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Research Article

Correlation Analysis between Stock Price and Accounting Profit Based on a Vector Autoregressive Model

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The study of accounting profitability was initiated by the famous American scholars Ball and Brown in the 1960s. In recent years, with the continuous development of market economy, the continuous improvement of the accounting legal system and accounting standards for enterprises has promoted the research on accounting profit in capital market in China. Due to the restriction of some objective conditions, there are not many valuable research results on the relationship between accounting earnings and stock price changes, and the research methods suitable for the study of accounting earnings still need to be explored and summarized. The China Securities Regulatory Commission (CSRC) has required listed companies to publish quarterly financial and accounting reports since 2002, and the condition of using the regression analysis method to study the accounting profit of listed companies is available. In this context, this paper designs a vector autoregressive model to study the correlation between stock price and accounting profit. First, combining the literature and the research results of accounting profit at home and abroad, this paper expounds the statistical analysis of accounting profit. Then, this paper analyzes the accounting profitability of listed companies in China from static and dynamic perspectives. Finally, according to the accounting profit status and profitability statistical analysis of accounting information, accounting profit and growth relationship, and accounting profit information and the relationship between stock prices, this paper is concluded. Also, this paper shows how to improve the profitability of listed companies and how can investors effectively use the accounting earnings information of listed companies for stock investment and put forward corresponding policy suggestions.

1. Introduction

The study of accounting profitability was initiated by the famous American scholars Ball and Brown in the 1960s, and with the development of economics, finance, and statistical technology, the birth and development of empirical accounting theory has been promoted. Positive accounting theory in the 1970s set off a significant accounting revolution, and positive accounting research absorbed the research results of economics and finance [1]. Therefore, the research on accounting profit in capital market and the relationship between accounting profit and stock price change has entered a new development branch of Western financial theory. The problem of accounting profit and the relationship between accounting profit and stock price change has become a major field of research [2–4]. The theoretical basis of the research is efficient market theory and capital asset pricing theory. This kind of research combining financial theory and capital market not only enriches the theoretical research of capital market but also provides reference for investors to make stock investment decisions and capital market practice.

With the continuous development of China's market economy, the continuous improvement of accounting legal system and enterprise accounting standards has promoted the in-depth development of China's research on accounting earnings in the capital market [5–7]. In the process of rapid development of capital market, there are still many practical problems: what is the status of accounting profit disclosed in the financial accounting report of the listed company, whether the accounting profit information disclosed by the listed company has information content, whether the accounting profit of the listed company is related to its growth, whether the accounting profit information of the listed company is related to the stock price fluctuation in the capital market, what is the correlation between them, and which are the theoretical and practical circles very concerned about the problem [8–12].

The financial accounting report published by listed companies is the main carrier of accounting information of listed companies. It is the main tool for transmitting accounting profit information of listed companies; it is an important document provided by listed companies to reflect the financial status of listed companies at a particular point in time and the cash flow of operating results during an accounting period. It is also a comprehensive reflection of the financial condition, operating results, cash flow, and operating management level of listed companies. At the same time, for investors to say, is also the important information for investors to stock investment decisions. Therefore, the financial and accounting reports of listed companies in the disclosure of accounting earnings information to make statistical analysis and study the effect of accounting earnings for the stock price have high practical value and also conduce to the development of empirical accounting theory research [13–15].

The purpose of statistical analysis of accounting earnings and the relationship between accounting earnings and stock price changes is to master the accounting earnings status and profitability of listed companies and to find the relationship between abnormal returns and unexpected earnings. In the process of statistical analysis, earnings need to be decomposed into expected earnings and unexpected earnings. The response of the capital market to unexpected earnings is the basis for testing the effectiveness of the capital market. Further analysis can be made on the content of accounting information, the degree of market reaction, and earnings reaction coefficient. In order to separate out unanticipated earnings, expected earnings should be confirmed first. Since accounting earnings of listed companies are not available in advance and difficult to test afterwards, an appropriate autoregressive model can be used to generate alternative variables for research.

Although the works of correlation analysis between stock price and accounting profit have received great attention [15–17], there are few valuable studies in this field in China, and the reason is that there is no mature financial analyst market in China and the accounting theory circle has not studied the profit prediction model suitable for China's listed companies.

