

## Research Article

# Fractal Characteristics, Multiple Bubbles, and Jump Anomalies in the Chinese Stock Market

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To consider the jump problem of the Chinese stock market, this paper takes the CSI 300 Index from April 2005 to November 2015 as the research object, uses the rescaled range analysis (R/S analysis) method to examine the fractal characteristics of the Chinese stock market in the past ten years, and deduces the possibility of multiple bubbles in the Chinese stock market. Based on this, combined with the log-periodic power law (LPPL) model, the stock market bubbles are identified in different periods. The results show that China's stock market has some anomalies in terms of positive bubbles, negative bubbles, and reverse bubbles, as well as the cross occurrence of reverse-negative bubbles. Besides, through a comparison with the major foreign stock markets, it is found that the fluctuation range of the Chinese stock market is much larger than that of the Dow Jones Industrial Average and the FTSE 100 indices in the same period and there are also more types of multibubbles, which is a connotative anomaly that makes the Chinese stock market different from other major stock markets. Furthermore, the bubble phenomenon in the Chinese stock market during the periods of 2005/4–2007/10 and 2015/6–2015/11 is studied, and it is found that there is a jump anomaly in the Chinese stock market. Finally, based on the above empirical analysis and the current state of the stock market, this paper provides some suggestions for improving the mechanism of the Chinese stock market.

## 1. Introduction

The origin of the financial bubble caused by a market jump can be traced back to the 16th Century. At that time, the French government continued to borrow and increase municipal investment, leading to a rapid “boom” in the financial market and the eventual inability of the government to repay what it borrowed, triggering sharp turbulence in the financial market. This encompassed the complete process from bubble to burst due to the early financial market jump anomaly. Of course, the most famous examples of this type of market jump leading to a financial bubble are the tulip mania events in Holland, the French Mississippi bubble events, and the British stock bubble events in the South Sea. The tulip mania events disrupted the Dutch economy completely, which then experienced a rapid financial decline, and the commercial economy transforms from prosperity to decline. The Mississippi bubble caused

thousands of banks and tens of thousands of businesses to go bankrupt, and countless people lost their jobs. The South Sea bubble exposed the British government to a century-long crisis of integrity. In addition, the market jump anomaly before and after the US subprime crisis in 2007 dragged the whole world into an economic crisis. It can be seen that financial bubbles generated by market jumps can result in tremendous economic damage. Therefore, it is important to accurately detect and identify market jump anomalies and the underlying financial bubbles. In the context of China, it is important to put forward suggestions and countermeasures that mitigate stock market jumps to promote the healthy development of the Chinese stock market and to maintain stable economic growth.

Prior research on financial market bubbles can be broadly divided into four groups: herd behavior, bubble theory, LPPL analysis, and the market jump anomaly. Among these four groups, the relevant research on herd

