Research Article

Quantitative Evaluation Model of Stock Market Liquidity by Macroeconomic Factors

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In order to further understand the effects of macroeconomic factors on the stock market volatility and liquidity and solve the problem that the traditional volatility measurement model loses high-frequency data information in the modeling of the influence of macroeconomic factors on stock market volatility, monthly consumer price index, daily exchange rate, and monthly money supply are taken as the main indicators to investigate the stock market liquidity in the research. Meanwhile, CARCH-MIDAS model is used to investigate the factors affecting stock market liquidity. Through the model test, it is found that the H value of the volatility effect model of the three factors is 0.0307, and the H value of the horizontal effect model is 0.0220, and the result of the horizontal effect model is closest to 1%. The results show that CARCH-MIDAS model is relatively accurate in quantitative evaluation and prediction of the stock market liquidity and volatility.

1. Introduction

The stock market has always been the “barometer” for the prediction of macroeconomic changes in a country and a region, and it is an important part of a country’s economy [1]. The stock market plays a crucial role in financing, resource allocation, and risk avoidance of a country. However, its internal mechanism and corresponding rules and regulations are still not perfect from the perspective of the development status of China’s stock market. This also leads to the fact that the country’s macroeconomic regulation policies must be used to avoid the large fluctuations in the stock market to a large extent [2]. In the process of traditional stock market volatility measurement model in the research of macroeconomic factors on the impact of the stock market liquidity and volatility, the same frequency data are mostly used to model. This method actually loses valuable information of high frequency data contains data, which are not conducive to explore the practical impact of macroeconomic for the stock market liquidity from the angle of the objective. Therefore, the method of constructing CARCH-MIDAS model is proposed to better investigate the influencing factors of stock market liquidity and provide scientific data reference for the quantitative evaluation and prediction of the stock market liquidity and volatility [3].

2. Literature Review

Hyeong connected the realized measure with the return rate and the volatility of stocks and constructed the realized GARCH model [4]. The GARCH model based on high-frequency data is studied to improve the prediction ability of volatility. The prediction effects of GARCH model on the stock market volatility under different distributions are compared with the empirical results. Because of the normal distribution we cannot describe the volatility “sharp peak and thick tail” characteristics effectively.

Zkul proposed the realized GARCH model in which the residual distribution was subject to the standard T-distribution and partial T-distribution and proved that compared with the standard normal distribution, the model of the standard T-distribution and partial T-distribution was more accurate in the prediction effect [5]. EGARCH model was superior to GARCH model in predicting the volatility. Yoon put forward the realized EGARCH model considering the leverage effect of the volatility and proved that the realized
3. Mixed-Frequency Data Volatility Model

3.1. Mixed-Frequency Data Sampling (MIDAS) Model. In order to solve the problem of data frequency in modeling, a compound regression model (MIDAS) regression model was prepared by the method of commercial modeling [11, 12]. The expression of the distributed lag model is as follows:

\[ Y_t = \beta_0 + \beta_1 B(L)X_t + \epsilon_t. \]  

In (1), \( B(L) \) is a multimarket function, but business models are often used to analyze relationships over time. Different from the distributed lag model, MIDAS model describes the relationship between explanatory variables and explained variables at different frequencies, and the weight function is introduced to the hysteresis polynomial to better deal with data with different frequencies and significantly improve the prediction ability of the model. The MIDAS model can be expressed as follows:

\[ Y_t = \beta_0 + \beta_1 B(L^{1/m}; \omega)X_t + \epsilon_t. \]  

In Formula (2), \( B(L^{1/m}; \omega) \) is a weighted polynomial function, namely:

\[ B(L^{1/m}; \omega) = \sum_k \phi(k; \omega)L^{k/m}. \]  

In Formula (3), \( K \) represents the maximum lag period, and \( L^{k/m} \) represents the lag operator:

\[ L^{k/m}X_t = X_{t-k/m}, \quad k \in [1, K]. \]

There are many forms of the selection of the weight function, mainly including the following three forms:

1. Almon Weight Function:

\[ \phi(k; \omega) = \frac{\omega_1 k + \omega_2 k^2 + \ldots + \omega_Q k^Q}{\sum_{k=1}^Q (\omega_1 k + \omega_2 k^2 + \ldots + \omega_Q k^Q)} \]  

In Formula (5), \( Q \) is the degree of freedom of the lag polynomial, and generally \( Q \) is less than \( K \) in order to reduce the estimated parameters to \( K - Q \).

2. Exponential Almon Weight Function

\[ \phi(k; \omega) = \frac{\exp\{\omega_1 k + \omega_2 k^2 + \ldots + \omega_Q k^Q\}}{\sum_{k=1}^K \exp\{\omega_1 k + \omega_2 k^2 + \ldots + \omega_Q k^Q\}}. \]  

When \( Q = 2 \), its general constraint condition is \( \omega_1 \leq 300, \omega_2 < 0 \).