2. Related Works

Chou et al. [18] first applied the concept of range to the field of finance and found that the Gaussian distribution was not sufficient to describe asset price changes in the price time series of financial markets. They proposed a CARR (conditional autoregressive range) model, which combines range with the GARCH model, to effectively depict the dynamic structure of range and concluded that the CARR model based on range is better than traditional GARCH [19]. When estimating financial time series with a large time span, we should consider whether the structure of the past data is consistent with that of the present data, that is, whether the model has undergone significant structural transformation. Taking this factor into account can improve the accuracy of the model estimation. Based on the CARR model, the parameter changes with time are considered when the study period is long [20–22]. Based on the CARR model, the parameter changes with time are considered when the study period is long to make an empirical analysis on the data of Taiwan stock market [23]. Tsionas and Kumbhakar [24] presented a time-varying conditional autoregressive range model to capture the possible structural shifts of range volatility. The empirical results show that the market volatility caused by the subprime crisis has spread from the US market to most of the tested markets. The research on the asymmetry of volatility is also an important aspect of the current research on the volatility of financial market. Most empirical results show that because of the existence of financial market volatility asymmetry, bad news is more likely to cause market volatility than good news, and on the basis of the CARR model, researchers describe the dynamic structure of asset price range with rising trend and falling trend, respectively, in order to describe the asymmetric behavior in financial market [25–27].

With the acceleration of economic globalization and financial integration, the global financial market is undergoing fundamental structural changes, which stimulates people to study the correlation and degree of correlation between financial markets. The Copula function is introduced into the GARCH model, and the Copula-GARCH model is established to dynamically analyze the correlation between financial variables [28]. Carvalho and Sáfadi [29] further discussed the significance of Copula theory for financial market risk analysis on the basis of previous studies and put forward the concept of conditional Copula function and applied it to the empirical test. Mo et al. [30] introduced how Copula function is applied to volatility correlation analysis of financial markets and combined Copula function with the GARCH model to study the autocorrelation structure of financial time series. Based on the combination of Copula theory and value-at-risk theory, the var-Copula model is constructed, and the correlation and structure between stock index and trading volume are discussed [31]. In this paper, a semiparametric multivariate Copula-GARCH model is established to analyze the risk of portfolio in China's open-end fund market. In addition, the relationship between Copula function and its corresponding Kendall rank correlation coefficient, Spearman rank correlation coefficient, and tail correlation coefficient are studied. This paper introduces how Copula function is applied to volatility correlation analysis of financial markets and combines Copula function with the GARCH model to study the autocorrelation structure of financial time series [32].

From the abovementioned analysis, we know that the abovementioned methods have studied the correlation analysis between stock price and accounting profit to some extent, but some problems still exist. On the other hand, no scholar has applied a vector autoregressive model to this field till now, so the research here is still a blank, which has great theoretical research and practical application value.

The contributions of this paper are as follows:

(1) The vector autoregressive model is first used to describe the correlation between stock price and accounting profit. Especially, the Copula function and CARR model are combined to study the correlation between the Shanghai Stock Index and Dow Jones Index, and the correlation between the two markets is analyzed.

(2) Furthermore, long-term data should be selected as samples for the study of volatility, so as to more comprehensively reflect the volatility and correlation characteristics of China's stock market.

This paper consists of five parts. The first and second parts give the research status and background. The third part is the proposed correlation analysis model. The fourth part shows the experimental results and analysis. The experimental results of this paper are introduced and compared and analyzed with relevant comparison algorithms. Finally, the fifth part summarizes the full paper.

3. The Proposed Correlation Analysis Model

3.1. The CARR Model. The form of the CARR model is similar to that of the GARCH model, The CARR (P, Q) model is shown in the following formulas:

$$\begin{aligned} R_t &= \lambda_t \varepsilon_t, \\ \lambda_t &= \omega + \sum_{i=1}^{p} \alpha_i R_{t-i} + \sum_{j=1}^{q} \beta_j \lambda_{t-j}, \\ \varepsilon_t &\sim iidf(\cdot)n, \\ R_t &= 100 \times \left[\ln P_t^{\text{high}} - \ln P_t^{\text{low}}\right] n, \end{aligned} \tag{1}$$

where R_t represents the range of the natural logarithm of the stock price P_t in phase t. λ_t represents the conditional expectation for the prediction of range R_t in t period when all information set I_{t-1} is known prior to period t. Conditional expectation for prediction of range R_t in t period $\lambda_t = E(R_t/I_{t-1}), \lambda_t \geq 0$.