behavior in the stock market is discussed first. Chen et al. [1] used a computational experimental platform to simulate market sentiment signals and then observed the stock price bubbles and collapse caused by herding behavior. Demirer et al. [2] studied the linear and nonlinear characteristics of the Taiwanese stock market by using the standard deviation of the cross section. Based on this, the sources and identification methods of herd behavior under different investment behaviors in the stock market were analyzed. Bian et al. [3] constructed a dynamic coevolution model of herd behavior in the stock market based on the self-preference of investors and the behavioral effects of neighbors and abstracted the dynamic characteristics of the evolution of herd behavior in the stock market through theoretical analysis and simulation. Based on the assumption of an arbitrage equilibrium, Blanchard and Watson [4] established a dynamic prediction model to simulate the formation process of financial bubbles and used repeated iterations to obtain rational bubble solutions. Based on the influence of other traders' behavior on the changes in investors' trading ideas, Liu et al. [5] constructed a model of the market's average investment attitude change and defined herd behavior by using the degree of stability of the financial market. Most experts agree that a serious consequence of herding is a market bubble. Some experts have also conducted a series of studies on market bubbles. For example, Froot and Obstfeld [6] pointed out that macroeconomic change is a major reason for the emergence and development of market bubbles and put forward a theory of endogenous bubbles in financial markets. Liu [7] improved the intrinsic investment value model of stocks and used it to calculate the Chinese stock market's intrinsic investment value and the absolute scale and relative scale of bubbles. Liao [8] used the intrinsic investment value model of stocks to calculate the intrinsic value of the Chinese stock market, and then, based on cointegration analysis of stock prices and their intrinsic value, they found that the Chinese stock market is invalid. Finally, by calculating the bubble value, this reference concluded that the Chinese stock market is moving toward a value regress. Shiller [9] pointed out that stock prices are easily affected by social dynamics and investors' concern for each other was likely to breed bubbles; therefore, a fashion bubble model was proposed. De-long et al. [10] established a noise trading model by introducing noisy traders in a traditional rational bubble model and attributed the reason for stock market bubbles to the cognitive biases of noise traders. Then, a positive feedback model was put forward, and the formation and bursting of stock market bubbles were analyzed using the behavioral characteristics and relationships of positive feedback traders and rational arbitrage. Topol [11] pointed out that the self-correction behavior that references the investment approaches of others could easily lead to market bubbles; therefore, an irrational behavior contagion model was established. There are also studies of foreign market bubbles as follows: Tarlie et al. [12] used a simple equity valuation model to test the possible formation of an equity bubble in the US. Liaqat et al. [13] applied the GSADF to identify multiple stock bubbles in the Pakistan Stock Exchange across different industrial sectors. Some

researchers have combined other markets and stock markets to study market bubbles. Zhao et al. [14] used six price series of international markets, the Chinese crude oil market and the Chinese stock market to test bubbles, and used the ranger causality test to identify the contagion effect between the oil and stock markets. Zhang et al. [15] detected bubbles in the defense sector in the Chinese stock market and how these bubbles can be impacted by the overall stock market and the defense industry.

It can be found that most of the above studies analyze the formation, development, and bursting of financial market bubbles from a backward perspective. It is difficult to provide forward-looking recommendations for the periodicity and transformation mechanism of market bubbles. The LPPL model, which will now be reviewed, seems to suit this kind of forward-looking problem better. Sornette et al. [16] used the LPPL model to conduct an empirical study of the characteristics of bubbles during a collapse. It is found that they exhibited logarithmic periodic oscillation characteristics. In a later study, it was also verified that the LPPL model could identify the stock market bubbles through the stock market bubbles in emerging markets [17]. Zhou and Sornette [18] conducted systematic expended research of the Chinese stock market, and by applying the LPPL model to the Chinese stock market as an example, they found that the Chinese stock market has stronger logarithmic periodic vibrations than other mature markets. Furthermore, the housing prices in some regions of the United States were taken as the research object, and the measurement of the bubble and prediction of the price fluctuations were carried out using the logarithmic periodic oscillation measure [19]. In the context of the financial derivatives market, Zhou and He [20] studied the reasons for the continual rise of metal futures prices after China's financial crisis using the LPPL model, D test, and periodic vibration envelope analysis. It was found that the rising prices of copper futures and zinc futures were more influenced by speculative bubbles; however, the speculative bubble for aluminum futures was not obvious, and the metal futures prices were greatly affected by the demand. Ji and Gao [21] studied the bubble formation mechanism and analyzed the bubbles and antibubbles in China's Shanghai and Shenzhen stock markets, as well as the changes in the Chinese stock market under the double bubble form, by using the LPPL model. It was found that the conversion mechanism of the two markets tended to be the same and had some anomalies. Recently, Shu and Zhu [22] used the LPPLS confidence indicator to study the daily data of the CSI 300 index and to test the existence of bubbles in the Chinese stock market. The results suggested that this method can be used to predict the future positive and negative bubbles and their burst times, thus reducing the damage caused by the collapse of a bubble. In addition to the LPPL model, Hong et al. [23] proposed a new asset pricing model and studied stock market bubbles and various forms of asset price changes using this measurement model; however, the effects of bubbles on the stock market under various changes were not analyzed. Greenwood and Nagel [24] analyzed the influence of inexperienced investors on stock market bubbles, focusing on the relationship between the reversal of a bubble's formation and

