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Forecasting market volatility and corporate strategic planning based on time series analysis in business administration

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Abstract In this paper, a system framework for financial market volatility forecasting and corporate strategic planning is constructed by taking the multi-intelligence body interaction model as the core and combining the time series analysis method. By building an Agent-based financial market volatility model, it simulates the dynamic impact of investors' attitude propagation on stock prices. The applicability of the model is also verified with the empirical data of the Shanghai Stock Exchange Composite Index (SSE) from 2008 to 2020. The study further systematically elaborates the theory of smoothness and long memory of time series, focuses on the quantitative role of Hurst index on market trend, and optimizes the symbolization process of financial volatility data through wavelet control method and adaptive symbol space division technique. In the empirical part, this paper takes the Shanghai stock market as the research object, and develops the statistical analysis from the three dimensions of stock price index, intraday amplitude and price-earnings ratio. The volatility prediction based on 2020 high-frequency data (20-minute intervals, a total of 2904 samples) shows that the improved wavelet control method predicts the MAPE value as low as 2.98%, and the sign matching rate reaches 90.65%. The consistency between the model simulation data and the real market distribution is verified by normal distribution test (μ=0.2189, σ=1.3169). The study finally proposes an integrated strategic planning method that integrates dynamic response mechanism, data security synergy and quantitative forecasting model, which helps enterprises adapt to and lead the market changes and realize sustainable development.

Index Terms time series analysis, market volatility forecasting, SSE of Shanghai Composite Index, wavelet control method, multi-intelligence body

I. Introduction

Market volatility is one of the important indicators of market trading activities and has a great impact on investors. The increase of market volatility will increase the uncertainty and risk of investment, investors need to take more risks to get higher returns, it also means the increase of investment opportunities, investors can get better investment returns by grasping the market volatility [1]-[3]. In order to obtain data and insights about market information, industry dynamics and consumer demand, through the market volatility prediction, enterprises can obtain accurate market information, understand the size of the market, the growth trend, the competitive landscape, etc., to provide decision-making support and strategic guidance to help enterprises to identify potential market opportunities and grasp market opportunities, to cope with the market risk, and to formulate the corresponding marketing strategy and sales strategy and provide strategic grasp for the long-term development of enterprises [4]-[8]. Its importance lies in the fact that it provides enterprises with basic data for market access and helps them to understand the market demand and competitors' situation.

Enterprise strategic planning is an important part of enterprise management, which plays a vital role in the development and success of enterprises. In the competitive market environment, enterprises need to rely on strategic planning to determine their own development direction, so as to obtain competitive advantages [9]. By clarifying the development objectives of the enterprise, enterprise strategic planning enables enterprises to better formulate corresponding strategies and tactics and effectively allocate resources, and also improves the execution efficiency and organizational coordination of the enterprise, so that the enterprise can better cope with the changes in the market and the challenges of competition [10]-[12]. Under political conflicts, economic data quality, policy changes, and epidemics, market volatility has increased and corporate strategic planning cycles have changed, traditional business management methods are no longer applicable, and management matrix and human forecasting methods are difficult to comprehensively, efficiently, and accurately perform market volatility forecasting and corporate strategic planning [13]-[16]. It is urgent to develop new methods to cope with this dilemma.

The article constructs a systematic framework for market volatility forecasting by taking the multi-intelligence body interaction model as the core and combining the time series analysis method. By introducing a multi-type and multi-intensity contact interaction mechanism, an Agent-based financial market volatility model is developed to simulate the impact of investors' attitude propagation on stock prices. Investors are categorized into strong, weak and neutral, and the attitude propagation and stock price dynamics are simulated through a Poisson process, and the validity of the model is verified by comparing with the empirical data of the Shanghai Stock Exchange Composite Index (SSE). We also systematically elaborate the smoothness and long memory theory of time series analysis, focusing on the quantitative role of Hurst index on market trends, and provide methodological support for the comparison between the model simulation data and the real market data. On this basis, a symbolization method and an improved algorithm based on wavelet control are proposed to optimize the symbolization process of financial volatility data through dynamic scaffolding segmentation and adaptive spatial division. The adaptive symbol space division method dynamically adjusts the interval density through Shannon entropy to enhance the information retention ability in the data-dense region, so as to capture the local features of financial fluctuations more accurately. The limitations of traditional symbolization methods in financial data feature retention are addressed.

II. Financial market volatility modeling and time series symbolic analysis methods

II. A. Constructing Agent-based stochastic interaction financial market volatility models

This study will utilize a multi-type multi-intensity contact interaction system to construct an Agent-based stochastic financial market volatility model. In this study, the particles of the multi-type multi-intensity contact process model represent the attitudes of the financial market towards investment. The attitudes towards investment can be categorized into three types according to the different intensity levels: strong, weak and neutral attitudes, with the strong and weak attitudes corresponding to the particles of type “2” and type “l”, respectively. Because the investment attitudes of different investors in the real stock market are not always at the same level, some investors are more confident in their own decisions, while others are less certain and are relatively easy to be influenced by other investors and change, so the classification of investment attitudes according to the level of intensity is also justified in the real world.

