High frequency volatility model based on leverage, volume price relationship and VIX index

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Abstract: Volatility is the degree of financial asset price volatility, is the uncertainty of asset return rate measurement, used to reflect the risk level of financial assets. The higher the volatility, the more severe the volatility of financial asset price, the stronger the uncertainty of asset return rate; the lower the volatility, the more smooth the volatility of financial asset prices, the stronger the certainty of asset return rate. Based on the HAR-RV model, the LHAR-RV-V model is constructed by considering the influence of leverage effect, volume price relationship and market panic factors on volatility. An empirical analysis of the 5-minute high-frequency data of CSI 300 index by using the LHAR-RV-V-V model shows that LHAR-RV-V model has better out-of-sample prediction ability than other models, and the prediction results are quite robust.

1. Introduction

In the financial market, it is of great significance for enterprises and individuals to avoid risks and reduce asset volatility. The accurate description of asset return volatility is of great significance for investors to construct asset portfolio, measure and manage financial risks, and design financial derivatives. In recent years, with the continuous development and improvement of financial markets, the financial systems of countries around the world are becoming more and more correlated. At the same time, the financial risks caused by the volatility of asset returns are getting bigger and bigger, and it is increasingly difficult to predict the volatility of asset returns. The financial crisis of 2008 amply illustrated how volatility in financial markets can quickly spread to other countries. In order to avoid risks, predict asset volatility and avoid financial crises, scholars have continuously explored and created a variety of volatility prediction models. In the earliest days, volatility was measured by daily return rate. However, with the rapid development of science and technology, the trading of various financial products became more and more frequent, and the amount of information contained in the intraday trading data and the influence of structural errors became more and more significant. More importantly, if the return rate is used to measure volatility, the estimation and prediction models established on this basis are generally low-dimensional or even univariate. In this case, realized volatility, a new measure of volatility, is proposed. Compared with other volatility measurement models, realized volatility has two advantages: first, realized volatility is calculated based on high-frequency data; second, it is suitable for volatility modeling and prediction in the high-dimensional multivariate variable environment of financial economy.

Although the academia and the industry have a long history of exploration and research on volatility models, they are still constantly innovating and improving the model to improve the prediction effect of the model. In 1982, Engle [1] proposed the famous ARCH model, which had a good description of the aggregation of financial asset volatility represented by stocks, and gained extensive theoretical and application attention. Bollerslev [2] proposed GARCH model as a typical representative. The introduction of GARCH model greatly expanded the application scope of ARCH class. Subsequently, other ARCH class models improved based on this model emerged in an endless stream. Great success has also been achieved in characterizing the volatility of daytime data. Although GARCH model has been widely used, it still has defects. In the GARCH model, the conditional heteroscedasticity of the current period will be affected by the conditional heteroscedasticity of the previous period, and the model cannot measure the long-term volatility well. In order to overcome these difficulties, Clark put forward stochastic fluctuation model (SV) in 1973. Scholars prove that SV model can describe the characteristics of peaks well, and can better predict long-term volatility compared with GARCH model.

In recent years, with the development of information technology and the application of Internet technology, it is possible for researchers to obtain high-frequency return data, which further updates the research direction of volatility model. Merton acquired minute-level data of high frequency in 1986 and obtained realized high-frequency volatility model based on minute-level data fitting for the first time. This method makes up for the defect of low accuracy of the previous low-frequency model and improves the fitting accuracy of the model significantly. Bollerslev and Andersen [3] used quadratic variation and return decomposition theory to prove that realized volatility is the real volatility under the conditions of infinite samples of return series and zero-mean assumption. Even though high frequency data can reflect a large amount of information, the market micro noise will lead to the autocorrelation of high frequency returns, so the estimation error of realized volatility will occur. To reduce this error, find an optimal frequency so as to avoid noise as much as possible. Chinese scholar Tang Yong [4] took the high-frequency data of Shanghai Composite Index as an example and empirically found the rationality of 5-minute sampling frequency data. Liu et al. [5] studied more than 400 different volatility estimators and empirically found that it was difficult to significantly beat the realized volatility estimated with 5-min sampling data, at least in a statistical sense. In view of the above analysis, this paper also selects 5-min interval as the sampling frequency of empirical data.