3. Beta Weight Function
3.2. GARCH-MIDAS Model. Since the volatility has the characteristic of “sharp peak and thick tail,” GARCH model can well describe the nature of volatility, so most literature on the stock market volatility use GARCH model [15, 16]. The yield Formula in the model is

\[ r_{it} = \mu + \sqrt{\tau_{i} g_{i,t}} \varepsilon_{i,t}, \forall i = 1, 2, ..., N_{t}, \]  

(8)

In Formula (8), \( r_{it} \) represents the logarithmic rate of return on the \( i \) th day of the \( t \) th month. \( \mu \) is usually assumed to be constant and \( 0. \) \( \tau_{i} \), \( g_{i,t} \) are the long-term and short-term components of conditional variance, respectively. \( \varepsilon_{i,t} \) is the random disturbance term in the Formula, and

\[ \varepsilon_{i,t} | \Phi_{1-i,t} \sim N(0, 1). \]  

(9)

That is, \( \varepsilon_{i,t} \) obeys the standard normal distribution under the condition of \( \Phi_{1-i,t}. \) In Formula (9), \( \Phi_{1-i,t} \) represents the historical information set, and \( N_{t} \) is the number of days in the \( t \) th month. The short-term component \( g_{i,t} \) of volatility follows the GARCH(1,1) distribution, namely:

\[ g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^{2}}{\tau_{t}} + \beta g_{i-1,t}. \]  

(10)

In Formula (10), \( \alpha, \beta \) are parameters, \( \alpha > 0, \beta > 0, \) and \( \alpha + \beta < 1. \) \( \tau_{t} \) represents the long-term component of volatility. The realized volatility \( RV_{t} \) is used to model the long-term component \( \tau_{t} \), which is expressed as follows:

\[ \tau_{t} = m + \theta \sum_{k=1}^{K} \phi_{k}(\omega_{1}, \omega_{2}) RV_{t-k}. \]  

(11)

In Formula (11), the realized volatility \( RV_{t} \) is

\[ RV_{t} = \sum_{i=1}^{N_{t}} r_{i,t}^{2}. \]  

(12)

In Formula (12), \( K \) represents the maximum lag order of the variable and \( \phi_{k}(\omega_{1}, \omega_{2}) \) is a weight formula constructed based on Beta polynomial function. In order to avoid excessive parameters, parameter estimation of the model is simplified by referring to Engle (2008). Therefore, \( \omega_{1} = 1 \) is assumed in the research and polynomial function with single weight is used, namely:

\[ \phi_{k}(\omega_{1}, \omega_{2}) = \frac{f(k/K; \omega_{1}, \omega_{2})}{\sum_{k} f(k/K; \omega_{1}, \omega_{2})}. \]  

(13)

In Formula (13),

\[ f(x; \omega_{1}, \omega_{2}) = \frac{\Gamma(\omega_{1} + \omega_{2})}{\Gamma(\omega_{1}) \Gamma(\omega_{2})} x^{\omega_{1}-1} (1 - x)^{\omega_{2}-1}, \]

(14)

\[ \cdot \Gamma(\omega) = \int_{0}^{\infty} e^{-x} x^{\omega-1} dx. \]

The above formulas together constitute the GARCH-MIDAS model of realized volatility, which is expressed as follows:

\[ r_{i,t} = \mu + \sqrt{\tau_{i} g_{i,t}} \varepsilon_{i,t}, \]

(15)

\[ g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^{2}}{\tau_{t}} + \beta g_{i-1,t}. \]

In order to make more effective use of data, \( t \) is logarithmically processed to obtain:

\[ \log \tau_{t} = m + \theta \sum_{k=1}^{K} \phi_{k}(\omega_{1}, \omega_{2}) RV_{t-k}. \]  

(16)

The above formula is the logarithmic GARCH-MIDAS model.

3.3. Building a GJR-GARCH-MIDAS Model Based on Changed Knowledge

3.3.1. Volatility Decomposition Theory. Scientists around the world now generally believe that volatile markets lead to long-term weakness and short-term product defects. The GARCH-MIDAS model developed by Engle (2012) is one of the models conforming to the volatility decomposition theory. This model can be gradually developed from GARCH model [17, 18]. The traditional GARCH(1,1) model is shown as follows:

\[ r_{t} = \mu + \sqrt{h_{t}} \cdot \varepsilon_{t}, \varepsilon_{t} \sim N(0, 1), \]  

(17)

\[ h_{t} = \omega + \alpha \cdot (r_{t-1} - \mu)^{2} + \beta \cdot h_{t-1}. \]  

(18)

In formulas (17) and (18), \( r_{t} \) is the daily return rate of the stock market, and \( \mu \) is a constant term. Further, the theory based on volatility decomposition can be expressed as follows:

\[ r_{i,t} = \mu + \sqrt{\tau_{i} g_{i,t}} \cdot \varepsilon_{i,t} \sim N(0, 1). \]  

(19)

As the above model needs to decompose volatility into long-term and short-term components, the long-term component is \( g_{i,t} \), and the short-term component is \( \tau_{i} \). \( t \) represents the long-term range of weeks, months, or years, and \( i \) represents each day.