inexperienced stock market investors. Ackermann [25] analyzed the relationship between a market bubble and market mechanisms and found that every mechanism change would lead to bubble inversion. Protter [26] analyzed the application of martingale theory, based on no-arbitrage, to financial bubbles. Besides, Protter [26] reviewed the bubble detection methods and corresponding explanations and proposed an alternative bubble detection method. Based on the theory of financial physics, Herzog [27] proposed a new model for detecting financial bubbles and added the random jump to correct it. This method is different from the previous bubble models. It redefines the form of asset bubbles and analyzes the occurrence process and nature of financial bubbles from a unique perspective. Also, the research on market jump anomalies mainly includes the following studies: Xiao [28] analyzed the basic efficiency of the valuations of the Chinese stock market using the listed companies from 1992 to 1999 as the research object. Jerzmanowski and Nabar [29] studied the effect of financial market jump anomalies on welfare using the stock market, research input, and productivity. Based on historical data and simulation, Christiano et al. [30] found that inflation will fall when there are jump anomalies in the market and welfare losses can be reduced by adjusting interest rates. Narayan et al. [31] constructed a welfare forecast measurement model and conducted a series of empirical studies on whether market jump anomalies can predict economic welfare. These studies show that the worse the business performance is, the higher the valuation ratio, and this is more likely to cause stock market jump anomalies.

The abovementioned studies are related to the theory of financial bubbles from four aspects: the herding effect, the bubble theory, the LPPL model, and the market jump anomaly. However, for the market jump anomaly, there are relatively few studies on the emergence, development, and bursting of financial bubbles. The Chinese stock market mechanism is not perfect at present, and there is much speculative behavior. This will also lead to the Chinese stock market more easily triggering jump anomalies and financial bubbles than foreign stock markets. Therefore, this paper will measure the bubble anomalies in the Chinese stock market, compare the bubble characteristics of major foreign stock markets, and then study the development of jump anomalies in recent years.

The rest of this paper is organized as follows: Section 2 is the theoretical introduction, including the definition and classification of financial market bubbles, the fractal method of bubble detection, and the LPPL model for bubble identification. Section 3 is the empirical analysis, including the introduction of data, bubble detection, and fractal characteristics, as well as the different jump trends of the Chinese stock market. The last part summarizes the main research results and suggestions for this paper.

## 2. Methods on Bubble Classification, Detection, and Identification

The existence of a market bubble is evident to anyone; however, its theoretical background and quantitative description have not been unanimously recognized by

academia. Therefore, this section will start with the definition of a market bubble and combine the fractal theory and the LPPL model from this field to analyze the feasibility of market bubble detection and identification.

### 2.1. Definition and Classification of Financial Market Bubbles.

A common and simple definition of a market bubble is that a financial asset or a series of financial assets experience a sharp rise in market prices relative to their real values or there is a continuous plunge in financial assets, resulting in market values falling below their real values [6]. The processes of skyrocketing or plunging also constitute jump anomalies in financial markets. Price inflation corresponding to the formation process of market bubbles represents bubbles or positive bubbles; and the collapse of prices corresponds to the process of the market bubble bursting, which has been defined as negative bubbles in relevant past research. This division is based on the comparison of market prices and actual values and the trend of the price change, which is reasonable to a certain degree. However, this paper argues that the distinction between bubbles and negative bubbles is not enough to fully reflect the bubble phenomenon in the market. Therefore, considering the impact of the speed of the price trend change on the market bubble, the bubble phenomenon in financial markets is instead divided into four categories: positive bubbles, negative bubbles, reverse bubbles, and reverse-negative bubbles. The specific forms are shown in Figures 1–4:

- (1) Positive bubble: the price has a sharply rising trend, with the price rising above its actual value, and the rising trend gradually increases. See Figure 1 for the details.
- (2) Negative bubble: the price has a sharp downward trend, with the price falling below its actual value, but the downward trend gradually weakens. See Figure 2 for the details.
- (3) Reverse bubble: the price has a sharp downward trend, with the price falling below its actual value, and the downward trend gradually increases. See Figure 3 for the details.
- (4) Reverse negative bubble: the price has a rising trend, with the price rising above its actual value, but the rising trend gradually weakens. See Figure 4 for the details.

