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Retraction

Retracted: M&A Short-Term Performance Based on Elman Neural Network Model: Evidence from 2006 to 2019 in China

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] M. Xiao, X. Yang, and G. Li, "M&A Short-Term Performance Based on Elman Neural Network Model: Evidence from 2006 to 2019 in China," *Complexity*, vol. 2020, Article ID 8811273, 15 pages, 2020.

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Research Article

M&A Short-Term Performance Based on Elman Neural Network Model: Evidence from 2006 to 2019 in China

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Based on the event study method, this paper conducts the analysis on the short-term performance of 1302 major mergers and acquisitions (M&A) in China from 2006 to 2019 and takes the cumulative abnormal return (CAR) as the measurement index. After comparing the five abnormal return (AR) calculation models, it is found that the commonly used market model method and the market adjustment method have statistical defects while the Elman feedback neural network model is capable of good nonlinear prediction ability. The study shows that M&A can create considerable short-term performance for Chinese listed company shareholders. The CAR in window period reached 14.45% with a downward trend, which is the win-win result achieved through the cooperation between multiple parties and individuals driven by their respective rights and interests in the current macro-microeconomic environment in China.

1. Introduction

Before 2005, the problem of tradable shares and nontradable shares existed in China's stock market. The controlling shareholders who held nontradable shares were not concerned about the rise and fall of stock price; therefore, the interests of shareholders holding tradable shares cannot be guaranteed. The share-trading reform, launched in 2005 and completed in 2006, made nontradable shares traded, and all shareholders pay more attention to stock prices. 2006 is known as "the year of M&A" [1] because listed companies began to improve the stock price and trading activity through M&A activities.

In 2008, China Securities Regulatory Commission promulgated "Administrative Measures for M&A of Listed Companies," which marked the coming of the era of loose policies of M&A. Since then, a series of policies has been put forward to make the M&A activities more market-oriented.

In the following 10 years, M&A activities of listed companies play an important role in different stages of China's economic development, structural adjustment, transformation, and upgrading. However, the volume and amount of M&A transactions of listed companies increased substantially and attracted the investors to pursue and hype. In 2019, China Securities Regulatory Commission revised "Administrative Measures for M&A of Listed Companies" to strengthen the supervision, prevent arbitrage through M&A, and promote M&A rationality. According to the statistics of Wind, the average amount and number of M&A transactions in China in 2006–2019 were 4.42 trillion Yuan and 5,182, and the number of M&A transactions in the past 3 years exceeded 15,000. M&A has been one of the most important ways of resource allocation for a long time in China's capital market [2].

Since the completion of the share-trading reform in 2006, the discussion about whether M&A can produce performance and whether it can be used for market value management have never stopped.

2. Literature Review

2.1. M&A Short-Term Performance Literature

2.1.1. Synergy Effects Theory. The synergy effects theory was first proposed by Hermann Haken in 1971 and systematically elaborated in 1976. Since then, it has been applied to the study of M&A motivation theory. According to the efficiency theory proposed by Jensen and Ruback, the important motivation of M&A is that the acquirer and acquiree hope to achieve synergy effects through integration [3], including management, operation, finance, diversification, and other types of synergy [4–7]. M&A gains created by synergy effects will be redistributed among stakeholders, most of which will be transferred to shareholders of both parties during the M&A implementation process [8, 9]. In academic research, the concept of M&A performance is proposed for measuring the synergy effect, and it is divided into long-term performance based on financial index method and short-term performance in view of the event study method [10, 11]. The research object of this paper is the short-term M&A performance of the acquirer. Namely, the CAR on stocks of listed companies in the window period before and after the announcement date is applied as a measure [12].

2.1.2. Research on Short-Term Performance of Foreign M&A. The empirical study on the short-term performance of M&A in foreign academics started early (Table 1), and there is no consensus on whether M&A can create short-term performance. Some scholars believe that M&A brings significant positive or negative short-term gains to the acquirer, while others hold that M&A are uncontrollable, which is impossible to bring definite short-term performance to the acquirer.

This paper argues that the inability to reach a consensus conclusion is related to five waves of M&A experienced by Western countries represented by the United States. Scholars have sufficient M&A samples, and the differences in sample scope and time span lead to inconsistent conclusions.

2.1.3. Research on Short-Term Performance of Chinese M&A. The empirical research on short-term performance of Chinese M&A started late (Table 2). Due to the speculation and pursue of M&A related stocks by China's stock market for many years, most of the research conclusions focused on the positive short-term performance, and a small number of studies draw different conclusions.

The common feature of short-term M&A performance research in China is that the sample size is small, the coverage period is short, so the sample representativeness and conclusion accuracy are affected, which is related to the objective fact that China's M&A market develops late and the sample of M&A events is small. Zhang empirically analyzed 1,326 M&A events in 1993–2002 based on event study method and concluded that the M&A had a negative impact on the acquirer with −16.76% CAR during the window period. This literature is rare M&A performance research based on larger sample sizes. However, all the event samples occurred before 2005's share-trading reform, and most of them have no exact M&A announcement date. Chen et al. (2017) found that the share-trading reform had a positive impact on China's M&A performance [34], because the improvement of stock liquidity enhanced the reaction speed of stock prices to major decisions of company managers [35]. Therefore, it is necessary to make further researches on the short-term performance of China's M&A after share-trading reform.

2.2. Literatures of M&A Short-Term Performance Measurement

2.2.1. Event Study Method. Bruner proposed four measurement methods of M&A performance as follows: the event study method, the financial index method, the case-study method, and the management personnel interview method. Among those, the event study method is one of the most important methods for scholars to study M&A performance. The event study method is a general term for a series of methods for measuring the degree of influence of an event on the price of a particular financial asset [36] and has been widely accepted by scholars after improved by Ball and Brown [37] and Fama et al. in the study of market effectiveness [38].

The calculation of the impact of M&A events on stock prices by abnormal return (AR) has become the mainstream method for M&A performance research at home and abroad [39]. AR refers to the return difference between the stock's actual return rate and the normal (predicted) return rate under the assumption without the M&A transactions. The primary task in the calculation of AR is how to design a model to predict normal return.

2.2.2. Algorithms of AR. The AR algorithms commonly applied by scholars include the market adjustment method and the market model method [40]. The former assumes that the normal return is the market index return rate, while the latter calculates the normal return based on the capital asset pricing model (CAPM). In addition to utilizing the above traditional methods, foreign scholars have tried other methods to improve the accuracy of AR. For instance, Gregory [41] adopted the market model method, risk- and size-adjusted model, simple size-adjusted model, and value-weighted three-factor model proposed by Fama and French to calculate AR in M&A, finding significant differences in different AR algorithms. Besides, in the study of 1,164 M&A events in the United States from 1955 to 1987, Agrawal et al. [15] utilized the AR algorithms from the studies of Dimson and Marsh [42], Lakonishok and Vermaelen [43], and Ibbotson [44].