ε_t is the disturbance term. Its distribution is assumed to follow the distribution of a density function f with a unit mean. ω represents the existence of uncertainty factors in range and can also represent the initial level of range. α_i is the lag coefficient of range, which can represent the short-term influence brought by the mean of range conditions. β_j is the lag coefficient of range condition mean, which can represent the long-term influence brought by the range condition mean. In order to satisfy the stability condition of the CARR model with an extreme long-term condition, the following equation should be satisfied:

$$\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1 \tag{2}$$

It is an indicator reflecting the persistence of fluctuations. The closer this indicator is to 1, the stronger the persistence of fluctuations, and when the disturbance term ε_t obeys the unit exponential distribution, the logarithmic likelihood function of the CARR model is expressed as

$$L\left(\omega, \alpha_i, \beta_j, R_1, R_2, \cdots, R_T\right) = -\sum_{t=1}^{T} \left[\ln\left(\lambda_t\right) + \frac{R_t}{\lambda_t}\right] \tag{3}$$

Weibull distribution is a more spiritual exponential distribution, and when ε_t obeys Weibull distribution, the logarithmic likelihood function of the CARR model is expressed as

$$\begin{aligned} L\left(\omega, \alpha_i, \beta_j, R_1, R_2, \cdots, R_T, \gamma\right) = \sum_{t=1}^{T} \ln\left(\frac{\gamma}{R_t}\right) + \gamma \ln\left[\frac{\Gamma(1 + 1/\gamma) R_t}{\lambda_t}\right] \\ - \left[\frac{\Gamma(1 + 1/\gamma) R_t}{\lambda_t}\right]^{\gamma} \end{aligned} \tag{4}$$

3.2. The GARCH Model. In the study of volatility in financial markets, the GARCH (P, Q) model has been widely used, and its model form is as follows:

$$\begin{aligned} r_t &= \mu_t + a_t, \\ a_t &= \sigma_t e_t, \\ \sigma_t^2 &= \chi_0 + \sum_{i=1}^{P} \chi_i a_{t-i}^2 + \sum_{j=1}^{q} \delta_j \sigma_{t-j}^2, \\ r_t &= 100 \times \left[\ln P_t^{\text{close}} - \ln P_{t-1}^{\text{close}}\right], \end{aligned} \tag{5}$$

where r_t represents the return rate of the natural logarithm of the stock price at time t. σ_t^2 is the prediction variance of a_t in the previous period based on past information, namely, the conditional variance. From the conditional variance equation, it can be seen that the forecast variance of the current period will be affected by the long-term mean (constant term χ_0) and the prediction variance of the previous period σ_{t-j}^2 (GARCH term) and the information about the fluctuation in the previous observation a_{t-1}^2 (ARCH term).

χ_i represents the short-term impact of random events on volatility, and δ_j is an indicator of the long-term impact of random events on volatility. They must also meet the following constraints:

$$\sum_{i=1}^{P} \chi_i + \sum_{j=1}^{q} \delta_j < 1. \tag{6}$$

When the residual term of the GARCH model obeys normal distribution, the log-likelihood function form of the GARCH model is

$$L_N = -\frac{1}{2} T \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \log \sigma_t^2 - \frac{1}{2} \sum_{t=1}^{T} \frac{a_t^2}{\sigma_t^2} \tag{7}$$

In short, (6) is the constraint of (7), and (7) is the objective function of (6).