3.3.2. GJR-GARCH-MIDAS Model Construction. The GJR-GARCH-MIDAS model adopted in the research is based on the transformation of Formula (17). Further, the above
In the following form:

\[ g_{t,t} = \left(1 - \alpha - \beta \right) \cdot \frac{\left(\alpha + \gamma \cdot I_{t-1:t} \right) \cdot \left(\tau_{t-1:t} - \mu \right)^2}{\tau_t + \beta g_{t-1:t}} \quad (20) \]

In Formula (20),

\[ I_{t-1:t} = \begin{cases} 0 & \text{if } I_{t-1:t} \geq \mu, \\ 1 & \text{if } I_{t-1:t} < \mu. \end{cases} \quad (21) \]

In Formula (20), \( I_{t-1:t} \) describes leverage effect, while \( \gamma \) represents the influence degree of leverage effect [19]. While knowledge of market volatility is rarely used as a long-term indicator, perceived weakness could mean:

\[ RV_t = \sum_{i=1}^{N} r_{i,t}^2. \quad (22) \]

Thus, the long-term component of volatility can be expressed as follows:

\[ \text{Int}_t = m + \theta \cdot \sum_{k} \psi(w_1, w_2) \cdot RV_{t-k}. \quad (23) \]

In Formula (23), \( \psi \) is the weight polynomial, and the beta weight function is adopted. \( K \) represents the total number of periods of past variable values to be summed up. \( \theta \) represents the summation effect, reflecting the influence of past realized volatility on the long-term components of current volatility. \( m \) is a constant term.

3.4. Building GJR-GARCH-MIDAS Model Based on Macroeconomy

3.4.1. Single-Factor Model. According to the volatility decomposition theory, the long-term component is described by a single macroeconomic variable, that is, \( X_{t-k} \) is used instead of \( RV_{t-k} \), and the MIDAS term is defined in the following form:

\[ \text{Int}_t = m + \theta \cdot \sum_{k} \psi(w_1, w_2) \cdot X_{t-k}. \quad (24) \]

In Formula (24), \( X_{t-k} \) represents the horizontal value of \( k \) period after a macroeconomic variable. The determination of \( K \) is generally confirmed according to experience and BIC and other criteria.

3.4.2. Two-Factor Model. The model only determines the impact of macroeconomic changes and does not take other factors into account. Therefore, the researchers decided to incorporate macroeconomic variables and understand stock market volatility in the model to develop a two-factor model [20] which is as follows:

\[ \text{Int}_t = m + \theta_{RV} \cdot \sum_{k} \psi_k(w_1, w_2) \cdot RV_{t-k} + \theta_{K} \cdot \sum_{k} \psi_k(w_1, w_2) \cdot X_{t-k}. \quad (25) \]

In Formula (25), \( K_{RV} \) is the lag period of realized volatility of the stock market, and \( K_{K} \) is the lag period of macroeconomic variables.

4. Empirical Analysis of Shanghai Composite Index

4.1. Variable Selection and Processing. The data were collected from January 2013 to December 2022 [21, 22]. The Shanghai Composite Index is that the daily trading data were obtained, and its logarithmic return rate was calculated. For the stability of model estimation, the logarithmic return rate was multiplied by 100 [23, 24]. Monthly data are collected for all macroeconomic indicators. However, since GDP is generally calculated quarterly or annually, the research adopts monthly industrial added value (IP) above designated scale as the proxy variable of monthly GDP according to the practice of previous researchers. All data can be obtained from China Tai’an database, RESSET database, China Economic Database, and Tushares data network.

The results of the different characteristics are shown in Table 1 below:

As can be seen from the above, the skewness and kurtosis of all the differences are not 0, and it can be seen for the first time that all the differences do not obey the normal distribution [25–30]. Among them, it can be seen that the yield difference of the Shanghai Composite Index is large, and its kurtosis is also large, indicating that the exchange rate is heavy and the exchange rate is significant close to the means [31–35]. Similarly, it can be seen that the kurtosis of the central parity of the exchange rate reaches 20.67, while the mean value is only 0.00 and the standard deviation is only 0.01. Therefore, it can be known that the value of this variable is very close to 0 with a small variation range.

Since all macroeconomic variables are time series data and are affected by the overall economic environment, the correlation among variables is inevitable. Now the correlation of the data of various macroeconomic variables is analyzed. The results of the analysis are shown in Figure 1.

Among them, CPI represents consumer price index, IP represents industrial added value, income represents financial income, outcome represents financial expenditure, consumption represents total retail sales of social consumer goods, ex_rate represents central parity of exchange rate, con_index represents consistent index, Rate_deposit represents the deposits of financial institutions.

The correlation between M2 and all kinds of deposits in financial institutions is the largest, reaching 0.83, which is easily explained economically. As M2 increases, when China lacks sufficient investment channels, people tend to deposit their funds in banks, so all kinds of deposits in financial institutions increase, and vice versa. Second, it can be seen that the consensus index generally has a strong correlation with other macrovariables. Therefore, it can be said that it can represent the macroeconomy as a whole to some extent. There is a strong correlation between CPI and the total retail sales of consumer goods, because CPI represents the consumer price index, and a moderate increase in the index means that the price of consumer goods rises, which
inevitably leads to an increase in the total retail sales of consumer goods. Generally speaking, the correlation between various variables is not extremely strong. Therefore, it is meaningful to investigate the correlation between these variables and stock market volatility separately.