Almost all of Chinese scholars adopt the market adjustment method or the market model method, lacking the attempt and exploration of the AR algorithm. Zhang compared the market adjustment method with the market

Table 1: Overview of short-term performance research on foreign M&A.

Conclusion category	Author	Time published	Number of samples	Sample year	Research conclusion
Positive short-term performance	Madden Gerald	1981	86	1997–1979	One day before and after the M&A announcement, the CAR was significantly positive, but when the window period was extended, the CAR was significantly reduced [13]
	Healy and Palepu	1992	50	1979–1984	Enterprises with highly similar products obtained more positive M&A performance and are the acquirees' capital productivity was raised significantly [14]
	Agrawal et al.	1992	1,164	1955–1987	About half of the acquirer shareholders were able to obtain a positive CAR, and the CAR gradually decreased with the extension of the window period [15]
	Humphery-Jenner and Powell	2014	17,647	1996–2008	M&A samples from 45 countries showed that the acquirer created positive short-term performance, which decreased with the increasing national governance intensity [16]
Negative short-term performance	Dodd	1980	172	1973–1976	The CAR of the acquirer in about half of the sample during the 2-day window period before and after the M&A announcement was significantly negative [17]
	Higson and Elliott	1998	830	1975–1990	The CAR of the acquirer in window period was significantly negative [18]
	Hans	2006	110	1993–2001	M&A not only brought negative cumulative returns to the acquirer but also continued to decline as the window period increased [19]
Uncontrollability	Jarrell.	1988	663	1962–1985	According to the time of M&A announcement, the samples were divided into three groups; the CAR of the acquirer was inconsistent among the three groups, and there was no significant difference [20]
	Bruner	2002	N/A	1971–2001	After the summary of 130 classics from 1971 to 2001, it was concluded that there was uncertainty in the short-term M&A performance [21]
	Yook	2004	75	1989–1993	The short-term performance for acquirer was not significant due to the influence of the premium of the acquisition target [22]
	Uddin	2009	373	1994–2003	M&A did not bring significant short-term performance to the acquirer [23]

Table 2: Overview of short-term performance research on Chinese M&A.

Conclusion category	Author	Time published	Number of samples	Sample year	Research conclusion
Positive short-term performance	Li and Chen	2002	349	1999–2000	M&A brought significant wealth increase to the acquirer shareholders, especially the acquirer shareholders with larger proportion of national or legal person shares [24].
	Liu et al.	2009	749	1998–2004	During the window period, acquirer shareholders received an average of 1.39% CAR, explaining the conclusion based on the industry cycle theory [25]
	Deng et al.	2011	312	1997–2000	Non-associated M&A created significant returns for the acquirers, and the associated M&A did not create wealth for shareholders [26]
	Zhang and Sheng	2016	55	2010–2016	M&A in the Internet finance industry brought significant positive short-term performance, and mixed M&A performance was better than horizontal and vertical M&A performance [27]
	Li and Song	2017	333	2010–2013	M&A created significant short-term M&A gain and increased as risk investor participation grows [28]

Table 2: Continued.

Conclusion category	Author	Time published	Number of samples	Sample year	Research conclusion
Negative short-term performance	Zhang and Lei	2003	216	1999–2001	The wealth of the acquirer shareholders did not increase due to M&A activity, and the CAR rose first and then decreased, and the reduction was greater than the increase [29]
	Zhang	2003	1,326	1993–2002	M&A had a negative impact on the acquirer with−16.76% CAR during the window period [12]
	Zhu and Chen	2016	517	2011–2013	Technology M&A brought significant negative short-term performance to the acquirer, but the company's establishment period and equity concentration were conducive to improving M&A performance [30]
Uncontrollability	Chen and Zhang	1999	95	1997	Due to the immature capital market in China, the main M&A stocks did not show significant fluctuations, and the stock market did not respond significantly to M&A [31]
	Yu and Yang	2000	18	1993–1995	In the M&A, the enterprise value of the acquirer did not rise, and the shareholders were not able to obtain returns, which did not benefit the development of the enterprise [32]
	Yu and Liu	2004	55	2002	The M&A performance of the acquirer was not significant, and lacked continuity. From the perspectives of M&A motives and methods, the causes for the high failure rate of M&A in China were analyzed [33]

model method, finding the same conclusion in measuring M&A performance. In addition to adopting the above two methods, Cong made an attempted to utilize the listed company's return on net assets per share to minus the market interest rate to calculate the AR [45], which has become a rare Chinese literature on the AR algorithm research.

The market adjustment method and the market model method have distinct advantages and disadvantages. The former is simple in calculation but lacks theoretical and statistical basis. The latter possesses theoretical basis, but its hypothesis testing results were rarely discussed systematically in previous literatures. The empirical study of this paper shows that the regression equation coefficients cannot pass the significance T test, which is related to the nonlinear characteristics of the stock price series and is ignored usually due to the passing of F test with the regression equation. In order to solve the nonlinear problem, this paper designs another two traditional regression models and one artificial intelligence model to calculate AR and compares the fitting effect, prediction accuracy, and significant difference between the five models, which fills in the literature blank about AR algorithm. The accuracy of AR calculation is the basis of all the literatures on the application of event study method, which directly affects the results of events. Therefore, it is necessary and meaningful to carry out the research of AR algorithm.

2.2.3. Artificial Neural Network Algorithm. With the continuous improvement of chaos and fractal theory, considerable studies have proved that the stock price series owns nonlinear characteristics [46–50], and scholars have begun to utilize some data mining techniques to solve complex nonlinear problems [51]. Artificial neural network (ANN) is an adaptive nonlinear dynamic system composed of a large number of neurons through extremely flexible and extensive connections [52], with self-learning, self-organization, and self-adaption functions, which can reveal the complexities contained in data samples [53, 54], and has been widely applied in financial time series studies since the 1990s [55]. Moreover, it has proven to be more suitable for stock forecasting than traditional linear models [56]. Ican and Çelik [57] compared 25 literatures based on neural network predicting stock prices, holding that selecting the appropriate stock data (input information) and neural network structure have an important influence on the fitting effect. According to the topology of neuron connections, neural networks can be divided into forward networks (such as BP neural networks) and feedback networks (such as Elman neural networks). In contrast to forward network, feedback networks can achieve information feedback and have associative memory functions. Weng and Lin [58] compared the short-term prediction effects from stock prices of three neural networks (RBF, BP, and Elman). The empirical results revealed that the prediction ability of Elman feedback neural network was higher than that of the other two forward neural networks.

The core idea of Elman feedback neural network originates from the simple recurrent neural network model proposed by Jeffrey Locke Elman in 1990, consisting of input layer ($L1$), hidden layer ($L2$), connection layer ($L3$), and output layer ($L4$) (Figure 1), which is frequently applied for dynamic modeling or time series prediction [59]. The input information (XN) enters the hidden layer neurons through the input layer neurons, and the output information of the hidden layer is calculated and stored by the connected layer neurons and then enters the hidden layer as input information again, repeating iteratively until the error function and the weight reach a stable balance state (Figure 2).