3.3. Analysis of the Overall Situation and Changing Trend of Accounting Profit. According to the disclosure in the 2017 annual report, 9 companies have withdrawn more than 500 million Yuan of goodwill impairment, and 3 companies have withdrawn more than 1 billion Yuan of goodwill impairment. From 2015 to 2020, the total amount of goodwill impairment loss recognized by A-share listed companies was 1.067 billion Yuan, 1.606 billion Yuan, 2.621 billion Yuan, 7.923 billion Yuan, 10.137 billion Yuan, and 36.339 billion Yuan. In order to intuitively analyze the growth range and development trend of the recognized goodwill impairment loss of A-share listed companies from 2015 to 2020, this paper will analyze the total amount of financial loss and the change of annual growth rate of financial loss from the perspective of different years, and the specific results are shown in Figure 1:

As can be seen from Figure 1, the current total financial loss presents an increasing trend. This is mainly due to the emergence of the wave of mergers and acquisitions, which indirectly affects the change of goodwill impairment scale. The period of 2017–2019 was the peak period of capital market M&A. A large number of enterprises have been confirmed in the merger process, and their total financial losses have been continuously expanded in the subsequent measurement due to the economic situation, business problems, and betting agreements. Compared with the total financial loss of 1.606 billion Yuan in 2016, the rate of expansion of financial loss over the five-year period is amazing, which also shows the need to pay attention to financial loss. In 2017, the annual growth rate of financial loss reached 202.29%, and the amount of financial impairment loss increased nearly twice. In 2019, the annual growth rate of financial loss decreased, which was due to the gradual cooling of merger and acquisition activities. The annual growth rate of financial impairment reached its peak again in 2020.

In addition, since mergers and acquisitions occur frequently and widely among A-share listed companies in China, and companies involved in mergers and acquisitions occur in all industries. However, due to the operating environment of each industry, there are differences in business models and unique characteristics of different industries, and the performance of financial losses in different industries is also different. In this paper, according to the standards of CSRC, the listed companies with financial losses from 2015 to 2020 are distinguished by industry, and the current situation of financial losses in different industries is compared, as shown in Figure 2.

As can be seen from Figure 2, the financial losses of different industries vary greatly, among which the manufacturing industry, which occupies the first place, has a financial loss of nearly 32.4 billion Yuan in six years, accounting for 57% of the total financial loss. Manufacturing industry is the most basic and stable industry in China's economic development, and the proportion of listed companies in manufacturing industry is also the highest in Shanghai and Shenzhen stock markets. The information transmission, software, and information technology service industry ranked second, and its higher financial loss is mainly related to the characteristics of other industries. Similarly, the culture, sports, and entertainment industry also has a high valuation, with a financial loss of 1.939 billion Yuan, which indicates that the business goodwill recognized by the industry with a high valuation is at greater risk of financial loss. Through the abovementioned analysis of the current situation of goodwill impairment in China, it can be concluded that the total financial loss shows an increasing sequence every year and keeps expanding. The total financial loss reached a small climax in 2015 and ushered in the outbreak moment of financial loss in 2017. At present, the confirmation of high financial loss is no longer the economic behavior of a few individual enterprises. The continuous expansion of financial loss scale shows that financial loss plays an important role in enterprises themselves, investors, and stock market prices, which also fully shows that the research of this paper is important.

4. Experimental Results and Analysis

4.1. Introduction to the Dataset. In this chapter, the daily data of the Shanghai Composite Stock Index and Dow Jones Index from January 4, 2002, to June 17, 2014, were selected to conduct research. The data of the two indexes were excluded from the date of incompatibility. After sorting out, there were a total of 2913 daily data extreme differences observed in September 2008 on the 14th, and Lehman Brothers announced that it was preparing to file legal documents for bankruptcy protection, which was the time point when the global financial crisis broke out. The sample data were divided into two sections, A and B. The period of data in section A was from January 4, 2002, to September 12, 2008. The data in section B cover the period from September 16, 2008, to June 17, 2014.

In order to verify the effectiveness of the proposed method in machine translation, the experimental hardware environment is Intel (R) Core (TM) I7-8550U CPU @ 1.80 GHz, 8.0 GB memory, SSD 512 GB, Windows 10 Professional operating system model training and testing using Google's open-source deep learning framework Tensorflow, and the experimental data analysis software environment and test environment are Pycharm 2018 professional edition.