Before modeling and analyzing financial time series, it is usually required that the analyzed series have stationarity [36–42]. If the data is not stable, it indicates that the statistical law of time series is not fixed and will change with time. Therefore, data stationarity test is essential before modeling. ADF test is used to test the stationarity of each exponential logarithmic return rate. The ADF test results are shown in Table 2. As can be seen, the p-value for each parameter is equal to 0.01, so the negative hypothesis is rejected that the log return behind each indicator value is a stable point. Further analytical modeling can be done. Table 3 shows the Kolmogorov–Smirnov normal test results.

4.2. The Model Estimation Based on the Realized Volatility. In the study, the infrequent frequency of product changes was first used to describe the MIDAS time difference from the GJR-GARCH-MIDAS model to the product model. Replicate log returns. From the definition of RVt volatility knowledge, N is the time-varying frequency of the data, which is rarely volatility knowledge. Since the relationship between macroeconomic variables and stock market volatility is studied, macroeconomic variables are usually monthly data, so the known volatility can also be obtained as monthly data. So N is 22. Table 4 shows the model estimation results of Shanghai Composite Index return based on realized volatility.

Through the parameter estimation, it can be seen that the realized volatility with a lag of 16 periods still has an impact on the long-term component of volatility. From the parameter estimation results, except for the parameter that is not significant, all other parameters are significant at the 1% level. From Table 4, a +β +Υ/2 <1, it can be seen that the estimated model is stable. In terms of the practical significance of the model parameters, the parameter μ represents the mean value of the rate of return, and the test result shows that the average value of the returned value is 0. The value is 0.0099, which is the aggregate effect of realized volatility, which means that realized volatility in the past can have a positive impact on the long-term component of current volatility, indicating that the theory of volatility component decomposition exists in the Shanghai Composite Index.

5. An Empirical Analysis of the Impact of Macroeconomic Factors on Stock Market Volatility

5.1. Data Preprocessing. In order to reflect the basic trend of the data itself more accurately, each series is firstly adjusted seasonally. Methodologically, the additive model in the X-11 seasonal adjustment method is used. The X-11 seasonal adjustment method is the standard adjustment method of the US Department of Commerce. In the additive model, the series can be decomposed into the sum of trend terms and seasonal terms. This method is a seasonal adjustment method.
method based on the moving average method and can adapt to the nature of various economic indicators. Table 5 shows the results of seasonal adjustment for monthly macroeconomic explanatory variables.

According to the seasonal adjustment report, 11 statistics (M1-M11) are given to judge the quality of the seasonal adjustment. These statistics take values between 0 and 3, but only the values less than 1 are acceptable (the less the better). Finally, by using the linear combination of these 11 statistics, a composite indicator (Q statistic) for evaluating the quality of seasonal adjustment is calculated, and the result whether to reject or accept is given. It can be seen from Table 5 that the seasonal statistical results of money supply and consumer price index are all rejected.

As can be seen from Figure 2, China’s exchange rate has begun to stabilize. The main reason is that on July 21, 2013, China implemented an exchange rate system. In 2013, on the basis of the exchange rate reform in 2022, China proposed to adhere to the market supply and demand as the basis for adjustment with reference to a basket of currencies, so the Chinese exchange rate maintained a stable trend.

### 5.2. Data Descriptive Statistics

In the research, descriptive statistical analysis on the macroeconomic explanatory variables and the explained variables of the Shanghai Composite Index is conducted, and indicators such as mean, standard deviation, variance, skewness, and kurtosis are selected. The calculation results are shown in Table 6. The sample interval of daily data is from August 1, 2011, to September 30, 2022, and the sample interval of monthly data is from August 2022 to September 2021. M1 means money supply, CPI means consumer price index, ER means USD/RMB exchange rate, and SCI means Shanghai Composite Index. All the above data for descriptive statistical analysis are sample raw data.

It can be seen from Table 6 that the standard deviation of money supply M1 is 95999.7638, indicating that the dispersion of money supply data is relatively large. The reason is that China’s money supply M1 is mainly subject to the national macrocontrol. From 2011 to 2022, China’s monetary policy has gone through a process from prudent to tight to lose to prudent, so its degree of dispersion is relatively large. The standard deviation of the Shanghai Composite Index SCI is 912.5329. From the statistical characteristics, it shows that the dispersion degree of China’s Shanghai Composite Index is also relatively large, mainly due to the large fluctuation of the Chinese stock market in 2008 and 2016. The standard deviations of the consumer price index CPI and the USD/RMB exchange rate ER are 2.1511 and 0.6253, respectively, indicating that the data of the USD/CNY exchange rate ER is close to the average, and the data are more stable.