In 2004, Corsi [6] created har-RV model for the first time according to the heterogeneous market hypothesis created by Muller [7], which described the heterogeneity in the market by summating the realized volatility in different holding periods. Although the model itself is not a long memory model, it can describe the long memory characteristics of realized volatility by summing up volatility of different time lengths. Traders, speculators general trading days, the high frequency traders, value investors and institutional investors, such as low frequency traders of assets holding period is longer, with the same information at the same time all kinds of traders even respond to the time also each are not identical, so for each type of traders expected, such as the reaction of different, can lead to different types of volatility. Moreover, the model is relatively simple to use. This innovation enables the realized volatility model to fully consider the effect of volatility at different moments on the volatility of a certain day. Har-rv model obtains daily volatility, weekly volatility and monthly volatility, and combines the three volatility together according to relevant proportional coefficients to obtain a nested model. The realized volatility model can fully consider the autocorrelation of realized volatility and is simple to operate. Therefore, it is widely used. Bollerslev and Diebold [8] decomposed the realized volatility into two different components, continuous and jump, and established har-RV-CJ model to predict the realized volatility, thus greatly improving the prediction accuracy of financial asset return volatility. In addition, Corsi et al. [9] found that when the frequency of continuous jumps in high-frequency data is very high, the Z-statistic based on multiple power variation proposed by Huang and Tauchen [10] may not be recognized, so that part of jumps are included in the continuous estimation component of volatility, thus affecting the prediction ability of realized volatility to future volatility. Subsequently, Corsi et al. [9] proposed har-RV-RJ model based on C_TZ statistics by using the modified threshold multiple power variation. Mcaleer and Medeiros [11] proposed multiple flexible stationary transformation model to extend the model to capture the nonlinearity and long-term autocorrelation of time series. It can be seen from the above research literature that the realized volatility based on high frequency data has certain advantages in describing the volatility of financial assets.

Wei Yu [12], a Chinese scholar, made a comparative analysis of stock market volatility prediction models by using simulation trading data of CSI 300 stock index futures, and concluded that the predictive ability of ARFIMA-LNRV model and SV-RV model is better than that of GARCH family model. Wen Fenghua et al. [13] constructed lHAR-RV-V model to study volatility by considering leverage effect and volume price relationship of financial market, and found that the prediction ability of lHAR-RV-V model was stronger than that of ARFIMA and HAR-RV models no matter in sample or out of sample. Sarwar [14] research shows that VIX index can not only be used as a market fear index in the United States, but also has a significant correlation with the markets of China and other brics countries, so it can also be used as a fear index in The Chinese market. Therefore, on this basis, the fear index (VIX) is added into the LHAR-RV-V model as an explanatory variable, and a new model lHAR-RV-V-V model is constructed and empirically-analyzed in Chinese stock market to further reveal the relevant characteristics of Chinese stock market volatility.

2. Theoretical framework of LHAR-RV-V model

According to Metron's research, the theoretical basis for building the realized volatility model is the multi-variable continuous time stochastic volatility model of logarithmic price of financial assets:

$$dY_t = \left(\mu + \beta\sigma_t\right)dt + \sigma_t dW_t \tag{1}$$

Where Y_t is the logarithmic price of asset, μ is the drift term, β is the risk coefficient, which is a local and bounded process, σ_t represents instantaneous variance, and W_t is a Brownian motion process. According to the formula, logarithmic asset price is affected by risk coefficient value and instantaneous variance value. In the actual modeling process, the asset price can be obtained from the price information at that moment, and then the logarithmic subtraction is obtained, which is the price fluctuation of the asset. Its calculation formula is as follows:

$$\mathrm{r}_{(\Delta t, t)} = \ln(P_t) - \ln(P_{t-\Delta t}) \tag{2}$$

Since the realized volatility model conforms to the assumption of zero mean, the realized volatility (RV) is usually expressed by the following formula after the calculated changes in asset prices:

$$\sigma^2(T, \Delta t) = \sum_{i=1}^{n} r^2\left(\Delta t, t_i\right) \tag{3}$$

Where $\sigma^2(T, \Delta t)$ represents realized volatility, T represents the time length for calculating volatility, Δt represents the time interval for calculating realized volatility, $r^2(\Delta t, t_i)$ and represents the square of logarithmic return rate.