4.2. Experimental Result Analysis. In this stage, the weekly data of the Shanghai Composite Stock Index and Dow Jones Index from September 16, 2008, to June 17, 2014, in section B are selected for research, and the data of the two indices that do not correspond to the date are removed. After sorting out, a total of 269 weekly data extremely poor observation values are obtained [17].

Table 1 is the estimation results of ECARR models with different lag orders. From the table, it can be clearly seen that most coefficients of the ECARR (1,2) model and ECARR (2,2) model are not significant at the significance level of 5%,

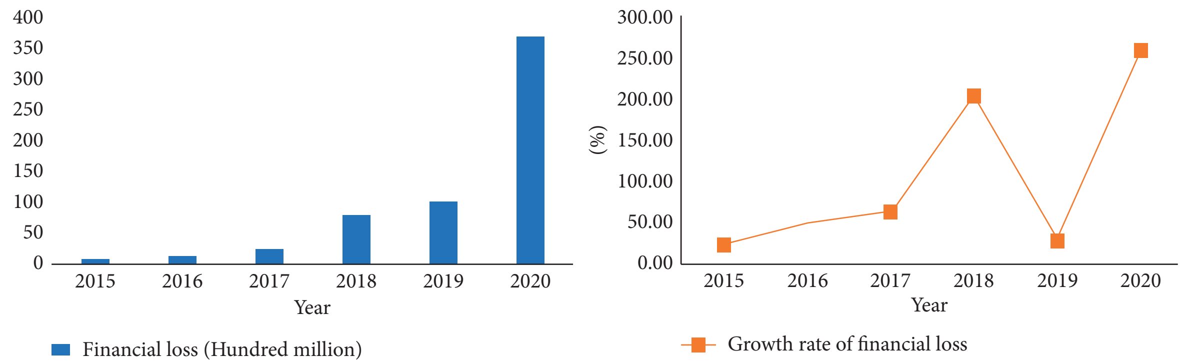

Figure 1: Chart of changes of financial loss and annual growth rate of A-share listed companies from 2015 to 2020.

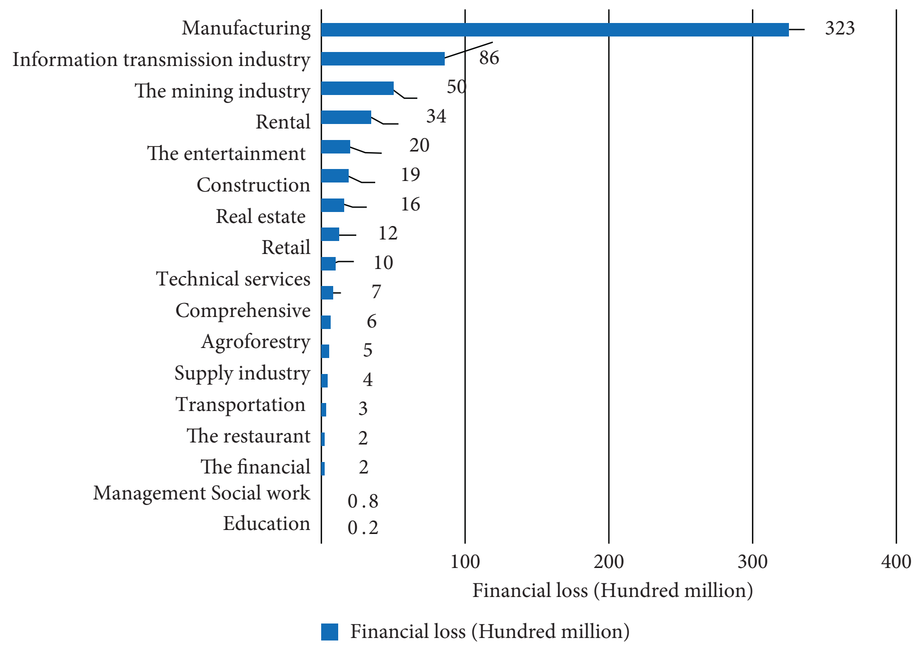

Figure 2: Financial losses of A-share listed companies in different sectors from 2015 to 2020.

Table 1: Comparison of different lag order estimation results of the ECARR model based on B segment weekly data.