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### Table 2: ADF test results of the logarithmic return of each Shanghai index.

| Log rate of return | p value |
|--------------------|---------|
| Shanghai composite index | 0.01 |
| Business sector index | 0.01 |
| Real estate industry index | 0.01 |
| Industrial index | 0.01 |
| Utility industry index | 0.01 |
| Composite industry index | 0.01 |

### Table 3: Kolmogorov–Smirnov test results of logarithmic returns of each index.

| Log rate of return | D value | p value |
|--------------------|---------|---------|
| Shanghai composite index | 0.0846 | 0.001 |
| Business sector index | 0.0749 | 0.001 |
| Real estate industry index | 0.0700 | 0.001 |
| Industrial index | 0.0800 | 0.001 |
| Utility industry index | 0.0844 | 0.001 |
| Composite industry index | 0.0804 | 0.001 |

### Table 4: Model estimation results of Shanghai Composite Index returns based on realized volatility.

| Coefficient | Standard error | p value |
|-------------|----------------|---------|
| \( \mu \) | 0.0134 | 0.0177 | 0.4475 |
| \( \alpha \) | 0.0699** | 0.0000 | 0.001 |
| \( \beta \) | 0.8931*** | 0.0000 | 0.001 |
| \( \theta_{RV} \) | 0.0099*** | 0.0035 | 0.0051 |
| \( \gamma \) | 0.0374** | 0.0024 | 0.001 |
| \( m \) | 0.3702 | 0.2571 | 0.1500 |
| \( w_2 \) | 2.3822*** | 0.4044 | 0.001 |
| BIC | 16627.29 | -8284.00 |

**Note**: *, **, *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

### Table 5: The diagnostic results of seasonal adjustment.

| Variable | Q statistic | Result |
|----------|-------------|--------|
| M1 | 1.56 | Reject |
| CPI | 1.14 | Reject |

### Figure 2: M1 level value after a unified order of magnitude.

5.2 Data Descriptive Statistics. In the research, descriptive statistical analysis on the macroeconomic explanatory variables and the explained variables of the Shanghai Composite Index is conducted, and indicators such as mean, standard deviation, variance, skewness, and kurtosis are selected. The calculation results are shown in Table 6. The sample interval of daily data is from August 1, 2011, to September 30, 2022, and the sample interval of monthly data is from August 2022 to September 2021. M1 means money supply, CPI means consumer price index, ER means USD/RMB exchange rate, and SCI means Shanghai Composite Index. All the above data for descriptive statistical analysis are sample raw data.
file is not much larger, and the tail is shorter than that of the well-distributed, similar to rectangular partitions. The kurtosis of the consumer price index (CPI) and the Shanghai Composite Index (SCI) were positive at 0.439 and 1.385, respectively. The observations of these two sample data are more concentrated and have longer tails than the normal distribution. The kurtosis of the consumer price index CPI is closest to 0, so the consumer price index CPI is closest to the normal distribution.

5.3. The Test Results of Single-Factor Improvement GARCH-MIDAS Model. First, the exogenous description effect of stock market volatility anomalies is studied from the perspective of phase effect and volatility effect. Commodity monthly returns and returns, including exchange rates for daily metering, price levels, and USD/CNY exchange rates are designed based on a GARCH-MIDAS mixed model of macroeconomic exogenous variables. Combining the magnitudes of the monthly macroeconomic exogenous variances into $[0, 10]$ yields the rate value, and the rate of change is obtained from the raw data of macroeconomic variables using the AR(p) model, residual sum of squares possible. As shown in Tables 7 and 8, the model estimation results based on the single-factor horizontal effect and the single-factor fluctuation effect are, respectively, shown.

According to the results in Tables 7 and 8, it can be seen that the BIC value and LLH value of each model are estimated at the same level by taking the single correction level mode and change mode as an example, and the game of all MAE and RMSE values is roughly the same equal. The error between the monthly realized volatility estimated by each model and the realized volatility calculated by using the original data is relatively small, so it can be considered that the effects of each model in the single-factor horizontal effect model and the single-factor volatility effect model are basically the same.

Table 9 presents the significance and direction of the coefficients of various macroeconomic variables. It can be seen that the coefficients of the level values of each variable in the single-factor model are in line with market experience. The coefficients of phase effect and volatility effect on the exchange rate of USD and RMB against RMB are also significant.

5.4. The Test Results of Multifactor Improved GARCH-MIDAS Model

5.4.1. The Two-Factor Horizontal Effect Affecting Stock Price Volatility. The significance of each variable coefficient under the two-factor horizontal effect. It can be seen from the results that each horizontal effect mixing model has only one variable coefficient that is significant, and the other variable coefficient is not significant. At the same time, the coefficient of the multifactor model under the horizontal effect of the money supply is significantly positive, which is the same as the estimated result of the single-factor horizontal-effect model. The coefficient of the multimodel in the horizontal ratio of the USD/RMB exchange rate is negative, similar to that of the single model. The results of estimating the phase interference model are the same. It is not important to estimate the occurrence of multiple impact models based on the customer value proposition.

In real markets, it is important to simultaneously measure the impact of multiple macroeconomic variables on the stock market. At the same time, according to Tables 10 and 11, it can be seen that the estimated coefficients of the three two-factor horizontal effects GARCH-MIDAS are roughly in an important direction on the basis of the single-factor estimated coefficients. Component models, including estimated coefficients for horizontal models based on income and consumer value. Predictions from various GARCH-MIDAS models suggest that income levels have a positive impact on the transformation of China’s commodity markets, which is similar to one of the benefits of estimating amounts, when the relationship between the value level of the CPI and the volatility of Chinese stock market prices is not significant. The main reason is that the impact of different macroeconomic variables on the market can cause one-to-one inconsistencies, which may differ from the results of individual tests.