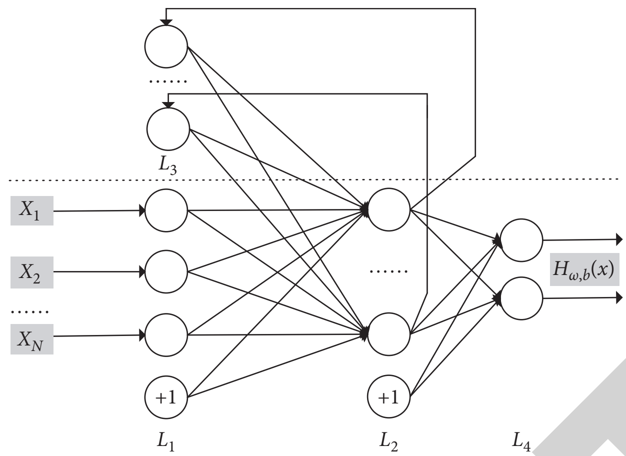

Figure 1: Elman neural network structure diagram.

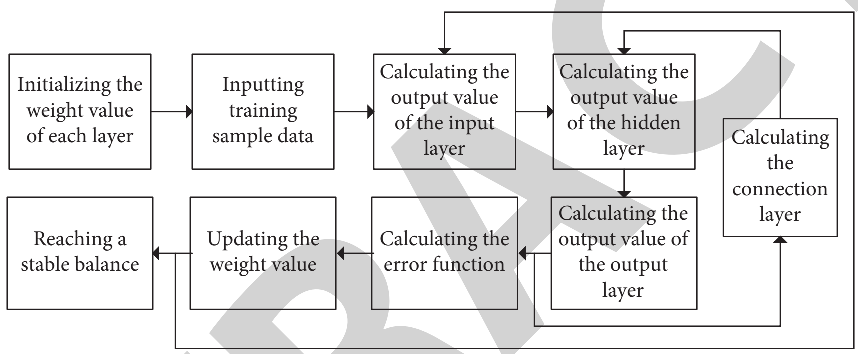

Figure 2: Elman neural network operation logic.

Among these, the activation functions of the output layer and the connection layer are linear functions, and the activation function of the hidden layer is a nonlinear function [60].

Since the beginning of this century, Elman neural network has been widely applied in the research on stock trading strategy and trading timing. Sitte and Sitte demonstrated that the S&P500 index can be predicted, through applying the Elman neural network [61]; Huang et al. utilized the Elman neural network to forecast the direction of the stock market and achieved better predictions [62]. Hyun and Kyung introduced the idea of the genetic algorithm based on Elman neural network for financial time series prediction, and the prediction accuracy was further improved [63]. Chinese research on Elman neural network for stock forecasting started late, and scholars have modified the structure or parameters of Elman neural network to study different financial time series predictions. It is agreed that Elman neural network has better nonlinear prediction ability [64–66].

3. Data and Methodology

3.1. The Innovation of This Paper. Scholars inside and outside China mainly adopt the market adjustment method and market model method to calculate AR. This paper applies another three models, including the Elman neural network model, to compare and improve the rigor and accuracy of AR calculation, which is the first academic attempt. In addition, this paper takes the Chinese share-trading reform as the starting point and selects almost all M&A events with trading suspension and resumption as research sample to study the changes of M&A performance over the past 14 years, which makes up for the shortcomings of the small coverage period of Chinese M&A samples.

3.2. Sample Selection. This paper collects 2,358 major M&A events of listed companies from 2006 to 2019 from the Wind M&A database. The remaining 1,302 M&A events are the total sample, after eliminating 1,056 events failed, unfinished, or in which listed companies as acquiree, or no exact M&A announcement date due to the small transaction volume.

3.3. Research Model. The short-term M&A performance indicator adopts the cumulative abnormal return (CAR) of the window period, which is 21 days around M&A announcement, marked as (−10, 10) with 0 being the announcement day. In this paper, five models are applied to predict the normal return and then calculate the AR. The merits and demerits are compared by three factors: the determinable coefficient (R^2), the root mean-squared error (RMSE), and the significant difference test. The model design adopts Matlab math software [67].

3.3.1. Market Adjustment Method. Under the market adjustment method, it is not necessary to determine the observation period. The market index yield is directly subtracted from the stock actual return to calculate the AR. Due to its simple calculation, it is widely applied. As a matter of fact, this model is to assume the constant term and the risk coefficient in the CAPM model as 0 and 1, respectively. This assumption is neither theoretical nor consistent with the reality.

3.3.2. Market Model Method. The market model method equation is given as follows:

$$\widehat{R}_i = \beta_{im} * R_m + \alpha + \varepsilon. \tag{1}$$

The market model method is a unary linear model based on CAPM theory (equation (1)). It is necessary to predict the constant term α and the risk coefficient β_{im} according to the linear relationship between stock return and the market yield in the observation period. This paper makes the improvements as follows: first, the observation period of each M&A event is selected by finding trading day range with highest correlation coefficient between the stock return and the market yield before the window period, so as to improve the goodness of fit. The average value of the highest correlation coefficient of all samples in the observation period is 0.6444. If the observation period is set as fixed interval of 50 days before the window period, the average value is 0.5566, which shows that the linear relationship in the observation period is significantly improved. Secondly, on the basis of the first fitting, the noise outliers outside the two standard deviations near the fitted line are eliminated (Figure 3(d)), and then the second fitting is performed. The confidence interval (Figure 3(b)) after eliminating abnormal value is more concentrated than before (Figure 3(a)).

After excluding the outliers, there are only 224 events whose constant term α and risk coefficient β_{im} both pass the significance test (0.05), and the average coefficient R^2 is 0.5479, indicating that the explanation and prediction ability of market yield to stock return is weak under the unitary linear model, which is consistent with the doubts about the CAPM theory in the previous literature [68]. In this case, this paper attempts the unary nonlinear model.

3.3.3. Unary Nonlinear Model. The unary nonlinear model equation is given as follows:

$$y_i = \beta_1 e^{\left(\beta_2/\left(x_i+\beta_3\right)\right)} + \varepsilon_i, \quad \varepsilon_i \sim N\left(0, \delta^2\right). \tag{2}$$

Considering that the distribution of AR is dense with a large fluctuation, the negative exponential function (equation (2)) with the trend of steepness first and then slowness is selected as the unary nonlinear regression model. This paper makes the improvements as follows: First, in order to cover the stock return history as much as possible and avoid the long-term observation period to damage the goodness of fitting, we take 5 trading days as the step value for each event. From 30 days before the window period, the observation period will be gradually expanded forward for fitting. The observation period with the smallest root mean-squared error (RMSE) is selected as the optimal observation period, and the average observation period of all samples is 51 days. Secondly, the second time fitting is eliminated on the basis of the first fitting, and the improvement effect of the goodness of fit is significant (Figure 4).

After the elimination of the outliers, there are only 83 events whose all the three parameters β_1, β_2, and β_3 pass the significance test (0.05), and the determination coefficient R^2 is 0.5472, which is mainly due to the fact that it is difficult to predict the specific analytical formulae of the nonlinear relationship in practice. In this case, a one-dimensional polynomial model can be tried to gradually fit the measured points.