The MRIC interaction model is now applied to the price of a stock in a financial market. Suppose that the market for this stock consists of M (M is large enough) traders at the one-dimensional point $\{0,1,\cdots,M\}$. At the beginning of trading day $t(t=1,2,\cdots,T)$, we randomly select two groups of traders (with initial densities of θ_1 and θ_2) who hold a weak attitude and a strong attitude, respectively. Assuming that each trader can propagate his/her attitude multiple times during the day and letting l be the duration of trading time within each trading day, we denote by $P_t(s)$ the stock price at the moment s during the t th trading day, where $s\in[0,l]$. In order to have interpreted and simulated the model, for a one-dimensional MRIC model with a bit pattern space of $\{0,1,2\}^Z$, the propagation range of particles in the system is $L\leq 2$. For each pair of points $x,y\in\{0,1,\cdots,M\}$, their distance is $|x-y|=L$, let $\{T_1m^{(x,y)},m\geq 1\},\{T_{2m}^{(x,y)},m\geq 1\}$ with $\{U_m^{(x)},m\geq 1\}$ are Poisson processes with rates $2^{-(L-1)}\lambda_1$, $2^{-(L-1)}\lambda_2$ and 1, respectively. For better understanding, the example of $\{T_m^{(x,y)},m\geq 1\}$ is explained in detail. We consider a Poisson process $K(t)$ with rate $2^{-(L-1)}\lambda_1$. In this process, there are jump points, defining the time of the m th jump point as $\{T_{1m},m\geq 1\}$. Then, we let $\{T_{1m}^{(x,y)},m\geq 1\}$ denote the moment of the m th jump point from x to y. where x and y represent different traders, and the number of neighbors of each trader is 2L. For each propagation from $\{x\}$ to $\{y\}$ (which are all Poisson processes with rate $2^{-(L-1)}\lambda_1$ and are independent of the other Poisson processes), at the time point $\{T_{1m}^{(x,y)},m\geq 1\}$, a red directional arrow is placed from x to y. This indicates that if trader x takes a weak attitude and trader y takes a neutral attitude, then trader y will be infected by x to take a weak attitude. Similarly, we place the blue arrow at the point in time $\{T_{2m}^{(x,y)},m\geq 1\}$ from x to y according to a Poisson process with rate $2^{-(L-1)}\lambda_2$. This suggests that if trader x takes a strong attitude, then no matter what attitude trader y takes, eventually trader y will be infected by x taking a strong attitude. Along the time axis $\{U_m^{(x)},m\geq 1\}$ of each trader x we place δ at x according to a Poisson process of strength 1 and independent of other Poisson processes, δ which serves to restore the attitude of the trader x from the other attitudes to the neutral one.

The stock price dynamics of the multi-type, multi-intensity contact interaction system proceeds as follows: in this stochastic financial market volatility model, investors with weak attitudes are provided with information that is represented by a standard uniformly distributed random variable ξ_t on (-1, 1); similarly, for investors with strong attitudes this paper defines ζ_t (independent of ξ_t). They then make some decisions about trading positions accordingly and these investors send bullish, bearish or neutral signals to their neighbors. Due to the availability of up-to-date tools and reliable sources of information, investors with strong attitudes are very confident in their investment information, and thus they are more confident in their trading position decisions. In this model constructed, this paper assumes that changes in market demand are the most important cause of stock price volatility. According to the MRIC interaction system, traders in the system can influence other traders in the system through the propagation of their investment attitudes, acting on each other, and eventually the market demand will change. Then, this paper assumes that based on the information they receive, their decisions are influenced in terms of the parameter γ and represented by $\gamma\zeta t$, where γ is considered as an index of the ratio between the weak and strong attitudes. The rest of the traders will have a neutral attitude towards the market.

For $s \in [0,l]$ and $t = 1,2,\cdots,T$, the stock market demand for a system with multiple types of multi-intensity contact interactions is as follows.

$$\mathrm{B}_t(\theta_1,\theta_2,s) = (\xi_t \cdot |\{x : \eta_S^{\theta_1,\theta_2}(x) = 1\}| + \gamma\zeta_t \cdot |\{x : \eta_S^{\theta_1,\theta_2}(x) = 2\}|) / M \tag{1}$$

where $|A|$ denotes the base of the set A , θ_1 and θ_2 represent the initial density, and M denotes the number of traders. In order to quantify the impact of changes in excess demand on prices, we set the depth parameter $\beta(>0)$ of market price volatility. Then, we define the stock price on the t th trading day as

$$\mathrm{P}_t = \mathrm{P}_{t-1} \exp\{\beta \mathrm{B}_t(\theta_1,\theta_2,s)\} \tag{2}$$

Then:

$$\mathrm{P}_t = \mathrm{P}_0 \exp\left\{\beta \sum_{k=1}^{t} \mathrm{B}_k(\theta_1,\theta_2,s)\right\} \tag{3}$$

where P_0 is the initial stock price at $t=0$. The logarithmic return of the stock price from t to $t+1$ can be defined as

$$r(t) = r_t = \ln \mathrm{P}_{t+1}(s) - \ln \mathrm{P}_t(s) \tag{4}$$

In addition, the simulated simulation data of the stochastic financial market volatility model constructed in this section will be compared with the Shanghai Stock Exchange (SSE) Composite Index, since the SSE Composite Index is a representative stock index of the Chinese stock market. And the empirical data SSE and the eight sets of simulation data are randomly sorted in order to study their complexity and topological behaviors, so as to draw more plausible conclusions.