For example, when estimating the value of a two-factor horizontal model, the effects of macroeconomic factors on market volatility are initially similar to those estimated for horizontal structure effects. The GARCH-MIDAS model has slightly different test results for the two horizontal values of USD/RMB exchange rate and income. It can be seen that when both the income and the cost of goods in the Chinese market are fully determined. In the case of the lateral effect, the lateral value of the currency is closely related to the Chinese stock market, as is the lateral value of the income when considering the USD/CNY exchange rate and total payment amount. Although it has a good relationship with the Chinese stock market.

5.4.2. Two-Factor Volatility Effect Affecting Stock Price Volatility. The significance of each variable coefficient under the two-factor fluctuation effect. From the results, it can be seen that only the two-factor model based on the fluctuation effect of the money supply and the consumer price index is not significant, and the other multifactor fluctuation models only have one variable is significant. At the same time, on the one hand, the estimated result of the variable coefficient of the multifactor fluctuation model of money supply is significantly positive, which is the same as the estimated result of the single-factor fluctuation effect model. The estimation results are the same, and both are significantly negative.

At the same time, according to Tables 12 and 13, it can be seen that the estimated coefficients of the three-factor, two-factor volatility GARCH-MIDAS are estimated in the same direction as the estimated coefficients of the separate model, in addition to standard volatility effects based on income and consumer value. The estimation results show that the fluctuation of money supply is not significant, and the fluctuation of money supply based on the fluctuation effect model of money supply and USD/RMB exchange rate is positively significant.
### Table 6: Descriptive statistics.

| Variable | Sample period         | Mean          | Standard deviation | Variance         | Skewness | Kurtosis |
|----------|-----------------------|---------------|--------------------|------------------|----------|----------|
| M1       | 2011.08.01–2022.09.30 | 247200.7103   | 95999.7638         | 9216000000       | 0.106    | −0.987   |
| CPI      | 2011.08.01–2022.09.30 | 102.7659      | 2.151              | 4.627            | 0.580    | 0.439    |
| ER       | 2011.08.01–2022.09.30 | 6.7855        | 0.625              | 0.391            | 0.897    | −0.441   |
| SCI      | 2011.08.01–2022.09.30 | 2706.1836     | 912.5329           | 832716.276       | 0.980    | 1.385    |

### Table 7: Single-factor level effects.

| Variable | M1L | CPIL | ERL |
|----------|-----|------|-----|
| M        | 0.0005* (1.3765) | 0.0001 (0.1521) | 0.0005* (1.4022) |
| A        | 0.0526*** (10.5549) | 0.5575*** (8.9760) | 0.0538*** (10.6083) |
| B        | 0.9411*** (137.2133) | 0.3529*** (4.6973) | 0.9413*** (142.0535) |
| M        | 0.0006** (2.1456) | 0.0034*** (70.4076) | 0.0003** (2.1229) |
| θ_l      | 0.0001* (1.6201) | −0.0004*** (−70.6836) | 0.0108* (−1.4658) |
| ω_l      | 1.2325 (0.1653) | 4.3098*** (10.3896) | 1.0048** (1.8133) |
| g_0      | 0.1016 (0.9878) | 0.0011 (0.0023) | 0.1686 (1.0898) |
| BIC      | −5.4798 | −5.0909 | −5.4793 |
| LLH      | −7248.3738 | −6736.2355 | −7247.7314 |
| MAE      | 0.0023 | 0.0062 | 0.0022 |
| RMSE     | 0.0035 | 0.0081 | 0.0034 |

**Note.** * is significant at 10% level; ** is significant at 5% level; *** is significant at 1% level.

### Table 8: Single-factor fluctuation effect.

| Variable | M1V | CPIV | ERV |
|----------|-----|------|-----|
| M        | 0.0008* (1.5297) | 0.0001 (0.3877) | 0.0005* (1.3921) |
| A        | 0.7750*** (10.9102) | 0.0526** (10.1796) | 0.0533*** (10.4209) |
| B        | 0.2249*** (3.1662) | 0.9437*** (141.716) | 0.9422*** (143.0517) |
| M        | 5.8586*** (2.7296) | 0.0004* (1.5068) | 0.0004*** (1.9639) |
| θ_v      | 0.0001*** (2.6722) | −0.0001 (−0.3259) | −0.9664*** (−1.7606) |
| ω_v      | 1.0457*** (13.0019) | 7.9103 (0.2899) | 1.3265*** (3.4844) |
| g_0      | 0.0129 (0.6009) | 0.5849 (1.0262) | 0.1579 (1.0693) |
| BIC      | −5.1196 | −5.4583 | −5.4816 |
| LLH      | −6154.2148 | −6406.2665 | −7250.7634 |
| MAE      | 0.0066 | 0.0023 | 0.0022 |
| RMSE     | 0.0077 | 0.0035 | 0.0033 |

**Note.** * is significant at 10% level; ** is significant at 5% level; *** is significant at 1% level.

### Table 9: Significance of each macrovariable.

| Effect     | M1       | CPI       | ER        |
|------------|----------|-----------|-----------|
| Horizontal effect | Significantly positive at the 10% level | Significantly negative at the 1% level | Significantly negative at the 10% level |
| Wave effect | Significantly positive at the 1% level | Not significant | Significantly negative at the 1% level |
For example, when estimating the results of the above two-factor volatility effect model, the impact of macroeconomic factor volatility on stock market price volatility is actually similar to that estimated by a variant of the model. It can be seen from the calculation that in the Chinese commodity market, when the exchange rate between the two sources of income and consumers is determined, the exchange rate of currency and consumer goods will not interfere with the exchange of Chinese commodities, while comprehensively considering the USD/CNY exchange rate and the earnings exchange rate, the earnings exchange rate has a positive impact on the Chinese market, when the USD/CNY exchange rate has little impact on the Chinese market. Chinese stock markets are volatile.