It can be seen from the above formula that if the realized volatility of the day is to be calculated, the volatility of each moment should be summed up theoretically, that is, Δt small enough and the sampling frequency is large enough. In other words, a sufficiently high sampling frequency will make the calculated realized volatility closer to the real volatility. However, if the influence of white noise phenomenon on market transaction is considered, the frequency cannot be selected as sufficiently large, because too large sampling frequency will cause large market microstructure error. Therefore, it is necessary to choose an appropriate frequency to balance these two errors. According to the conclusion of most scholars in this paper, when the frequency is 5 minutes, the errors of both are small. Therefore, this paper will use the five-minute high-frequency data of CSI 300 index to measure the realized volatility.

HAR-RV is a first order autoregressive model of realized volatility at different time intervals. Generally we divide traders into three categories: short term traders, medium term traders and long term traders, which correspond to daily traders, weekly traders and monthly traders respectively. Its general calculation method is as follows:

$$RV_{t+H}^{d} = \beta_0 + \beta_D RV_t^d + \beta_W RV_t^w + \beta_M RV_t^m + \varepsilon_{t+\mathrm{H}} \tag{4}$$

Where, RV_t^d is realized volatility of t period, RV_t^w is realized volatility of t period weekly $RV_t^w = \frac{1}{5}\left(RV_{t-5}^d + RV_{t-4}^d + \cdots + RV_{t-1}^d\right)$, RV_t^m and is the realized volatility of t period month, $RV_t^m = \frac{1}{22}(RV_{t-22}^d + RV_{t-21}^d + ... + RV_{t-1}^d)$ This model mainly reflects that market volatility is a complex mixed volatility superimposed by different volatility components, which is the result of the interaction of short, medium and long-term investors and other trading behaviors. Its partial regression coefficient directly measures the marginal impact of a particular type of trader's behavior on the overall volatility. At the same time, the model also describes the long memory characteristics of volatility well.

In order to further characterize the impact of negative returns in different cycles on realized volatility in the current period or in the future period, the LHAR-RV model is constructed:

$$RV_{t+H} = \beta_0 + \beta_D RV_t^d + \beta_W RV_t^v + \beta_M RV_t^m + \rho_D r_t^{d-} + \rho_W r_t^{w-} + \rho_M r_t^{m-} + \varepsilon_{t+H} \tag{5}$$

Where, $RV_{t+H} = \frac{1}{H}\left(RV_{t+1} + RV_{t+2} + \cdots + RV_{t+H}\right)$, r_t^{d-} represents t period corresponding to negative daily return, $r_t^{d-} = r_t I\{r < 0\}$, r_t^{w-} represents t period corresponding to negative weekly return, $r_t^{w-} = \frac{1}{5}(r_{t-5} + r_{t-4} + ... + r_{t-1}) I\ \{(r_{t-5} + r_{t-4} + ... + r_{t-1}) < 0\}$, r_t^{m-} represents the negative monthly return corresponding to t period, $r_t^{m-} = \frac{1}{22}(r_{t-22} + r_{t-21} + ... + r_{t-1}) I\{(r_{t-22} + r_{t-21} + ... + r_{t-1}) < 0\}$

Copeland [15] proposed the hypothesis of continuous information arrival. According to this hypothesis, market information gradually spreads outward step by step. In the process of continuous transmission of market information, price fluctuation and trading volume change, and with the increase of new information, price fluctuation and trading volume increase synchronously. In order to further investigate the relationship between price and quantity, based on the continuous information arrival hypothesis, it is preliminarily considered that the market information is not completely absorbed by the market fluctuation in the current period, so it has a certain influence on the future market fluctuation. Therefore, from the perspective of market volatility prediction, the possibility of the existence of heterogeneous trading volume is proposed, and the LHAR-RV-V model is constructed by adding it to the LHAR-RV model:

$$\begin{aligned} RV_{t+H} &= \beta_0 + \beta_D RV_t^d + \beta_W RV_t^w + \beta_M RV_t^m + \rho_D r_t^{d-} + \rho_W r_t^{w-} + \rho_M r_t^{m-} + \\ &\lambda_D \log\left(V_t^d\right) + \lambda_W \log\left(V_t^w\right) + \lambda_M \log\left(V_t^m\right) + \varepsilon_{t+H} \end{aligned} \tag{6}$$