II. B.Introduction to time series related concepts

By constructing a multi-intelligent body interaction model, we are able to simulate the dynamic evolution of market demand. However, the simulation data generated by the model needs to be validated in combination with the statistical properties of time series. To this end, this section will systematically introduce the theory of smoothness and long memory in time series analysis, laying the foundation for the subsequent comparative analysis of the model and empirical data.

II. B. 1) Stability

Strictly smooth: a time series $\{r_t\}$ is said to be strictly smooth if for all t , the joint distribution of any positive integer l and any k positive integers $(t_1,t_2,......,t_k),(r_{t_1},r_{t_2},......,r_{t_k})$ is the same as the joint distribution of $(r_{t_{1+l}},r_{t_{2+l}},......,r_{t_{k+l}})$.

Weakly smooth: a time series $\{r_t\}$ is said to be weakly smooth if, for all l , the mean of r_t and the covariance of r_t with r_{t-l} do not vary with time.

Smoothness is an important concept in the field of time series research, which is the basis for further analysis, and most of the models are built with the assumption that the series is smooth, such as the AR model, ARMA model and so on. The condition of strict smoothness is more strict, it requires that the joint distribution of the time series does not change with the translation of time, which is difficult to realize in practice, therefore, we generally only require that the series is weakly smooth, and the weak smoothness is manifested in the form of the time series shaking up and down around the same mean with the same amplitude in the time series plot.

II. B. 2) Long memory

The autocorrelation coefficient of a time series decreases with the increase of the time interval, but sometimes this decrease is slower, such as the polynomial speed of the decrease, this phenomenon of the slow decrease of the autocorrelation coefficient is called the long memory of the time series.

The commonly used indicator for describing the long memory of a sample series $r_1, r_2, \ldots\ldots, r_k$ is the Hurst indicator, which is calculated from the sample extreme deviation, the sample capacity, and the sample standard deviation, and has the following form:

$$H = \frac{\ln(R(n)/S(n))}{\ln(n)} \tag{5}$$

$$R(n) = \max_{1\le k\le n} \sum_{j=1}^{k} (r_j - \overline{r}_n) - \min_{1\le k\le n} \sum_{j=1}^{k} (r_j - \overline{r}_n) \tag{6}$$

where n is the sample capacity, $S(n)$ is the sample standard deviation, $R(n)$ is the sample extreme deviation, and $\overline{r}_n$ is the sample mean. According to the value of Hurst, the sequence also has different properties accordingly: when $0 < H < 0.5$, the sequence exists mean-reverting phenomenon: when $H = 0.5$, the sequence shows the nature of random wandering; when $0.5 < H < 1$, the sequence has some kind of deterministic tendency and the larger the value of H, the stronger the tendency.

II. C.Time series symbolization - wavelet control method

After clarifying the statistical features of time series, how to efficiently extract their hidden patterns becomes the key. In this section, we will turn to the study of symbolic methods to transform the complex financial fluctuation data into symbolic sequences through wavelet control techniques, and propose dynamic and adaptive improvement strategies for the shortcomings of traditional methods, so as to provide technical support for the subsequent pattern recognition in enterprise strategic planning.

The so-called symbolization is the transformation of a sequence of real numbers into a sequence of symbols. Different from the division on the basis of understanding emphasized by rough set and orbital symbolization, symbolization does not do too much analysis of the system features corresponding to the real number sequence, but directly coarse-graines them according to the numerical characteristics of the real number sequence, and then do various reasoning calculations to understand the system features after obtaining the symbol sequence, that is, "divide first, then calculate". In other words, the system is first divided into a large number of small particles according to a uniform rule, and then symbolic dynamics or statistical methods are applied to deduce the implicit “patterns” of the system. The main task of symbolization is to retain as much valid information about the system as possible with the smallest set of symbols.

The general methods of symbolization are mainly divided into two categories: first, the symbols are divided directly according to the numerical characteristics of the sequence without any preprocessing, which mainly includes static method, dynamic method and synthesis method, and we collectively refer to these three methods as the direct method; second, the sequence is first appropriately transformed and then divided, which is mainly the wavelet space method. Here in this paper, we mainly introduce the wavelet space method.