3.3.4. Unary Polynomial Model. Any function can theoretically be approximated by a polynomial model by segmentation (equation (3)). Hence, this paper is fitted from low order to high order, and the improvements are made as follows: first, each observation period of each M&A event is performed to fit from the first order to the tenth order. Secondly, 80 kinds of observation period are selected for each M&A event, which are 21 days, 22 days ... 100 days before the window period. Each event is fitted for 800 times based on the 1–10 order and 80 observation periods, and the equation with the smallest RMSE is selected as the optimal order and the optimal observation period:

$$y_i = p_1 x_i^n + p_2 x_i^{n-1} + \cdots + p_n x_i + p_{n+1} + \varepsilon_i, \quad \varepsilon_i \sim N\left(0, \delta^2\right). \tag{3}$$

The optimal order of all samples is 10, the optimal observation period is 33 days, and the average coefficient of R^2 is 0.6790. The fitting effect is greatly improved. However, when the model is utilized to predict AR in the window period, the unreasonable extreme value accounts for 16.70%. The high-order polynomial model can only fit the limited data in observation period, and when data that cannot be covered in observation period appear in window period, the amplification function of the high-order items in the model will destroy the prediction ability. Figure 5(a) illustrates a better approximation fitting of the fitted curve to the limited data in the observation period. When the Y-axis display range is expanded to show the overall trend of the fitted curve, Figure 5(b) reflects the excessive fluctuation characteristics of the high-order fitting curve. Therefore, when the order is limited to the 4th order or less, the extreme value is basically eliminated. However, the coefficient R^2 is reduced to 0.0163.

3.3.5. Elman Neural Network Model. The purpose of traditional regression analysis is to find the mapping relationship between independent variables and dependent

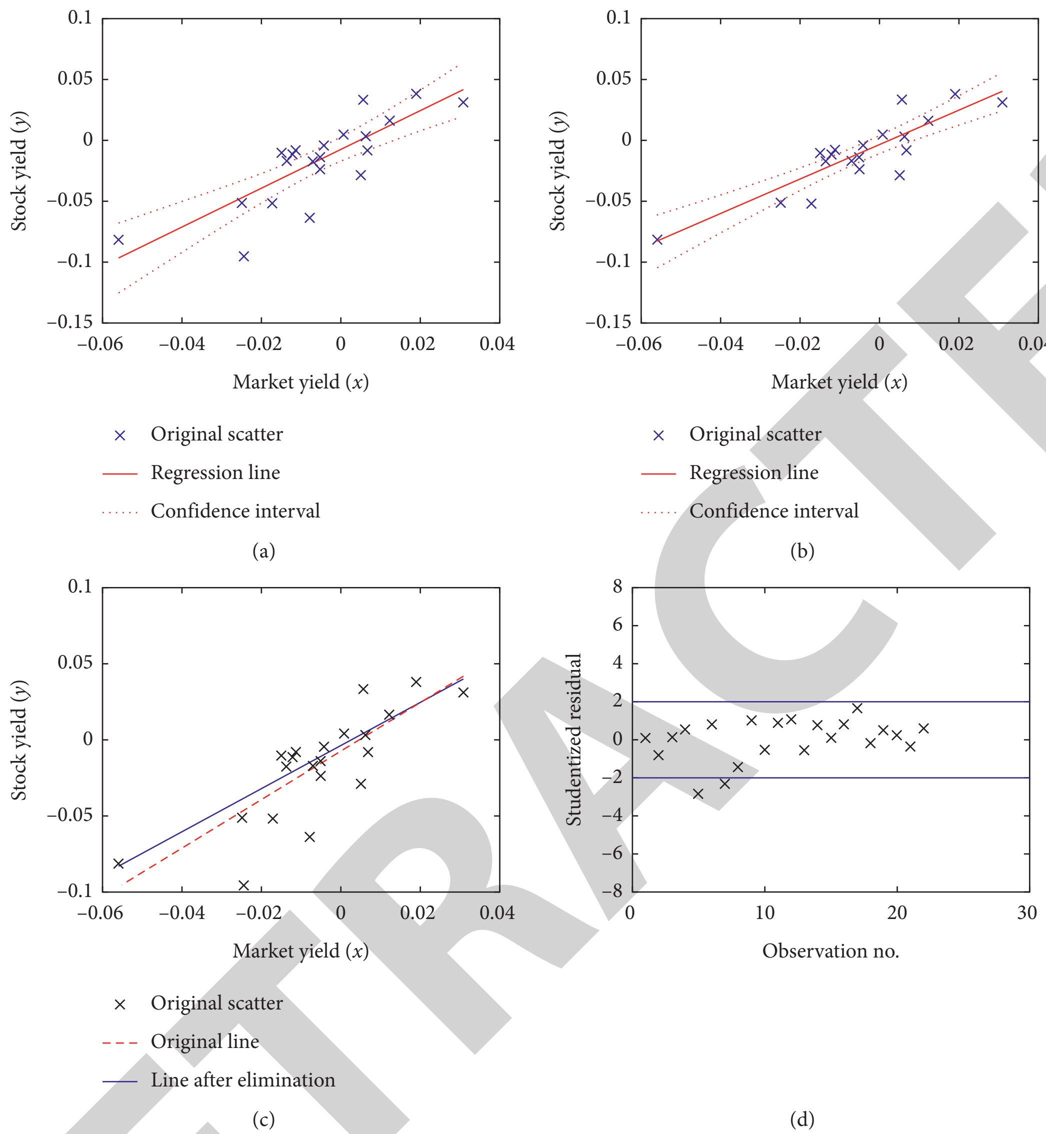

Figure 3: Market model method fitting map. (a) Before eliminating abnormal value. (b) After eliminating abnormal value. (c) Before and after eliminating abnormal value. (d) Studentized residual map.

variables. The results of the above four models show that it is difficult to find analytical expressions that satisfy both the hypothesis test condition and the predictive ability in practice. The main cause is that the complex relationship in financial time series is difficult to determine with the function of the analytical expression. As one of the data mining techniques, Elman neural network is widely applied in autonomous learning, associative storage, and high-speed optimization. Theoretically, it can handle arbitrary complex causal relationships, which is suitable for stock return forecasting.

The improvements are made in the Elman model as follows: first, the stock normal return is predicted by input information with individual stock's historical returns ($E1$) and market yields ($E2$), respectively. Secondly, the Elman model memory function is fully applied to cover the stock return history as much as possible with the observation period selected from 2 months after listing to before the window period. The average observation period of all samples is 1,940 days; the maximum number of iterations is 2,000, and the error tolerance is 0.00001. The iteration process is stopped when the mean-squared error (MSE) reaches the error tolerance. If the error tolerance is not reached after 2,000 iterations, then the parameters, such as the weight and activation function corresponding to the minimum MSE, are taken as the optimal solution. Figure 6 illustrates the process of reducing the MSE to 0.0005 after 2,000 iterations in one of the M&A events.