	ECARR (1,1)	ECARR (1,2)	ECARR (2,1)	ECARR (2,2)
Logarithmic likelihood	−423.0118	−423.2302	−423.5645	−422.4046
w	0.1619 (0.6656)	0.1677 (0.5941)	0.1643 (0.7288)	0.1852 (0.6104)
α_1	0.1955 (0.0263)	0.1879 (0.0310)	0.1947 (0.0249)	0.1844 (0.0355)
α_2			−0.1053 (0.4861)	0.1976 (0.5182)
β_1	0.7142 (0.0202)	0.6013 (0.2482)	0.8395 (0.0242)	−0.1801 (0.5251)
β_2		0.1126 (0.6278)		0.7469 (0.4109)

Table 2: Comparison of different lag order estimation results of the ECARR model based on B segment weekly data.

	ECARR (1,1)	ECARR (1,2)	ECARR (2,1)	ECARR (2,2)
Logarithmic likelihood	−423.7468	−423.2688	−423.5645	−423.5346
w	0.1719 (0.0256)	0.1877 (0.0941)	0.1999 (0.073)	0.1342 (0.0109)
α_1	0.1955 (0.0263)	0.1879 (0.0310)	0.1947 (0.0249)	0.1844 (0.0355)
α_2			−0.1011 (0.2661)	0.1456 (0.23578)
β_1	0.9242 (0.0002)	0.6823 (0.2212)	0.8175 (0.0022)	−0.1501 (0.5572)
β_2		0.1531 (0.2371)		0.7218 (0.2197)

Table 3: Comparison of different lag order estimation results of the WCARR model based on B segment weekly data.

	WCARR (1,1)	WCARR (1,2)	WCARR (2,1)	WCARR (2,2)
Logarithmic likelihood	−323.7458	−323.1688	−321.5645	−239.5346
w	0.219 (0.0256)	0.2877 (0.0941)	0.2399 (0.073)	0.2215 (0.0109)
α_1	0.2155 (0.0263)	0.2379 (0.0310)	0.2147 (0.0249)	0.1944 (0.0355)
α_2			−0.1011 (0.2661)	0.1556 (0.23578)
β_1	0.6342 (0.0002)	0.6133 (0.2212)	0.8175 (0.0022)	−0.1501 (0.5572)
β_2		0.1521 (0.2371)		0.7118 (0.2197)
γ	2.0525 (0.0000)	2.0573 (0.0000)	2.0501(0.0000)	2.0611(0.0000)

Table 4: Comparison of different lag order estimation results of the WCARR model based on B segment Dow Jones weekly data.

	WCARR (1,1)	WCARR (1,2)	WCARR (2,1)	WCARR (2,2)
Logarithmic likelihood	−223.7458	−223.1688	−221.5645	−239.5346
w	0.119 (0.0256)	0.1877 (0.0941)	0.1399 (0.073)	0.1215 (0.0109)
α_1	0.4155 (0.0263)	0.1379 (0.0310)	0.4647 (0.0249)	0.3944 (0.0355)
α_2			−0.1911 (0.2661)	0.2556 (0.23578)
β_1	0.4342 (0.0002)	0.2133 (0.2212)	0.4275 (0.0022)	−0.1801 (0.5572)
β_2		0.1521 (0.2371)		0.4118 (0.2197)
γ	2.3525 (0.0000)	2.3573 (0.0000)	2.0501(0.0000)	2.3611(0.0000)

and the ECARR (2,1) model and ECARR (2,2) model are not significant The ECARR (2,2) model also has negative coefficients, and the constant term of the ECARR (1,1) model also cannot pass the null hypothesis, so it cannot fit the sample data well. This paper tries to remove the constant term of the ECARR model and use the ECARR model without constant term to fit the sample data.

It can be clearly seen from Table 1 that most coefficients of the ECARR (1,2) model and ECARR (2,2) model are not significant at the significance level of 5%, and there are negative coefficients of the ECARR (2,1) model and ECARR (2,2) model; the constant term of the ECARR (1,1) model also cannot pass the null hypothesis, so it cannot fit the sample data well. This paper tries to remove the constant term of the ECARR model and use the ECARR model without the constant term to fit the sample data.