Let the state of the system be represented by the sequence $\{x_t, t = 1, \cdots T\}$, then x_t represents the state of the system at the moment t, and T denotes the total number of data in the sequence. Suppose that $\{x_t, t = 1, \cdots T\}$ corresponds to a sequence of symbols denoted by $\{s_t, t = 1, \cdots T\}$.

The wavelet space method, also known as the wavelet method, is symbolized in the following steps

(1) Do an energy spectral density analysis of the time series and select multiple frequencies of interest f_i;

(2) Select a continuous wavelet function and adjust the scale α of the wavelet function so that the center frequency of the mother wavelet $F_c = \alpha f_i$;

(3) Do a continuous wavelet transform on the time series to obtain multiple sets of wavelet coefficients on different scales;

(4) Arrange the wavelet coefficients between each other in the order of scale from small to large or from large to small to obtain a scale sequence;

(5) Do a static division of the scale sequence to obtain a symbolic time series.

It can be seen here that since the wavelet method is ultimately used to obtain the symbol sequence using the static method, the size of the symbol set for this method can also be adjusted. Wavelet method has some advantages in retaining effective information, but the computation is much more complex than the direct method, and the principle of wavelet method is not very clear, there are many problems need to be solved, so in this paper, only the symbolization method of the direct method is used. Of course, the wavelet method will also become a direction to continue the research of symbolic time series analysis in the future.

In addition, for the drawbacks of the existing traditional methods, some improved symbolization methods have been generated, such as dynamic labeled frame segmentation method and adaptive symbol space division method.

II. C. 1) Dynamic labeled frame segmentation method

The dynamic scalar segmentation method is mainly an improvement method generated to address the shortcomings of the time series symbolic analysis of complex dynamical systems in which a lot of key information is lost.

Because the states of the time series at different moments are geometrically and physically related, we introduce the concept of a scalar frame, where each state corresponds to a scalar frame, the horizontal axis of which is the criterion for symbolic partitioning, and the vertical axis is the corresponding state line of the system. With the help of computer storage theory, each state is represented in three-bit register notation as $S_n = S_{n1}S_{n2}S_{n3}$. Where S_{n1} denotes the relationship between the n th number and the $n-1$ th number, S_{n2} denotes the relationship between the n th number and the partition criterion, and S_{n3} denotes the relationship between the n th number and the $n+1$ th number. For example, take the 0, 1 division as an example

$$s_{n1} = \begin{cases} 1, & x_n \geq x_{n-1} \\ 0, & otherwise \end{cases}$$
$$s_{n1} = \begin{cases} 1, & x_n \geq a \\ 0, & otherwise \end{cases} \quad (7)$$
$$s_{n1} = \begin{cases} 1, & x_n \geq x_{n+1} \\ 0, & otherwise \end{cases}$$

Then, in the whole sequence of symbols $S_n = S_1 S_2 \cdots S_i \cdots$, each S_i is a code word corresponding to a string of three symbols.

II. C. 2) Adaptive symbol space division method

For a uniformly distributed signal, it is reasonable to use the traditional interval segmentation method, but the data to be analyzed in financial fluctuations are not always uniformly distributed, and data-dense regions contain richer information while data-sparse regions contain less information, so the number of segmentation intervals should be increased in data-dense regions and decreased in data-sparse parts.

First, the symbol sequence is obtained by the traditional interval partitioning method, and then its corresponding shannon entropy is used to determine whether to continue the partitioning or not. If $H(n)$ represents the shannon entropy of the symbol sequence after n symbol partitions, where: $H(n) = -\sum_i^n p_i \log p_i$, p_i is the probability of the occurrence of the i th symbol, it is defined that

$$\Delta H(n) = H(n) - H(n-1), n \geq 2 \quad (8)$$

Choose a threshold value $0 \prec \varepsilon_n << 1$, and if $\Delta H(n) \succ \varepsilon_n$, the region with the most occurrences of symbols can be considered to be divided into two regions.

III. Empirical Research on Shanghai Stock Market Volatility Characteristics Based on Time Series Analysis

In Chapter 2, by constructing a multi-intelligence body interaction model and a time series symbolization method, this paper establishes a theoretical framework for financial market volatility forecasting. In order to further verify the applicability of the model and explore the deep law of market volatility, this chapter takes the Shanghai stock market as the research object, and combines the empirical data with the multi-dimensional statistical analysis of volatility characteristics.

III. A. Statistical analysis of the volatility characteristics of the Shanghai stock market

The article takes the Shanghai stock market as the research object, conducts empirical research on the volatility characteristics of the Shanghai stock market, grasps the characteristics and laws of its volatility, which is of great significance for its own development as well as for promoting the development of the national economy. The study statistically analyzes the volatility of the Shanghai stock market.