The R^2 of the Elman model's fitting with individual stock return or market yield is 0.9859 and 0.9958, respectively. The latter is better than the former. This conclusion can also be obtained from the fluctuation of the residual plot (Figures 7 and 8), indicating that the linkage between individual stock return and the market yield is stronger than that between

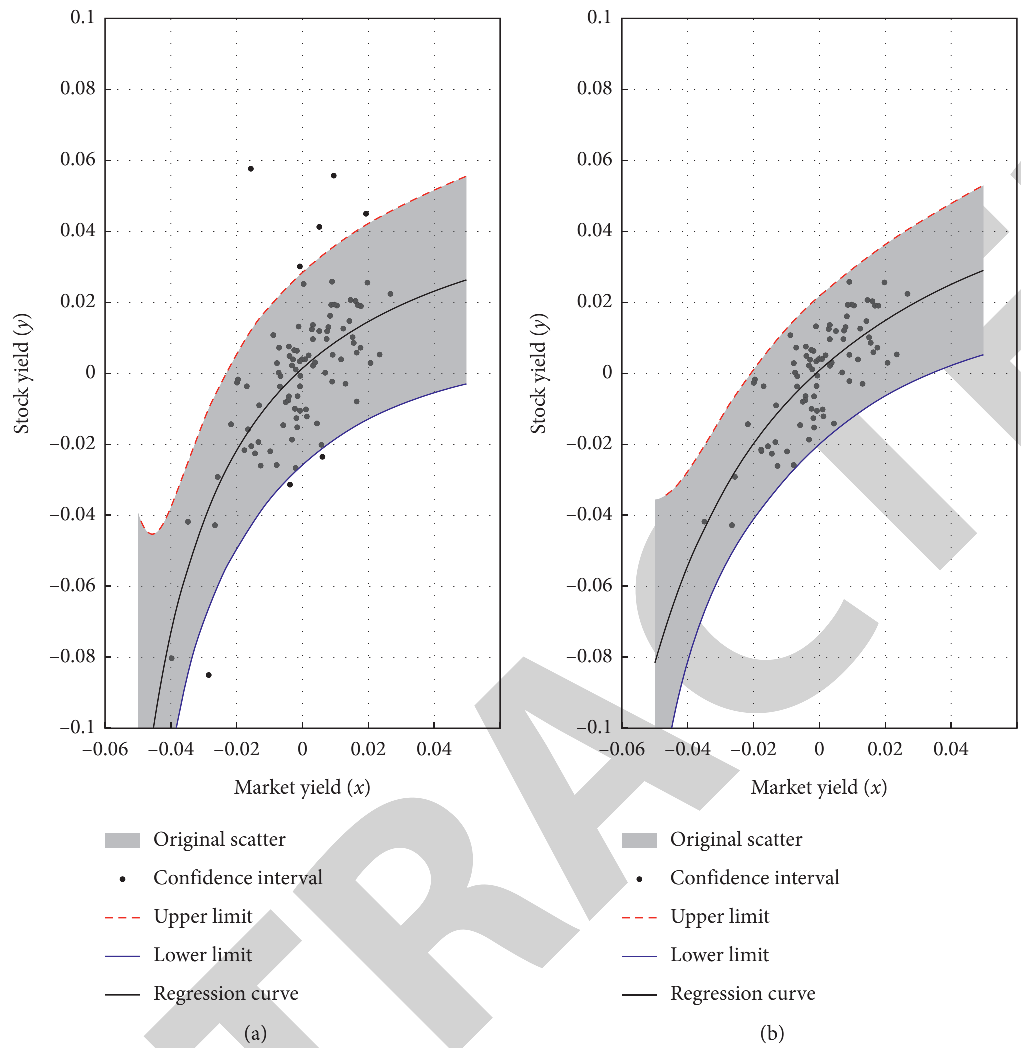

Figure 4: Unary nonlinear model fitting map. (a) Before eliminating abnormal value. (b) After eliminating abnormal value.

individual stock return and their own historical return. The fitting effect is shown in Figure 9.

4. Results and Discussions

The five models have different window yields (Table 3). When studying the AR in window period, the following important issues are rarely demonstrated or mentioned: (1) whether the yield rate during the observation period meets the assumptions of the classical theory and the regression model; (2) whether the mean of the AR in the window period is representative; (3) whether there is a significant difference between the window period's AR time series calculated by the five models; (4) whether the overall trend of the AR in each year is significant.

4.1. Normality Test of the Yield Rate in Observation Period. The financial time series is supposed to obey the normal distribution, which is almost the common assumption of all classical theories (such as CAPM theory) and the traditional regression model because the normal distribution possesses good additivity. Based on the central limit theorem, the totality can be considered to obey the normal distribution when the sample size is greater than 30. In this case, the hypothesis that the stock yield rate series obeys a normal distribution is widely dictated with its verification ignored. Considering the advantages as well as disadvantages of various methods, this paper utilizes six common normal distribution test methods (Table 4).

The data period of yield rate series was taken 50 days before the window period. The normality test was carried out for each individual stock and the market yield rate series. The mean skewness of individual stock and the market was −0.0242 and −0.8370, respectively. The mean kurtosis was 4.6782 and 6.6067 respectively, indicating that the sequence has a peak fat tail characteristic, which was verified through utilizing the other four methods. Although the results of JB, χ^2, and Lilliefors are slightly different, the conclusions are basically the same. Namely, the yield series of large proportion (up to 45.16%) does not obey the normal distribution, and the assumptions of the classical theory and the regression model are not true. Therefore, the statistical