Figures 1 and 4 are the original positive bubbles. Figures 2 and 3 are the original negative bubbles. The biggest difference between them is that the prices rise or fall at different rates. The speed of the changes in Figures 1 and 3 increases gradually, while the speed of the changes in Figures 2 and 4 decreases. By dividing market bubbles into four categories, we can better refine the characteristics of bubbles, which help us to distinguish and identify market bubbles. Furthermore, it helps us to compare domestic and foreign financial markets to further analyze the phenomenon of China's financial market's jump anomalies.

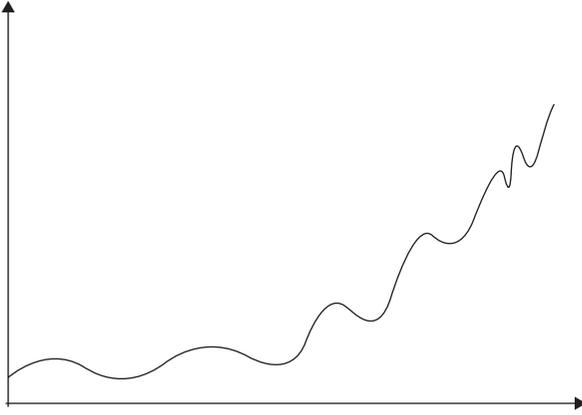


FIGURE 1: Positive bubble morphology.

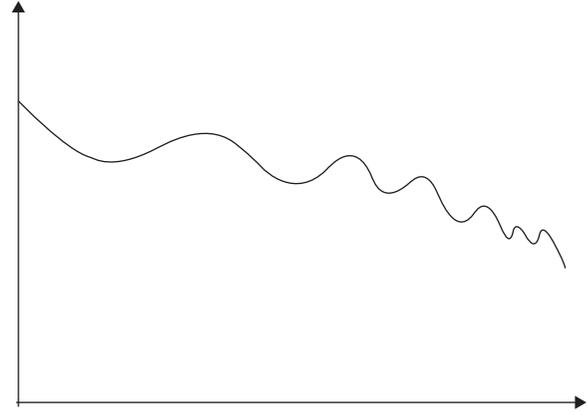


FIGURE 3: Reverse bubble morphology.

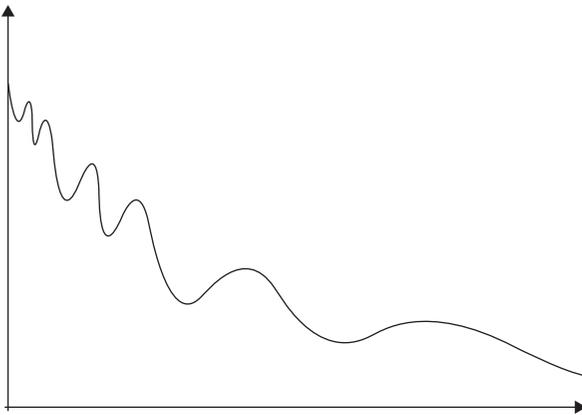


FIGURE 2: Negative bubble morphology.

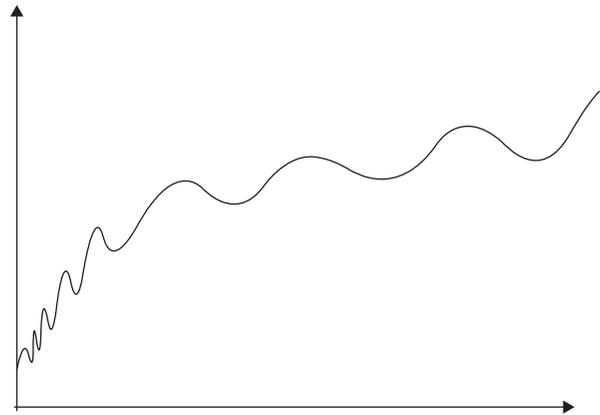


FIGURE 4: Reverse-negative bubble morphology.