III. A. 1) Analysis from the point of view of share price indices

Generally speaking, the overall volatility of the stock market can be divided into peaks, troughs and bands based on the characteristics of its process. Peak is the maximum value reached by the stock price index in a volatility cycle, trough is the minimum value reached by the stock price index in a volatility cycle, and band is the process of change of the stock price index from peak to trough or from trough to peak. To examine the overall volatility of the Shanghai stock market, we use the data from January 2, 2008 to January 31, 2020 for the SSE Composite Index. Figure 1 shows the chart of the SSE Composite Index, from which the overall volatility of the Shanghai stock market can be seen.

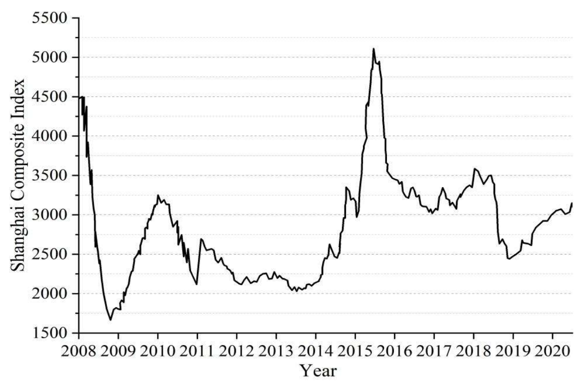

Figure 1: Shanghai stock market index trend

From the above chart, we can see that the SSE Composite Index has maintained an upward trend, which is consistent with the continued development of China's national economy. At the same time, we can also see that the volatility of Shanghai's stock market is still quite drastic. During the global financial crisis in 2008, the SSE index experienced a historic plunge. Taking the closing point of 5,261.56 at the end of 2007 as the starting point, the market opened a downward channel at the beginning of 2008 due to the spread of the U.S. subprime mortgage crisis and domestic inflationary pressure, and the decline reached 34% in January-March alone. Although the April-May brief sideways consolidation, but then the international financial turmoil (such as the Lehman Brothers bankruptcy) and domestic “large and small non-” release pressure superimposed, resulting in the index on October 28, fell to 1664.93 points of the year's lowest point, the end of the year closed at 1,820.81 points, a yearly decline of up to 65.4%. At the end of the year, “four trillion” economic stimulus plan launched for the market to inject a brief rebound momentum.

In 2009-2010, policy-driven became the main line of the market. Benefit from large-scale infrastructure investment and loose monetary policy, in 2009, the SSE index rebounded from the low 1849 points all the way to 3277.14 points, an annual increase of 80.5%. However, in 2010, the risk of economic overheating emerged, the central bank launched a cycle of interest rate hikes, coupled with the fermentation of the European debt crisis, the index retreated to 2808.08 points, an annual decline of 14.3%, showing the dual impact of policy and external shocks.

From 2011-2014, the market entered a period of prolonged oscillation. The slowdown in economic growth and exposure to shadow banking risks led to a further decline in the index to 2,199.42 points (21.7% annual decline) in 2011, followed by two years of sustained downturn, closing at 2,115.98 points in 2013. Until 2014, the central bank interest rate cuts and active financing and bond financing to promote the entry of leveraged funds, financial and real estate sector outbreak, the index rose 52.9% to 3234.68 points for the whole year, for the 2015 “leveraged bull” laid the groundwork.

2015 is a year of intense volatility. The first half of the over-the-counter capital frantic influx, small and medium-sized stocks soared, June 12, the SSE index rushed to 5178.19 points of the second highest point in history. But then the regulatory layer to clean up the allocation of capital triggered a liquidity crisis, thousands of stocks fell frequently, the index maximum retracement of 45%, barely closed at 3539.18 points at the end of the year, an annual decline of 9.4%. The ups and downs of this phase exposed the systemic risk of leveraged trading.

The market entered a restoration period in 2016-2017. the implementation of the melting mechanism in 2016 unexpectedly exacerbated volatility, the index fell 12.3% for the year, but the supply-side reforms drove the cyclical stocks to rebound; in 2017, under the expectation of accelerated inflow of foreign capital and the inclusion of A-shares in the MSCI index, the rise of the white horse stocks represented by Guizhou Moutai drove the index moderately up by 6.6% to 3,307.17 points, presenting a “structural slow bull” characteristics.

The U.S.-China trade war became the dominant factor in 2018. After the index briefly surged to 3,587.03 points at the beginning of the year, market panic spread due to the escalation of tariff conflicts and domestic deleveraging policies, bottoming out at 2,449.20 points on October 19, down 24.6% for the year. Despite the policy shift towards easing in the fourth quarter (e.g. tax cuts, bailout funds), investor confidence has been slow to recover.

The market took a turn for the worse in 2019. After hitting a low of 2,440.91 points at the beginning of the year, the establishment of the Science and Technology Innovation Board (STIB), sustained foreign capital inflows and the rise of tech sectors such as 5G pushed the index to rebound, rising 22.3% to 3,050.12 points for the year. Although weak economic data in the second half of the year constrained gains, monetary policy easing is expected to lay the foundation for the cross-year market. By January 1, 2020, the market continued this trend.

