + \hat{\alpha}_N \hat{\sigma}^2{}_{N,t} \tag{7}$$

where $\hat{\sigma}_{c,t}^2$ is the combination forecast. We consider the OLS fixed weights. The fixed weights allow for the initial period of 20 monthly forecasts to be used for estimating weights, while the remaining forecasts are used for the purpose of comparison.
5) the ordinary least square (OLS) time-varying weights are also considered on the basis of a regression-based averaging approach. For the OLS time-varying weights, combination weights are obtained by estimating Eq. (6) on forecasts from $t - 20$ to $t - 1$. We combine the various individual forecasts $\hat{\sigma}_{i,t}^2$ at month t using these weights and then roll the window of forecasts to get new combinations of weights.

3. Empirical result

Following Brailsford and Faff (1996), we evaluate the forecast performance by the symmetric and asymmetric statistical loss functions. The symmetric loss functions are the mean absolute error (MAE), the

[1] By the end of 2010, the New York Stock Exchange had 2317 listed companies with 13,394 billion dollars in market value, which converted a total of 88.71 trillion yuan for 6.6227 yuan per dollar.

[2] On May 21, 1992, the Shanghai Stock Exchange abolished the limit-up and limit-down price system, causing the Shanghai Stock Market Index to rise more than 104% on that day. This is the largest increase ever experienced.