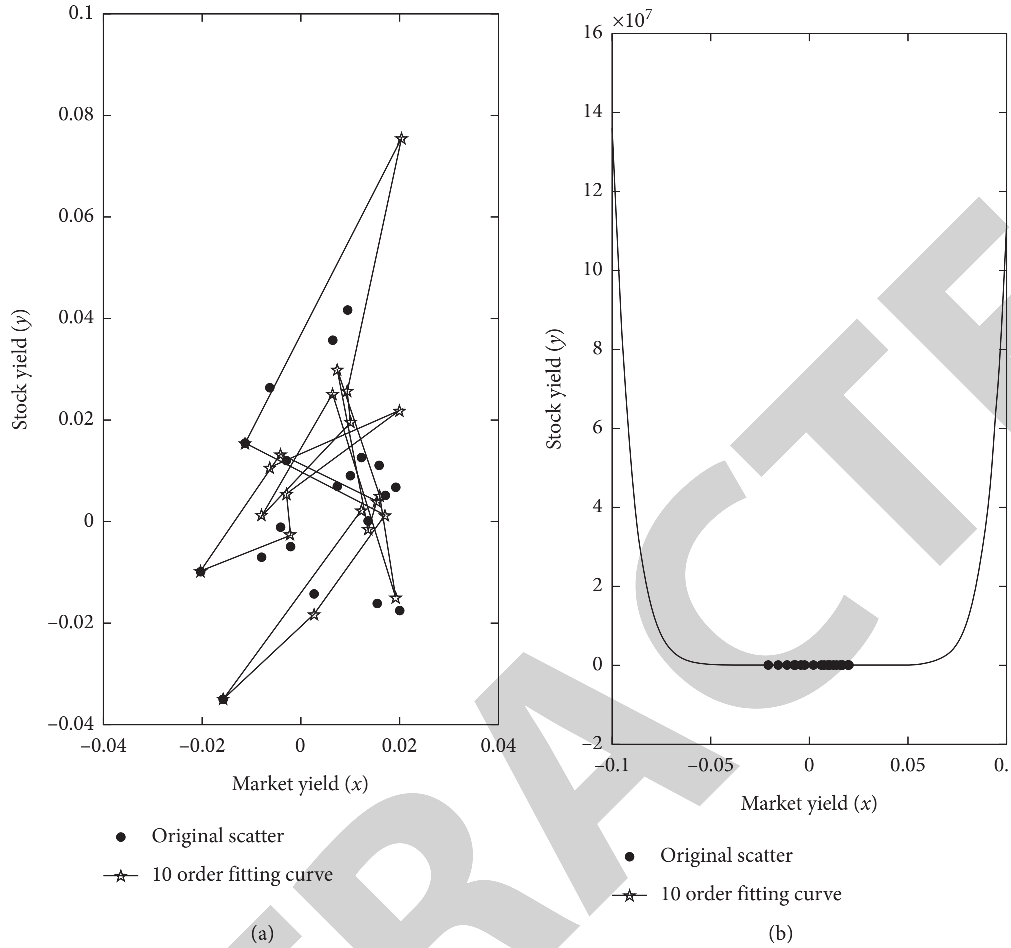

Figure 5: High-order polynomial model fitting map. (a) Original scatter VS predicted points. (b) High-order polynomial fittings.

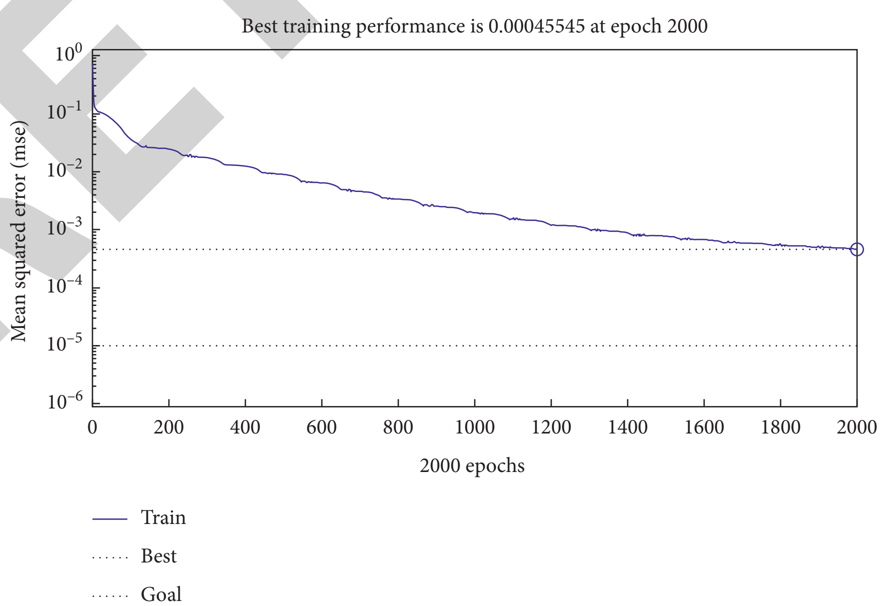

Figure 6: Elman iterative MSE convergence graph.

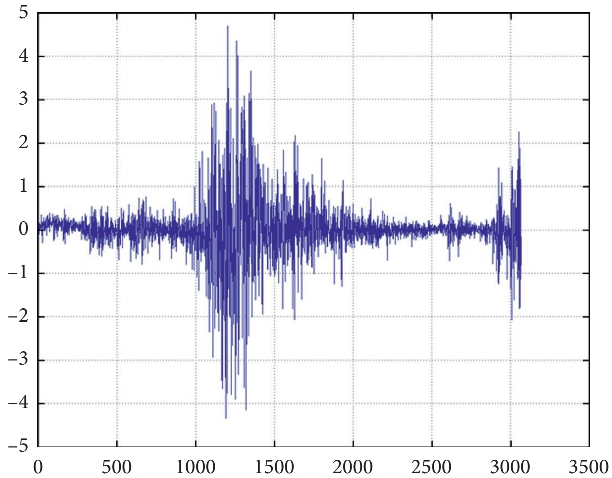

Figure 7: Elman residual plot under $E1$.

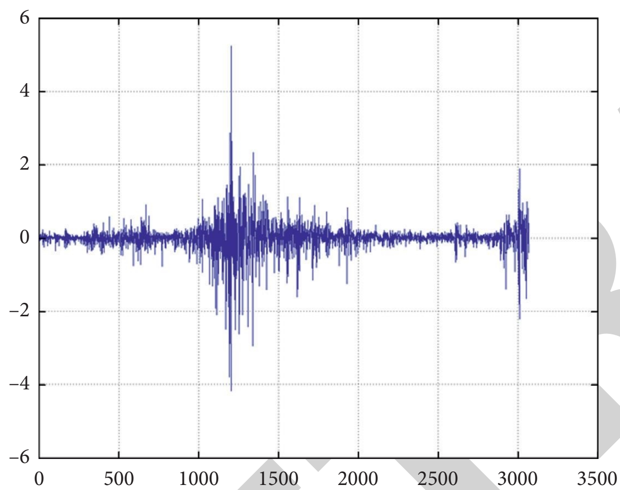

Figure 8: Elman residual plot under $E2$.

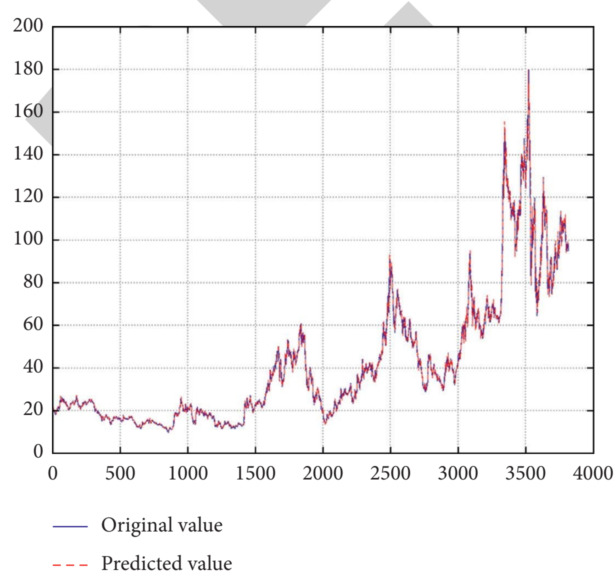

Figure 9: Elman model fitting map.

model without normality requirements for the data should be selected and applied.