III. A. 2) Analysis from the perspective of stock price amplitude

Due to the shortcomings of the stock price extreme difference indicator in terms of volume, we use the stock price amplitude as an indicator to describe the stock price change status between the extremes. Figure 2 below gives the intraday amplitude of the Shanghai stock market from January 2, 2008 to January 31, 2020, with the horizontal axis indicating the time and the vertical axis indicating the intraday amplitude (%).

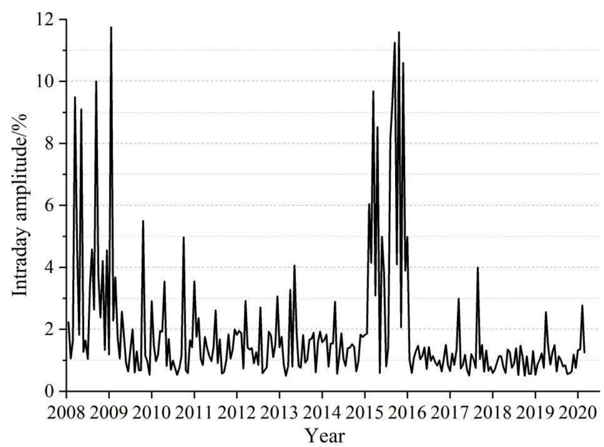

Figure 2: Shanghai stock market index swing

According to Figure 2, from January 1, 2008 to January 1, 2020, the intra-day amplitude of the Shanghai Stock Market Composite Index showed significant phase characteristics: extreme volatility in 2008: impacted by the global financial crisis, the annual amplitude exceeded 8% several times, the highest touching 12%, in October 2008, the single-day amplitude of more than 10%. 2009-2014 convergence of the oscillator: the amplitude fell back to the range of 2% -6%. 6% range, in 2010 after the launch of stock index futures market volatility short-term suppression, but in 2013 the “money shortage” event led to a brief rebound in amplitude to 5%. 2015 leveraged bulls and bears shock: the first half of the leveraged funds to promote the bull market in June, amplitude soared to 12%, June 26, a single-day amplitude of 11.53%, more than 8% for the year! The extreme volatility of up to 15 trading days. 2016-2020 low and stable: after the failure of the melting mechanism trial in 2016, regulatory enhancements such as strict control of leverage, foreign capital access, the amplitude of the rapid convergence of less than 2%, the average daily amplitude of 2017-2019 is only 1.5%-1.8%, close to the level of mature markets.

III. A. 3) P/E ratio

The price-earnings ratio is the ratio between the price per share and earnings per share, therefore, in the case of unchanged earnings per share, the movement of the price-earnings ratio is directly linked to the fluctuation of stock prices, which can directly reflect the volatility of the stock market. At the same time, the price-earnings ratio can reflect the market participants on the market's future earnings expectations, that is, a kind of confidence in the size of the future market bullish. Generally speaking, the higher the price-earnings ratio of a stock, the higher the motivation of investors to participate in the stock market and the higher the expected return on the stock. However, in an emerging market or a highly speculative market, an excessively high price-earnings ratio often carries a great deal of risk and can generate sharp stock market volatility. Therefore, from this perspective, the P/E ratio can also indirectly reflect and anticipate the volatility of the stock market. Figure 3 below shows the movement of the average P/E ratio of the Shanghai stock market from 2008 to 2020.