Where: $V_t^d = \sum_{j=1}^{48} v_{tj}$ (v_{tj} represents the JTH transaction volume in t period)

V_t^w Is the weekly trading volume corresponding to period t? $V_t^w = \frac{1}{5}(V_{t-5}^d + V_{t-4}^d + ... + V_{t-1}^d)$

V_t^m Is the monthly trading volume corresponding to period t? $V_t^m = \frac{1}{22}(V_{t-22}^d + V_{t-21}^d + ... + V_{t-1}^d)$

If the impact of market panic on market volatility is considered, market panic can be taken as an explanatory variable of the volatility model:

$$\begin{aligned} RV_{t+H} &= \beta_0 + \beta_D RV_t^d + \beta_W RV_t^w + \beta_M RV_t^m + \rho_D r_t^{d-} + \rho_W r_t^{w-} + \\ &\rho_M r_t^{m-} + \lambda_D \log\left(V_t^d\right) + \lambda_W \log\left(V_t^w\right) + \lambda_M \log\left(V_t^m\right) + \partial vix + \varepsilon_{t+H} \end{aligned} \tag{7}$$

The VIX index is a proxy variable for market panic.

3. The empirical analysis

In this paper, the high-frequency data of CSI 300 index from January 5, 2015 to December 31, 2020 are used every 5 minutes, excluding holidays and missing days, a total of 1415 trading days. The volatility data is from the Wind Financial Database, and the VIX data is from the Chicago Board Options Exchange (CBOE), and is matched with the CSI 300 index on trading days.

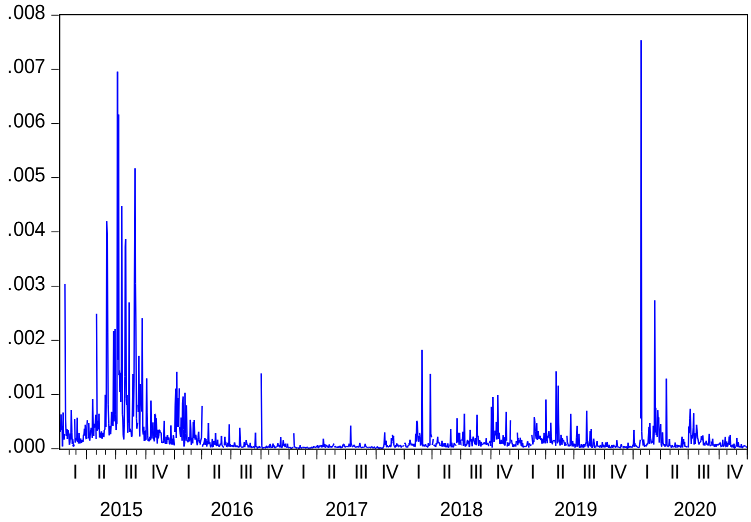

Figure 1. Daily realized volatility.

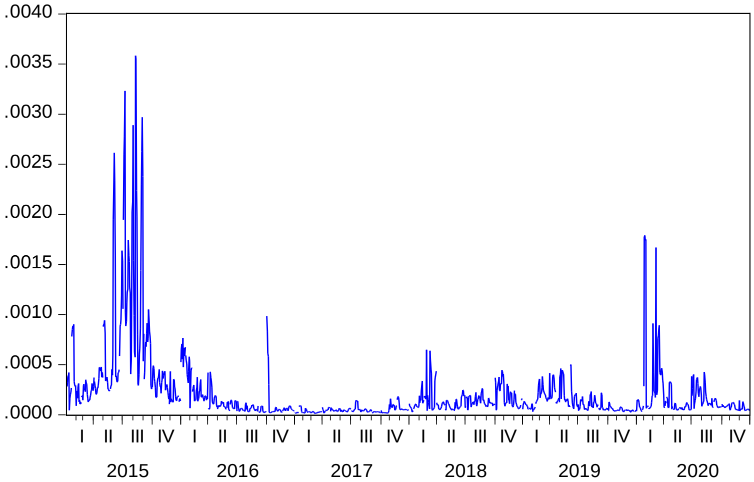

Figure 2. Weekly realized volatility.