**2.2. Fractal Method for Bubble Detection.** The development of bubble theory includes rational bubbles and the irrational bubbles along with the linear bubble and the nonlinear bubble. Consequently, many bubble detection methods and measurement theories have been derived. In recent years, financial physics classification theory and the LPPL model have been applied successfully to domestic and foreign financial markets; therefore, the present study is based on these two theories. In this paper, the fractal theory is mainly applied to measure the fractal characteristics of financial markets and then to judge whether the market has a positive feedback effect and whether the market has the resulting bubble phenomenon. The relevant theoretical analysis is as follows.

The fractal dimension is an important quantitative representation or basic parameter for studying market bubbles using fractal theory. It is not only the characteristic quantity describing fractal time series, but it can also be used to measure the degree of unevenness of time series, which are generally expressed by numbers with decimal points. The fractal dimension of a straight line is 1, the fractal dimension of a plane is 2, and the fractal dimension of a random walk between a straight line and plane is 1.5. In the calculation of the fractal dimension of a financial market, the most commonly used method is  $R/S$

analysis, which can calculate the Hurst exponent from fractal theory to obtain the fractal dimension. The fractal dimension corresponds to the nature of the changes in the price and return of a financial product. Because of the given exponent, this method can effectively detect bubbles in financial markets. The main steps of using the  $R/S$  analysis to analyze the fractal characteristics of a financial market are as follows.

First, transform the financial transaction data according to equation (1), and obtain an exponential logarithmic rate of return:

$$R_t = \ln P_t - \ln P_{t-1}, \quad (1)$$

where  $R$  stands for the rate of return,  $P$  stands for the financial transaction data, and subscript  $t$  stands for the transaction time.

Second, take  $R_t$  as the dependent variable and  $R_{t-1}$  as the independent variable in a regression model. Then, we can obtain the residual sequence  $X_t$  of  $R_t$  as follows:

$$X_t = R_t - (a + bR_{t-1}). \quad (2)$$

Furthermore, the residual sequence is divided into equal-length intervals of  $N$ , and the sum of the deviation of each interval is calculated using the following equation:

$$X_{t,n} = \sum_{u=1}^t (x_u - M_n), \quad (3)$$

where  $M_n$  is the mean value of the  $n$ th interval. After the accumulated deviation is obtained, the rescaled range  $R/S$  is constructed, and the following relationship is established:

$$\frac{R}{S} = K(n)^H, \quad (4)$$

where  $R = \max(X_{t,n}) - \min(X_{t,n})$  and  $S$  is the standard deviation of the sequence  $x_u$ .

Take the logarithm on both sides of equation (4) to obtain the following:

$$\log\left(\frac{R}{S}\right) = H \log(n) + \log(K), \quad (5)$$

where the estimated value of  $H$  is the Hurst exponent of the rate of return. For a theoretical proof, one can refer [31]. The Hurst exponent, based on the rate of return, can also be used to calculate the corresponding fractal dimension as follows:

$$D_s = 2 - H, \quad (6)$$

where  $1 \leq D_s \leq 2$  and  $H$  is the Hurst exponent. When  $D_s = 1.5$ , the rate of return series is a random walk; when  $1 \leq D_s < 1.5$ , it indicates that the smoothness of the rate of return series lies between a straight line and a random walk; and when  $1.5 < D_s < 2$ , it indicates that the rate of return series is coarser than a random walk.

Fractal theory can effectively find the similarity between the whole and the part, the chaos and the rule, and the transition between order and chaos and apply these concepts to financial markets to deepen our understanding of them. When the fractal dimension is from 1 to 1.5, the smoothness of the rate of return series is between a straight line and a random walk, the fractal structure is relatively stable, and the historical increments promote future incremental growth. This makes it is easy for a market bubble to form. Of course, fractal theory can simply detect the existence and relative strength of a bubble, but it cannot judge the duration of the bubble, the magnitude of the bubble, or the reversal time of the bubble. Therefore, further study of the existence of bubbles by using the LPPL model will be an effective supplement.