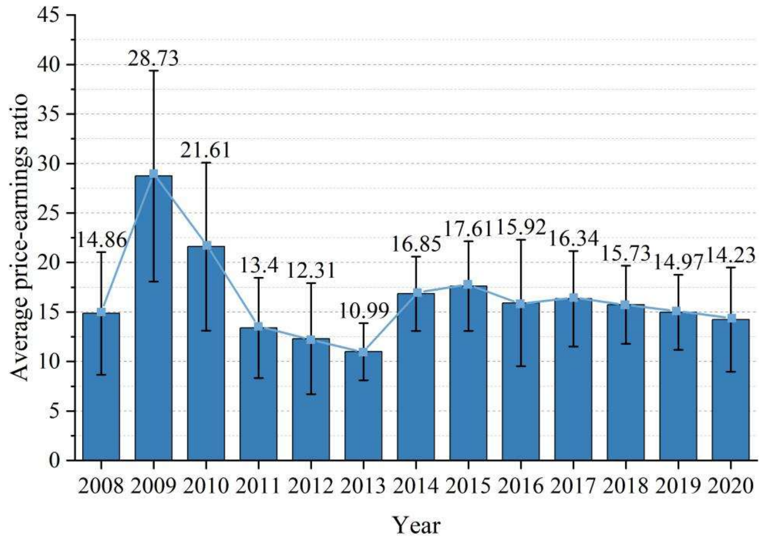

Figure 3: Shanghai stock market’s average PE of the year

According to the data in Figure 3, the average P/E ratio of Shanghai stock market showed significant fluctuation from 2008 to 2020. The P/E ratio dropped to 14.86x during the global financial crisis in 2008, and then rose sharply to 28.73x in the following year driven by the domestic 4 trillion stimulus policy, which became the highest point in the statistical cycle. Since then, the market has gradually retraced, and in 2011-2013, it continuously lowered to 12.31 times (2012), reflecting the slowdown in economic growth and low investor sentiment.In 2014-2015, the influx of leveraged funds pushed the valuation back up, with the P/E ratio reaching 16.85 times and 17.61 times, respectively.The regulatory cleanup of the over-the-counter (OTC) allocation of funds after the 2015 bull market triggered the market adjustment, and it retreated to 15.73 times in 2018. In 2018-2020, the price-earnings ratio stabilized at 14-15 times, 14.97 times in 2019 and 14.23 times in 2020, showing that the market is gradually returning to rationality. The overall data show the cycle characteristics of “crisis trough - policy-driven surge - deleveraging retracement - long-term stabilization”, the valuation pivot downward may be closely related to the deepening of the capital market reform, the promotion of the registration system and institutionalization of the investor structure. Closely related.

III. B. Forecasting high-frequency financial volatility based on time series analysis

Through the comprehensive analysis of stock price index, amplitude and price-earnings ratio, this paper preliminarily reveals the volatility pattern of Shanghai stock market. In order to further verify the predictive ability of the theoretical model in practice, this section makes short-term forecasts of market volatility based on the time series analysis method using 2020 high-frequency data, and evaluates the reliability of the forecasting results through the symbolization technique.

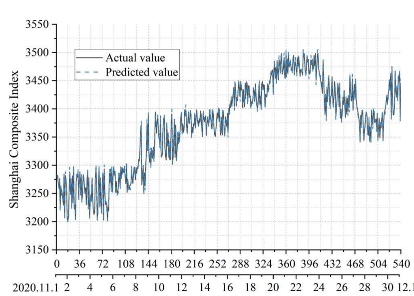

Figure 4: The curve of the actual and predicted values of the fluctuation time series

The study investigates the volatility of securities prices in the financial market and empirically analyzes and forecasts the volatility of the stock market, where the volatility of the stock market refers to the volatility of the stock index returns that can represent the overall characteristics of the market.

Figure 4 shows the curve of the actual and forecasted values of the time series of the volatility of the Shanghai Composite Index in November-December 2020 based on the wavelet control method.

In order to test the predictive effectiveness of the method, the MAPE metric is introduced, MAPE is the mean absolute relative error, calculated as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \tag{9}$$

where x_i is the actual value of the series, $\hat{x}_i$ is the predicted value of the series, and n is the number of prediction periods, the prediction is considered to be better if the MAPE value is lower than 10%. Using the above method to calculate the value of the MAPE indicator for the volatility time series of the Shanghai Composite Index is 2.98%, and the MAPE values are all lower than 5%, which shows that the use of the symbolic sequence comparison method to find historically similar sub-sequences, and then predict the value of the subsequent time series is more effective.

Regarding the prediction of the volatility range, the prediction of 540 volatility symbols for November-December 2020 can be obtained according to the steps of the volatility range prediction. Comparing the actual symbols of the Shanghai Composite Index with the predicted symbols, the proportion of symbols that are identical is 54.42%, the proportion of symbols that differ by one level (such as -1 and 0, 1 and 2) is 36.23%, the proportion of symbols that differ by two levels (such as -2 and 0, -1 and 1) is 6.33%, the proportion of sign difference level 3 (e.g. -1 and 2, -2 and 1) is 1.79%, and the proportion of sign difference level 4 (only -2 and 2) is 1.23%. It can be seen that the proportion of actual and predicted values corresponding to the same or similar (only one level of difference) symbols is 90.65%, which indicates that the proportion of fluctuation intervals that are the same or similar is high and the prediction effect is good. Judging the strength of fluctuations based on the value of the symbols does not focus on specific fluctuation values, but rather determines the interval in which the fluctuations are located from a large-scale perspective in order to judge the level in which the future risk is located.

III. C. Identification and Determination of Agent-Based Stochastic Interactive Financial Market Volatility Models

The high-frequency volatility prediction verifies the effectiveness of the time series symbolization method, but the reasonableness of the model still needs to be tested by statistical distribution characteristics. In this section, the distribution consistency between the simulation data of the Agent-based stochastic interaction model and the real market volatility is verified through the analysis of normal distribution QQ plots and histograms, so as to provide theoretical support for the application of the model in corporate strategic planning.

The normal distribution QQ plots and histogram distributions of stock market volatility forecasts based on Agent-based stochastic financial market volatility model and time series analysis are shown in Figures 5 and 6.