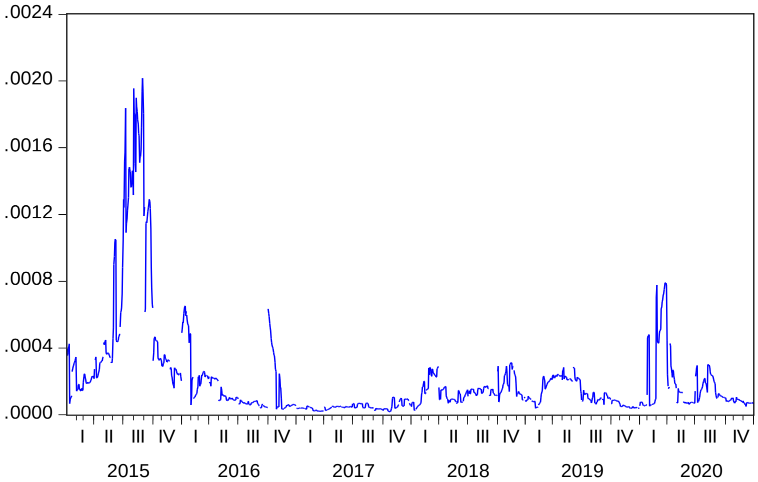

Figure 3. Monthly realized volatility.

It can be seen from the trend and volatility of the above three time series charts: First, after moving average processing, realized monthly volatility data is smoother than realized weekly volatility data and realized daily volatility. Because the averaging process weakens the impact of emergencies on daily volatility, heterogeneous traders observe volatility changes at different frequencies. Second, it can be seen from the figure that in any volatility trend, large fluctuations are often followed by relatively large fluctuations, and small fluctuations are followed by small fluctuations. The high volatility in 2015 was due to the impact of the stock market disaster, while the high volatility in 2019 was due to the epidemic.

Table 1. The RV and VIX descriptive statistics of CSI 300 index.

	RV_t^d	RV_t^w	RV_t^m	VIX
Mean	0.000213	0.000212	0.000211	2.13e-05
Median	8.33e-05	9.91e-05	0.000110	-0.006678
Maximum	0.007542	0.003584	0.002017	0.768245
Minimum	6.62e-06	1.31e-05	1.80e-05	-0.299831
Std. Dev.	0.000512	0.000365	0.000299	0.083859
Skewness	8.002351	4.862758	3.501498	1.404483
Kurtosis	86.32366	32.41611	16.44080	11.06031
Jarque-Bera	424440.1	56593.69	13542.55	4295.641
ADF	-15.53159***	-11.19797***	-4.168831***	-39.98984***

As can be seen from the above table, the statistical values of realized daily, realized weekly and realized monthly volatility data are not significantly different, and their mean value, maximum value and minimum value are all approximate. According to J-B statistical results, the P-values of JB statistics of realized daily, weekly and monthly volatility data and VIX index are all 0. Therefore, the four variables do not conform to normal distribution. Non-normal distribution is a necessary condition for realized volatility data series. Skewness >0 indicates that the data distribution is positively skewed compared with the normal distribution, and the dispersion degree on the right side of the data mean is strong. Kurtosis >0 indicates that the overall data distribution is steeper than the normal distribution and is the peak. From the unit root test results of volatility series, it can be seen that the daily realized volatility, Sunday realized volatility, monthly realized volatility and VIX index do not exist the unit root phenomenon, which is a stable process.