5.4.3. Three-Factor Mixed Effect Affecting Stock Price Volatility. In the estimation of the three-factor model, the representative mixture model, horizontal model, and fluctuation model are selected. The estimated results are shown in Table 14. The BIC and LLH values for each model are at the same level, and the MAE and RMSE values for the estimates are equal, so it can determine the benefit for each individual. The three-factor model is consistent.

In the estimated results of the three-factor mixed model selected as a representative, Table 15 shows the significance

### Table 10: Two-factor level effects.

| Variable | M1+CPI | ER + M1 | ER + CPI |
|----------|--------|--------|---------|
| M        | 0.0004* | 0.0005* | 0.0005* |
|          | (1.3628) | (1.3938) | (1.3933) |
| A        | 0.0520*** | 0.0516*** | 0.0538*** |
|          | (10.4582) | (10.4491) | (10.5955) |
| B        | 0.9425*** | 0.9427*** | 0.9410*** |
|          | (139.1835) | (139.6579) | (140.7851) |
| M        | 0.0013  | 0.0007** | 0.0006 |
|          | (0.4208) | (2.0865) | (1.8699) |
| $\theta_1'$ | 0.0001* | 0.0017 | -0.0103* |
|          | (1.4755) | (5.5678) | (-1.4668) |
| $\theta_1''$ | -0.0001 | 0.0001** | -0.0001 |
|          | (-0.2154) | (1.7625) | (-0.0743) |
| $\omega_1'$ | 1.0032 | 9.929 | 1.0771** |
|          | (0.1510) | (0.0946) | (1.8479) |
| $\omega_1''$ | 1.0071 | 1.0029 | 5.0243 |
|          | (0.0421) | (0.1844) | (0.0222) |
| $g_0$    | 0.1032 | 0.0867 | 0.1767 |
|          | (0.9517) | (0.9940) | (1.0792) |
| BIC      | -5.4739 | -5.4742 | -5.4733 |
| LLH      | -7248.52 | -7248.8531 | -7247.6557 |
| MAE      | 0.0023 | 0.0023 | 0.0022 |
| RMSE     | 0.0035 | 0.0037 | 0.0033 |

**Note.** * is significant at 10% level; ** is significant at 5% level; *** is significant at 1% level.

### Table 11: Coefficient significance of two-factor level values.

| Variable | M1+CPI | ER + M1 | ER + CPI |
|----------|--------|--------|---------|
| $\theta_1'$ | Significantly positive at the 10% level | Not significant | Significantly negative at the 10% level |
| $\theta_1''$ | Not significant | Significantly positive at the 5% level | Not significant |

### Table 12: Two-factor volatility effect.

| Variable | M1 + CPI | ER + M1 | ER + CPI |
|----------|---------|--------|---------|
| $\mu$    | 0.0005* | 0.0005* | 0.0005* |
|          | (1.4101) | (1.5737) | (1.3998) |
| $\alpha$ | 0.1023*** | 0.1535*** | 0.0533*** |
|          | (9.2659) | (8.7191) | (10.3449) |
| $\beta$  | 0.8976*** | 0.8464*** | 0.9430*** |
|          | (81.2374) | (48.0567) | (144.8464) |
| $m$      | 0.1215 | 0.2707*** | 0.0004* |
|          | (1.2350) | (2.4730) | (1.6072) |
| $\theta_1'$ | -0.0001 | 5.0009 | -1.1112* |
|          | (-1.0984) | (0.0119) | (-1.5044) |
| $\theta_1''$ | -0.0181 | 0.0001*** | 0.0001 |
|          | (-0.7499) | (2.3657) | (-0.9133) |
| $\omega_1'$ | 1.1918*** | 1.0001 | 1.3065*** |
|          | (3.6566) | (0.0057) | (3.8508) |
| $\omega_1''$ | 1.0001 | 1.1127*** | 1.0015 |
|          | (0.7556) | (4.6032) | (0.8239) |
| $g_0$    | 0.0005 | 0.0002 | 0.1357 |
|          | (0.6213) | (0.5154) | (1.0140) |
| BIC      | -5.4553 | -5.4296 | -5.4765 |
| LLH      | -7224.0285 | -7190.118 | -7247.9256 |
| MAE      | 0.0021 | 0.0020 | 0.0022 |
| RMSE     | 0.0030 | 0.0028 | 0.0033 |

**Note.** * is significant at 10% level; ** is significant at 5% level; *** is significant at 1% level.
of each variable coefficient under the effect of each three-factor mixed (level + fluctuation) effect. The three-factor models of volatility, money supply volatility, and consumer price index volatility are not significant, and the other two three-factor mixed models have two significant coefficients. Meanwhile, the USD/CNY exchange rate and lateral value coefficients are negative, the same as the estimates from the separate models, while the lateral rib coefficients are worth the money. Delivery is negative and only affects the estimated probability of the sample.