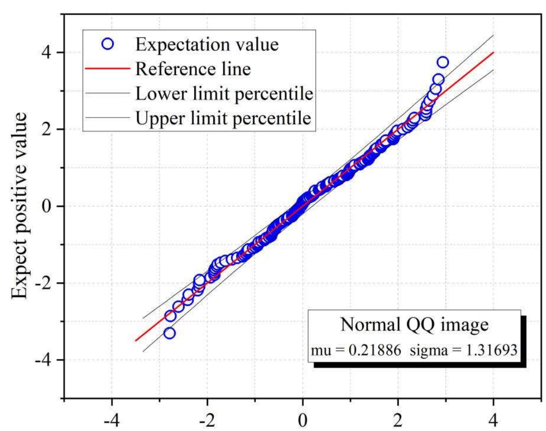

Figure 5: Normal distribution QQ graph

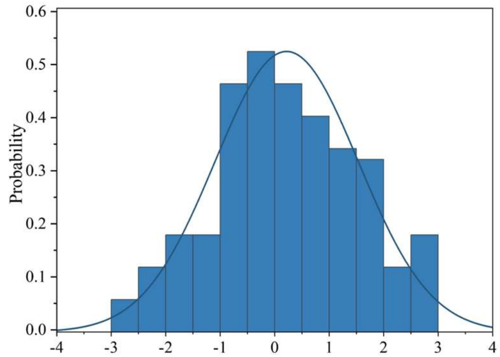

Figure 6: Normal distribution histogram

From the normal distribution, mu = 0.2189 and sigma = 1.3169, since the normal distribution is satisfied and the residuals are consistent with a white noise sequence, the model is reasonable.

IV. Corporate strategic planning strategy

Based on a multi-dimensional perspective, this paper constructs a set of integrated strategic planning methods integrating dynamic response mechanisms, data security and analysis capabilities, and quantitative prediction models.

(1) Establish a dynamic market strategy mechanism for rapid response

Enterprises need to improve the market information collection and analysis system, through professional teams and advanced tools to monitor market dynamics in real time. For example, by tracking consumer behavior data, competitors' strategies and industry trends, enterprises can quickly identify potential opportunities and risks, and provide data support for strategic adjustments. Second, optimizing the decision-making process is key. The traditional hierarchical decision-making system is inefficient and prone to missing market windows, and the decision-making chain needs to be shortened through flat management and cross-departmental collaboration mechanisms. For example, the introduction of data-driven decision-making models can improve the scientific and timely decision-making. Finally, the organizational structure needs to be transformed into a flexible one. By reducing the number of management levels, strengthening project-based teams and cultivating employees' innovation ability, companies can improve their response speed to market changes.

(2) Strengthen the synergy between data security and in-depth analysis

Data has become a core resource for enterprise strategy development, but the risk of data leakage and misuse is also on the rise. On the one hand, enterprises need to build a comprehensive data security management system. By establishing strict data collection, storage and transmission standards, and adopting encryption technology and leakage detection systems, security risks can be minimized. On the other hand, they need to strengthen their data analysis capabilities to explore the value of data. The establishment of an interdisciplinary data analysis team, combined with machine learning algorithms and big data processing platforms, can efficiently extract market trend information.

(3) Quantitative Forecasting and Strategic Planning Based on Time Series Analysis

Financial market fluctuations have an increasingly significant impact on corporate strategy, and time series analysis provides a methodological basis for predicting market trends. First, by constructing a multi-intelligence interaction model, the transmission effect of investor behavior on stock prices can be simulated. For example, investors are divided into three categories: “strong”, “weak” and “neutral”, and the Poisson process is used to simulate the propagation path of attitudes, which is verified by combining with the data of the Shanghai Composite Index. The model can effectively capture the dynamic changes of market demand. Secondly, the application of time series symbolization techniques, such as wavelet control method and adaptive space division method, can optimize the feature extraction of financial data. Shannon entropy dynamically adjusts the density of symbol intervals, which enhances the information retention ability in data-dense regions and can more accurately predict the fluctuation intervals. Finally, the prediction results are combined with strategic planning. Enterprises can dynamically adjust their investment portfolios or inventory strategies according to the volatility prediction results to reduce market risk exposure.

V. Conclusion

This paper systematically reveals the intrinsic law of financial market volatility and its guiding value for corporate strategy through the integration of multi-intelligence body interaction model and time series analysis. Empirical research shows that the volatility characteristics of the Shanghai stock market are significantly stage and event-driven: between 2008 and 2020, the average annual amplitude of the Shanghai Composite Index was 4.8%, with extreme events such as the global financial crisis, which led to a one-day amplitude of more than 10% in 2008, and the impact of leveraged capital, which reached an amplitude of 12% in 2015, leading to severe market shocks. The P/E ratio has gradually returned to rationality (14.23x in 2020) from the policy-driven high (28.73x in 2009), reflecting the trend of the market valuation pivot downward and investor structure optimization. The volatility prediction based on high-frequency data verifies the effectiveness of the improved symbolization method, with a low MAPE value of 2.98% and a symbol matching rate of more than 90%, which indicates that the method is highly reliable in capturing short-term volatility intervals. Meanwhile, the normal distribution consistency between the Agent model simulation data and the real market ($\mu = 0.2189$, $\sigma = 1.3169$) further corroborates the rationality of the model.

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