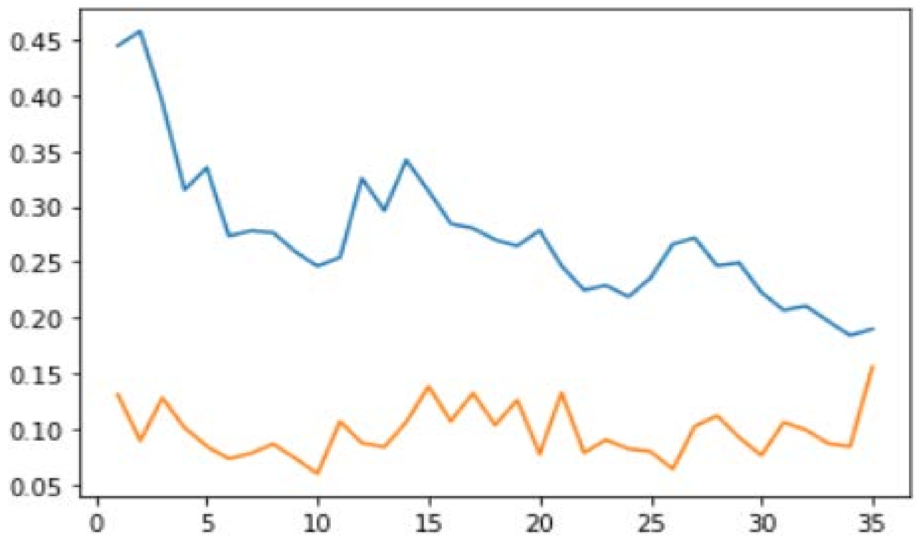

Figure 4. Correlation analysis between realized volatility autocorrelation and negative return and realized volatility.

As shown in the figure above, the realized autocorrelation curve of volatility (blue) shows a slow decay process, that is, the intensity of correlation between realized volatility gradually weakens over time. Therefore, it can be preliminatively inferred that the volatility of China's stock market has a certain long memory and the interaction between realized volatility is persistent, that is, the realized volatility in the past has a non-negligible influence on the realized volatility in the future in a certain time range. In addition, the correlation curve (yellow) representing negative return rate and realized volatility attenuates slowly and steadily, that is, negative return, which reflects the change of bad news, has a big impact on China's stock market and lasts for a long time. Therefore, it can be preliminarily concluded that China's stock market volatility has a significant leverage effect, and this leverage effect has a certain degree of continuity.

Table 2. Parameter estimation results of the model (h=1).

Model	HAR-RV	LHAR-RV-V	LHAR-RV-V-V
β_0	3.011e-05** (2.133)	-0.0031*** (-3.855)	-0.0031*** (-3.861)
β_D	0.2208*** (7.152)	0.2148*** (6.831)	0.2146*** (6.819)
β_W	0.0072 (0.115)	-0.0303 (-0.460)	-0.0310 (-0.471)
β_M	0.6355*** (9.284)	0.5501*** (7.004)	0.5512*** (7.008)
ρ_D		0.0003 (0.210)	0.0003 (0.207)
ρ_W		0.0034 (1.042)	0.0034 (1.048)
ρ_M		-0.0094 (-1.502)	-0.0094 (-1.504)
λ_D		1.321e-05 (0.229)	1.337e-05 (0.231)
λ_W		2.709e-05 (0.304)	2.714e-05 (0.305)
λ_M		9.707e-05 (1.254)	9.715e-05 (1.254)
∂			-4.255e-05 (-0.311)
R^2	0.285	0.296	0.296

The table above shows the estimation results (h=1) of the three volatility models in the total sample. In the short term, the daily realized volatility and the monthly realized volatility are significant at the significance level of 1%, which indicates that the overall volatility of China's stock market is superimposed by different cycle fluctuations in a single period. According to the heterogeneous market hypothesis proposed by Muller, it can also be seen that China's stock market volatility is jointly affected by the volatility of different components in the past, and the volatility of different components is caused by the behavior of investors with different holding maturities, which further confirms the existence of heterogeneity of Chinese stock market traders. The R2 of the three models were 28.5%, 29.6% and 29.6%, respectively.

Table 3. Parameter estimation results of the model (H =5).