To sum up, compared with the single-factor model and the three-factor model, the estimation results of the three-factor model are not significant. This is because the multifactor model has more estimated parameters than the model that introduces a single macrofactor. This may be problems such as overparameterization that make some coefficients no longer significant.

### Table 13: Coefficient significance of two-factor volatility.

| Variable          | M1+CPI          | ER + M1         | ER + CPI         |
|-------------------|-----------------|-----------------|------------------|
| \( \theta_1^1 \) | Not significant | Not significant | Significantly negative at the 10% level |
| \( \theta_2^1 \) | Not significant | Significantly positive at the 1% level | Not significant |

Note: * is significant at 10% level; ** is significant at 5% level; *** is significant at 1% level.

### Table 14: Three-factor mixture.

| Variable          | ERV + M1L+CPI (three-factor mixture) | ERL + M1L+CPI (three-factor level) | ERV + M1V+CPIV (three-factor fluctuation) |
|-------------------|--------------------------------------|------------------------------------|-------------------------------------------|
| \( \mu \)        | 0.0004*                              | 0.0005*                            | 0.0004                                    |
|                   | (1.3591)                             | (1.5801)                           | (0.9837)                                  |
| \( \alpha \)      | 0.0498***                           | 0.0518***                          | 0.5688***                                 |
|                   | (10.2851)                          | (8.9983)                           | (9.4800)                                  |
| \( \beta \)      | 0.9445***                           | 0.9419***                          | 0.4311***                                 |
|                   | (144.5195)                           | (110.5251)                           | (7.1803)                                  |
| \( m \)          | 0.0002                               | 0.0007**                           | -0.0739                                   |
|                   | (0.0785)                             | (1.6587)                           | (-0.4316)                                 |
| \( \theta_1 \)   | -0.5755**                           | -0.0251*                           | -4.9995                                   |
|                   | (-1.8597)                           | (-1.5454)                           | (-0.0061)                                 |
| \( \theta_2 \)   | -0.0001*                            | -0.0001*                           | 0.0001                                    |
|                   | (-1.2887)                           | (-1.2997)                           | (0.6980)                                  |
| \( \theta_3 \)   | 0.0001                              | 0.0001                             | 1.0401                                    |
|                   | (0.1137)                             | (0.0324)                           | (0.8253)                                  |
| \( \omega_1 \)   | 1.5402***                           | 1.0758*                            | 9.9993                                    |
|                   | (2.5768)                             | (1.4662)                           | (0.0043)                                  |
| \( \omega_2 \)   | 9.5854                               | 1.0101                             | 1.0005                                    |
|                   | (0.0382)                             | (0.1634)                           | (0.9365)                                  |
| \( \omega_3 \)   | 9.6721                               | 4.5075                             | 2.4398***                                 |
|                   | (0.0109)                             | (0.0108)                           | (2.7191)                                  |
| \( \vartheta_0 \) | 0.1692                               | 0.0895                             | -0.0001                                   |
|                   | (1.0022)                             | (0.9288)                           | (-0.0056)                                 |
| BIC               | -5.4703                              | -5.4894                            | -5.1914                                    |
| LLH               | -7251.6159                           | -6452.6558                         | -6312.7576                                 |
| MAE               | 0.0022                               | 0.0027                             | 0.0019                                    |
| RMSE              | 0.0034                               | 0.0045                             | 0.0024                                    |

Note: * is significant at 10% level; ** is significant at 5% level; *** is significant at 1% level; L is level, V is fluctuation.

### Table 15: The significance of each variable coefficient under the three-factor mixed model.

| Variable          | ERV + M1L+CPI (three-factor mixture) | ERL + M1L+CPI (three-factor level) | ERV + M1V+CPIV (three-factor fluctuation) |
|-------------------|--------------------------------------|------------------------------------|-------------------------------------------|
| \( \theta_1^1 \) | (5%) significantly negative          | (10%) significantly negative       | Not significant                           |
| \( \theta_2^1 \) | (10%) significantly negative         | (10%) significantly negative       | Not significant                           |
| \( \theta_3 \)   | Not significant                       | Not significant                    | Not significant                           |

6. Conclusions

Although the improved GARCH-MIDAS model used in the research has overcome the problem of the inconsistent frequency of macroeconomic variables and stock market data, in fact, the improved GARCH-MIDAS model can also...
introduce other factors. In the selection of macroeconomic explanatory variables, the calculation and selection are carried out from the perspective of macroeconomic factors. Subsequently, macroeconomic changes are estimated from two perspectives: phase effects and phase shifts. Second, estimates of single GARCH-MIDAS model improvements and estimates of multiple GARCH-MIDAS model modifications are presented. Combined with China’s real market conditions and similar theoretical analysis, the estimated results of each model are tested in detail. Through the model test, it is found that the H value of the volatility effect model of the three factors is 0.0307, the H value of the horizontal effect model is 0.0220, and the result of the horizontal test, it is found that the H value of the volatility effect model is the closest to 1%. The quantitative evaluation prediction results are relatively accurate.

**Data Availability**

The dataset can be accessed upon request.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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