Table 2 is the estimation results of ECARR models with different lag orders of constant terms removed. From the table, it can be clearly found that most coefficients of the ECARR (1,2) model without constant terms are not significant and are not included when the significance level is 5%. The coefficients of the ECARR (1,1) model with constant term are significant, so the ECARR (1,1) model without constant term fits the sample data better.

It can be seen from Table 3 that the logarithmic likelihood function of the WCARR model with different lag orders does not change significantly, which means that the model does not improve significantly with the increase of explanatory variables. The *PP* value is 0.3127. In addition, the *PP* value of 20 in the WCARR (2,1) model is 0.2449, and the *PP* value of 2 in the WCARR (1,2) model is 0.2079. In the case of a significance level of 5%, parameter estimation results are not significant, so the WCARR (1,1) model is adopted as it is more appropriate to estimate volatility.

It can be seen from Table 4 that the logarithmic likelihood function of the WCARR model with different lag orders does not change significantly in the WCARR (2,2) model. The *PP* value of 2 in the WCARR (2,1) model is 0.3004, and the *PP* value of 2 in the WCARR (1,2) model is 0.3217. When the significance level is 5%, the parameter estimation results are not significant, so the WCARR (1,1) model is more appropriate to estimate the volatility.

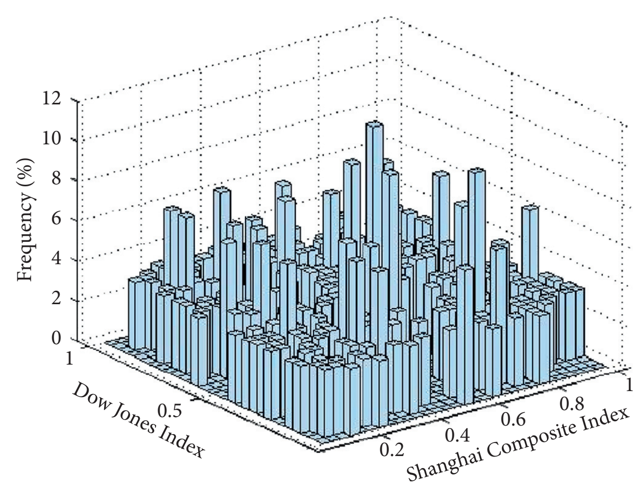

Figure 3: Empirical distribution of SSE index and Dow Jones Index extreme volatility series based on B segment weekly data.

From the abovementioned analysis, the logarithmic likelihood values of both the Clayton Copula and the normal Copula are relatively large, while the logarithmic likelihood values of the Copula-T and Gumbel Copula are relatively small through the corresponding Copula functions with experience. As can be seen from the evaluation method of Euclidean square distance between Copula and the fitting degree reflected by the logarithm likelihood function value of each Copula function, the Frank Copula function is relatively superior in describing the correlation degree and correlation pattern between the fluctuation sequence of the Shanghai Index and Dow Jones Index (Figure 3).

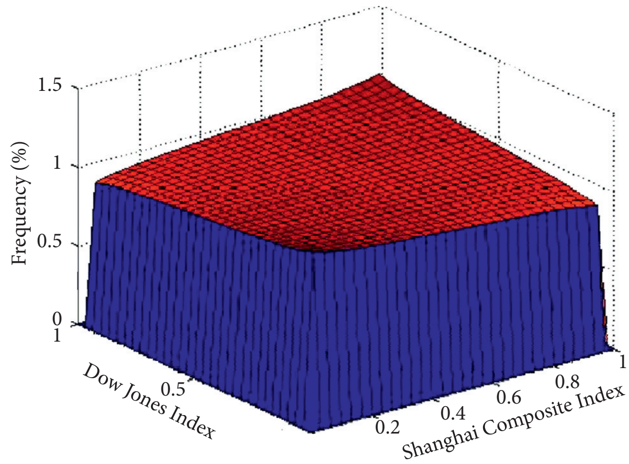

FIGURE 4: Normal Copula distribution of SSE index and Dow Jones Index extreme volatility series based on B segment weekly data.