Model	HAR-RV	LHAR-RV-V	LHAR-RV-V-V
β_0	4.347e-05*** (5.000)	-0.0043*** (-8.826)	-0.0042*** (-8.769)
β_D	0.0876*** (4.612)	0.0735*** (3.933)	0.0751*** (4.031)
β_W	-0.1452*** (-3.752)	-0.2113*** (0.7672)	-0.2067*** (-5.297)
β_M	0.8577*** (20.376)	0.7672*** (16.421)	0.7607*** (16.327)
ρ_D		0.0002 (0.214)	0.0002 (0.248)
ρ_W		0.0008 (0.404)	0.0006 (0.329)
ρ_M		-0.0108*** (-2.900)	-0.0107*** (-2.876)
λ_D		6.581e-05* (1.913)	6.485e-05* (1.892)
λ_W		4.926e-05 (0.930)	4.89e-05 (0.927)
λ_M		7.19e-05 (1.561)	7.141e-05 (1.556)
∂			0.0003*** (3.376)
R^2	0.451	0.494	0.498

The above table shows the estimation results (h=5) of the three volatility models in the total sample. In the medium term, the daily realized volatility, weekly realized volatility and monthly realized volatility are significant at the significance level of 1%. Moreover, THE VIX index is significant at the significance level of 1%, indicating that the VIX index is significantly positively correlated with RV. The R2 of the three models is 45.1%, 49.4% and 49.8% respectively.

Table 4. Parameter estimation results of the model (H =22).

Model	HAR-RV	LHAR-RV-V	LHAR-RV-V-V
β_0	6.336e-05*** (10.088)	-0.0058*** (-19.060)	-0.0058*** (-19.025)
β_D	0.0218 (1.605)	0.0059 (0.499)	0.0065 (0.555)
β_W	0.1045*** (3.765)	0.0208 (0.845)	0.0228 (0.927)
β_M	0.5708*** (18.908)	0.4254*** (14.462)	0.4226*** (14.375)
ρ_D		0.0009* (1.682)	0.0009* (1.708)
ρ_W		-0.0012 (-0.963)	-0.0013 (-1.014)
ρ_M		-0.0173*** (-7.720)	-0.0173*** (-7.260)
λ_D		6.333e-05*** (2.918)	6.306e-05*** (2.910)
λ_W		4.461e-05 (1.335)	4.431e-05 (1.328)
λ_M		0.0001*** (5.050)	0.0001*** (5.051)
∂			0.0001** (2.262)
R^2	0.551	0.683	0.684

The table above shows the estimation results (h=22) of the three volatility models in the overall sample. In the long run, the daily realized volatility changes from significant to insignificant, but the monthly realized volatility is still significant at the significance level of 1%. There is also a significant positive correlation between realized volatility and the volume of the reaction volume price relationship, and the VIX index is significant at the significant level of 5%, indicating that the VIX index is significantly positive correlation with RV. The R2 of the three models were 55.1%, 68.3% and 68.4% respectively.

To sum up, with the passage of time, the coefficient values of β_D, β_W and β_M generally show a trend of gradual decline, which indicates that China's stock market fluctuations have obvious long memory, that is, past stock market fluctuations continue to affect future stock market fluctuations. In addition, β_M in the estimated effective interval are significantly greater than β_D, which indicates that in the long run, the volatility of the stock market is mainly determined by the trading behavior of medium - and long-term investors. In other words, the trading behavior of medium and long term investors will not only affect their own investment decisions in a long period of time in the future, but also have a non-negligible impact on the behavior of short-term investors. Therefore, from the empirical point of view, we can also find that the speculative component of Chinese stock market is decreasing and investors are becoming more rational. Moreover, VIX index also has a significant impact on the change of long-term volatility in the future. As time goes by, R2 of the three models gradually increases, and the fitting effect of the models is getting better and better.

4. Conclusion

Based on the Shanghai and Shenzhen 300 index 5 min high-frequency data to carry on the empirical analysis, from the point of the results, the Shanghai and Shenzhen stock market in China is a heterogeneous market, there are three types of investors at the same time, technical analysis of short-term investors, institutional investors as the main investor and use fundamental analysis in the middle of the crowd for long-term investors. Among them, long-term investors have the greatest impact on the daily realized volatility, indicating that long-term investors have a greater impact on the stock market than short-term and medium-term investors. With the gradual improvement of China's stock market mechanism, long-term investors have the greatest influence on the stock market. However, medium-term investors, mainly institutional investors, also have a certain influence on the stock market. It can be seen from the side that many investors do not ignore the potential capacity of listed companies, and there is no excessive speculation in the market. In addition, from the results of model fitting, negative returns reflecting leverage effect, trading volume reflecting volume/price relationship, and VIX index, a proxy variable of market panic, have an impact on the volatility of CSI 300 market index.

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