The K-S test results are quite different from other methods because this paper replaces the population parameters with sample mean and standard deviation like other related literature practices. In essence, it has change the K-S test to Lilliefor test. However, the statistical software (such as Matlab and SPSS) defaults and utilizes the K-S test threshold table, and the mismatch between Lilliefor statistic and K-S test threshold table results in an incorrect conclusion [69].

4.2. Representative Test for Abnormal Return Mean. After the representative test, for each model, all the average ARs of every day in the window period (the abnormal return in Table 3) pass the significance test of the 0.005 level.

4.3. Significant Difference Test between the AR of the 5 Models. Although the average daily ARs in the window period under the five models are representative, the comparison between average daily ARs cannot infer whether there is a significant difference between AR series under different models. Since AR series do not have normality and homogeneity of variance, the Friedman test (two-factor rank variance analysis) of the nonparametric test method is applied to demonstrate significant differences between AR series of any two models on the same day.

The Friedman test results (Table 5) can be concluded in three aspects as follows: (1) there are 17 days(80.95%) with significant differences in 21 days' window period in AR series between the market adjustment method and the market model method, which means that the substitution of the former for the latter in some literatures is not rigorous and affects accuracy of AR. (2) Because the low-order polynomial method is too gentle and can only reflect the overall trend, there are 0 day with significant differences with the market adjustment method. (3) There are 20 or 21 days' significant difference between Elman model and other four models, which means Elman model is totally different from other models.

4.4. Significance Test of AR Series' Change in Window Period under Elman Model. The Friedman test is carried out on the significant difference of AR series in two adjacent days in the window period under the Elman model. The results show that there are significant differences in AR series between 2 days before and 3 days after the announcement date. In Figure 10, the 21 horizontal lines represent the rank and mean confidence intervals (0.05) of the daily AR series, and the vertical axis 11 represents the announcement day. There is no overlap in the projection of adjacent horizontal lines of the ordinate 9–14 in horizontal axis, indicating a significant difference in AR series between the two adjacent days.

The settlement results of the Elman model is shown as follows: (1) M&A news has been transmitted to the stock market at least 2 days before the announcement date, which causes the stock price to fluctuate significantly within 6 days

Table 3: The AR in window period and fitting result of the five models.

Window period	Actual return (%)	Abnormal return				
		Market adjustment method (%)	Market model method (%)	Unary nonlinear model (%)	Unary polynomial model l (%)	Elman (%)
−10	0.20	0.05	0.11	−0.01	−0.02	0.01
−9	0.43	0.26	0.30	0.44	0.15	0.14
−8	0.26	0.25	0.33	0.52	0.08	0.17
−7	0.07	0.09	0.15	0.28	−0.15	−0.04
−6	0.35	0.17	0.21	0.35	0.05	0.05
−5	0.15	0.20	0.33	0.10	0.03	0.03
−4	0.32	0.18	0.27	−0.40	0.08	0.04
−3	0.36	0.35	0.43	0.56	0.20	0.27
−2	0.36	0.33	0.45	0.42	0.10	0.30
−1	1.39	1.19	1.27	1.36	1.11	1.15
0	4.15	3.94	4.00	1.27	3.80	3.86
1	3.14	3.14	3.30	3.36	2.91	3.08
2	2.46	2.25	2.35	2.50	2.14	2.06
3	1.52	1.37	1.42	1.60	1.25	1.15
4	0.89	0.79	0.86	1.07	0.60	0.64
5	0.76	0.65	0.75	0.08	0.38	0.59
6	0.62	0.50	0.58	0.71	0.31	0.49
7	0.08	0.19	0.28	0.34	−0.04	0.13
8	0.33	0.23	0.34	0.26	0.01	0.26
9	0.13	0.11	0.22	0.05	−0.10	0.08
10	0.10	0.05	0.11	−0.21	−0.06	−0.01
CAR	18.07	16.28	18.03	14.65	12.84	14.45
R^2	—	0.2813	0.5346	0.5459	0.0163	0.9950

Table 4: Advantages and disadvantages of the normality test method and the events failed.

Testing method	Characteristics	Individual stock	Market
Skewness test (mean)	Simple but not comprehensive, susceptible to extreme peak values	−0.0242	−0.8370
Kurtosis test (mean)	Simple but not comprehensive, susceptible to extreme peak values	4.6782	6.6067
J-B test	Susceptible to outliers based on skewness and kurtosis	493 (37.86%)	588 (45.16%)
$\chi 2$ goodness of fit test	First grouping and posttesting, suitable for category data, easy to make false errors	275 (21.12%)	302 (23.20%)
Lilliefors test	Suitable for the unknown overall parameter, applying the sample statistic instead of the overall parameter	376 (28.88%)	588 (45.16%)
K-S test	Suitable for continuous quantitative data with units of measurement and test of full observation points	11 (1.90%)	14 (1.08%)

Table 5: The days with significant difference in the window period between 5 models.

Model combination	Market adjustment	Market model	Unary nonlinearity	Polynomial (low-order)	Elman
Market adjustment method	—	17 (80.95%)	9 (42.86%)	0	21 (100%)
Market model	17 (80.95%)	—	7 (33.33%)	13 (61.90%)	21 (100%)
Unary nonlinearity	9 (42.86%)	7 (33.33%)	—	11 (52.38%)	20 (95.24%)
Polynomial (low-order)	0	13 (61.90%)	11 (52.38%)	—	20 (95.24%)
Elman	21 (100%)	21 (100%)	20 (95.24%)	20 (95.24%)	—

around the announcement date. After that, the AR gradually decreases and creates a CAR of 14.45% in the window period; (2) after the announcement day, the AR, which is significantly different from the previous day, can still continue for 4 consecutive days. The impact of M&A disclosure on the stock market does not disappear immediately, and

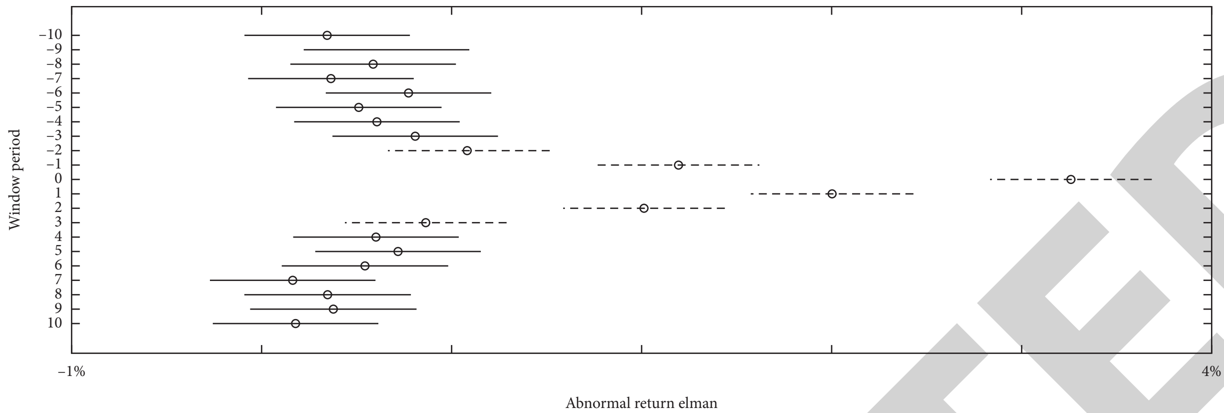

Figure 10: Significance test change in the window period.