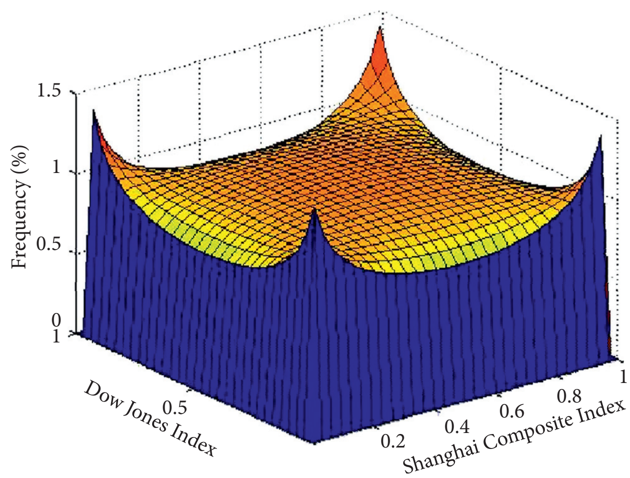

FIGURE 5: T-Copula distribution of SSE index and Dow Jones Index extreme volatility series based on B segment weekly data.

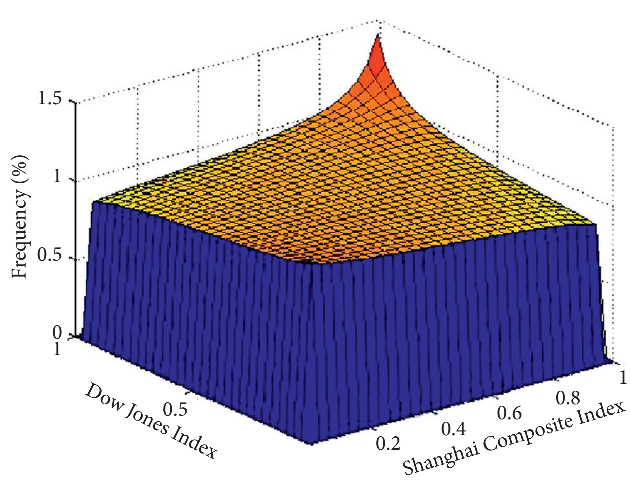

FIGURE 6: Gumbel Copula distribution of SSE index and Dow Jones Index extreme volatility series based on B segment weekly data.

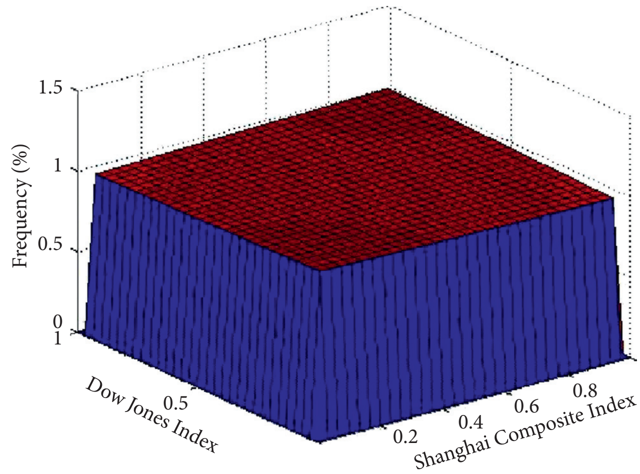

FIGURE 7: Frank Copula distribution of SSE index and Dow Jones Index extreme volatility series based on B segment weekly data.

As can be seen from Figures 4–7, the correlation between the Shanghai stock market and the American stock market is not high at the top and the bottom, and the correlation model has no obvious characteristics.

5. Conclusions

Research about financial market volatility is an important field in financial time series analysis, and with the development of modern information technology and the continuous improvement of the theory and tools of financial engineering, in the international financial market integration to speed up the process, it is particularly important to use scientific measurement methods to measure and characterize the volatility of financial market.

Based on the traditional volatility model and regression model, this paper studies the financial loss and stock price of the Shanghai stock market, and analyzes the correlation between the Chinese and American stock markets. Furthermore, correlation analysis between stock price and accounting profit under big data environment maybe the focus of further work.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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