Table 6: Annual distribution of research samples (1302) and cumulative average abnormal return.

Year	2006–2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	06–19
Number	18	25	32	34	56	99	183	299	237	151	131	37	1302
CAR (%)	45.21	31.02	26.90	13.91	8.88	24.30	26.18	28.25	8.84	−3.51	−3.45	12.36	14.45
Announcement day (%)	5.49	6.91	7.15	4.03	3.54	7.86	7.43	4.39	3.12	0.15	−0.27	3.84	3.86
Next day of announcement (%)	4.36	2.67	1.59	1.99	1.07	1.35	1.02	0.86	1.59	0.74	0.64	3.05	3.08

Table 7: Comparison of advantages and disadvantages of five AR models.

Model	Market adjustment method	Market model	Unary nonlinearity	Unary polynomial	Elman model
Advantage	Easy calculation	Simple calculation with theoretical basis	Simple calculation	Infinite fitting can be realized theoretically by increasing the order	Can solve complicated nonlinear causality problem
Disadvantage	Lack of theoretical basis	Difficult to pass equation parameters' significance test	Difficult to pass equation parameters' significance test	Low-order: Poor fitting; high-order: Poor predictive ability	The program is complicated; the output layer information is underutilized
Innovation attempt	None	Take maximum correlation coefficient's interval as observation period; eliminate the outliers	Selecting the best observation period by step progressive method; eliminate the outliers	Selecting the best observation period by the step progressive method; comparison of low-order and high-order fitting/ prediction results	Keep the observation period as much as possible; comparison of closing price and yield rate as input information

China's stock market has not yet reached the semistrong position according to the semistrong effective judgment standard.

4.5. Significance Test for the Change Trend of AR in Each Year. The average CAR in window period for each year (Table 6) was calculated by the announcement date of every M&A event based on the Elman model. The Friedman test results (P value of significance test is 0.0008) showed significant differences among the AR series in the 14 years, indicating that the M&A short-term performance had a significant downward trend and tended to be more reasonable. The low CAR in 2016–2018 was related to the stock market overall downturn and the regulatory measures to crack down on the speculation of M&A in the past years, and M&A transactions of listed companies tend to be rational.

5. Conclusions

5.1. Comparison of Algorithms for AR. The stock return series does not have normality, and the assumptions of the traditional regression model cannot be established. In the past research, the algorithm for AR mainly adopted the market adjustment method and the market model method. The former lacked theoretical basis, and the latter was short of statistical basis, affecting the calculation accuracy of AR. To achieve the minimum variance, the market model method has to take the average value of returns in observation period as the fitting result, and the market adjustment method is an extreme case under this rule, which can be reflected from the empirical result of R2 0.5346 and 0.2813, respectively. Therefore, the smaller the fitting result, the better the fitting effect, which leads to the predicted normal return underestimated and the CAR overestimated. These two methods have CAR 16.28% and 18.03%, respectively, and significantly greater than other three method's CAR.

In the first four traditional regression models, the unary nonlinear model has the best fitting effect with R^2 0.5459, higher than other three models, because it can deal with nonlinear problems in stock yield time series to some extent, which can also be confirmed by the result that its CAR 14.65% is closest to Elman model' CAR 14.45%.

Besides this, the fitting effect of unary polynomial model is inversely proportional to its prediction ability. With the increase of order, the fitting effect is gradually optimized with R^2 rising from 0.0163 in 4th order to 0.6790 in 10th order, while the higher order unary polynomial model' ability to predict is lost due to its huge volatility because the unary polynomial model cannot deal with the data distribution that stock yield time series fluctuates intensively in narrow numerical range.

The empirical results show that Elman neural network model is capable of solving nonlinear complex problems. It can fit the observation period data as well as predict the AR in window period with R^2 0.9950 and CAR 14.45%, which is significantly different from another 4 traditional regression models. However, Elman neural network model has shortcomings. Only the feedback of hidden layer information is considered in the structure, and the output layer information is not relearned [70]. In addition, although the neural network calculation logic is reasonable and easy to understand, the computer operating process is more like a black box, and few researchers have the ability to analyze the model code to explain why the fitting effect is so good.

The advantages and disadvantages among five calculation models for AR are revealed in Table 7.

5.2. Short-Term M&A Performance. The M&A short-term performance in the past 14 years has generally declined, which is related with the effectiveness of China's regulatory measures for M&A hype and speculation, leading to M&A short-term performance tending to be reasonable. The M&A of listed companies can create a 14.45% CAR of considerable short-term performance during the window period, indicating that the stock market is generally in recognition of listed companies' M&A activities and the expectations of the company's value is raised and reflected in stock price. However, in the process of stock price fluctuation, there was hype and speculation behavior on M&A, which was reflected in the fact that the M&A news was transmitted to the stock market at least 2 days before the announcement date, causing the stock price to rise significantly in advance. In addition, the significant change of AR has been prominent for 3 consecutive days after the announcement day. The long-term trading suspension (1302 M&A events were suspended for 111 days on average) did not digest the centralized or excessive response of the stock market to M&A news.

In addition, the AR is significant for 3 consecutive days after the announcement day, and investors can make use of the public information to obtain excess returns, which proves that China's stock market has not reached the semistrong form of efficiency.

5.3. Explanation of Chinese Short-Term M&A Performance. Chinese short-term M&A performance is highly related to the characteristics of China's stock markets. In the process of developing the real economy, China endows M&A great potential and space for value creation, which is reflected either in the economic structural adjustment at the macrolevel or in the industrial transformation-upgrading at the microlevel. The China Securities Regulatory Commission, undertaking the economic management functions as a government department [71], have formulated a series of supportive policies for M&A transactions since 2006, which gives M&A activities the crucial role in capital resource allocation. Besides, different from the western stock markets, which are dominated by institutional investors, China's stock market has 160 million individual investors, accounting for 99.76%, who are more likely to interpret M&A as a good signal and chase the stock, which leads to Chinese listed companies more willing to carry out M&A activities.

5.4. Enlightenments and Recommendations. For the majority of researchers, it is recommended to make full use of artificial intelligence method to explore nonlinear problems and compare innovation research with previous research in accordance with statistical principles, which will contribute to improving the rigorism of research modeling and the accuracy of the research conclusion.

Data Availability

Some or all data, models, or code generated or used during the study are available in a repository or online in accordance with funder data retention policies. All M&A events of listed companies between 2006 and 2019 are from the Wind M&A database, and all stock prices come from CITIC Securities Stock Trading Software.

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Conflicts of Interest

The authors declare that there are no conflicts of interest.

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