**2.3. LPPL Model for Bubble Identification.** As mentioned above, the main reason for stock market bubbles is the mutual imitation of traders, which triggers a positive feedback effect in the market, and this in turn leads to rapid price increases. Some researchers have conducted theoretical studies and constructed the descriptive models of the phenomenon. Among them, a seminal study is the study of Johansen and Sornette [17] that verified that positive feedback effects in financial markets can lead to the formation and rupture of bubbles. Furthermore, they analyzed the similarity between this phenomenon and earthquakes and used the LPPL model from financial physics to carry out groundbreaking research on market bubbles. Relevant

research related to the LPPL model is now discussed. Johansen et al. [32] introduced a time series model for asset prices. It is described by using the following equation:

$$\log p(t) = A + B(t_c - t)^\alpha + C(t_c - t)^\alpha \cos(\omega \ln(t_c - t) + \phi), \quad (7)$$

where  $\log p(t)$  denotes the logarithm of financial product transactional data or asset prices at time  $t$ ;  $t_c$  indicates the time when the bubble bursts, which is the critical transformation time;  $t_c - t$  is the difference between time  $t$  and the critical time;  $A$  indicates that the value of  $\log p(t_c)$  may be reached when the bubble lasts until the critical time  $t_c$ ;  $B$  represents the rate of increase of  $\log p(t_c)$  before the bubble bursts, when  $C$  is approaching 0;  $C$  represents a scale factor for the fluctuation of the exponential growth;  $\alpha$  is the exponent of the power growth;  $\omega$  indicates the oscillation frequency, that is, the fluctuation speed;  $\phi$  is the phase parameter; and  $\alpha$  and  $\omega$  are generally used to determine financial bubbles.

According to Greenwood and Nagel [24], the behavioral model of asset prices is as follows:

$$dp = \kappa p(t)h(t)dt, \quad (8)$$

where  $dp$  indicates the change of the unit time price or index,  $\kappa$  denotes the possibility of the price or index falling when the bubble bursts,  $p(t)$  is the price or index at the time  $t$ , and  $h(t)$  is the risk rate at the time  $t$ . According to equation (8), the series transformation is carried out, and the final equation (7), namely, the LPPL model, is established by setting the trader behavior mode and imitation factor and using a Fourier transformation.

The LPPL model compares the market collapse with a critical point and uses the power law to fit the price or its logarithm. Because traders imitate each other and form collective effects through positive feedback, the price is similar to logarithmic periodic vibration; therefore, a final market collapse can be explained by market dynamics, which are also the theoretical basis of the LPPL model.

### 3. An Empirical Study of Jump Anomalies in the Chinese Stock Market

Based on the history of the development of the Chinese stock market, we can subjectively find that since 2006, the stock market has started to form bubbles and exhibit certain jumps. In 2007, the CSI 300 index broke through 5800 points, and then it fell rapidly in 2008, reaching a minimum of 1627.76 points. The extent of the decrease was over 72%. Besides, since the end of 2014, the stock market has entered another round of continuously increasing and jump. The CSI 300 index broke through 4000 points on March 30, 2015, a new 7-year high. Then, it broke through 5000 points on May 25, 2015, until it reached 5353.75 points. The continuous jump in the stock index has aroused the theoretical circles. Therefore, it is important to use appropriate methods to detect and identify the stock market bubbles accurately and to provide some suggestions for the jump anomalies in China's stock market. It is of great significance to maintain

and promote the stable and healthy development of China's stock market and its effects on China's economy.

**3.1. Data Source and Basic Characteristics.** To study the bubbles and jumps in the Chinese stock market, the present study selected the transactional data of the CSI 300 index from April 8, 2005, to November 5, 2015, as the research sample. The CSI 300 index is compiled by grading technology based on liquidity and market value and is comprised of 300 A-shares selected from the Shanghai and Shenzhen stock markets through a certain screening process. The CSI 300 index tends to reflect the trends of the Shanghai and Shenzhen markets as a whole, and the return of mainstream investment. The trading points of the CSI 300 index were collected as sequential data for the present study, with 2570 data collected in total. The specific trend is shown in Figure 5.

As seen from Figure 5, there were two bull market jumps in the CSI 300 index in October 2007 and June 2015. The closing point was much higher than that in other periods, which showed a strong jump feature. The mega bull market in 2007 fell to a low in November 2008, and the mega bull market in 2015 also stabilized after a sharp decline. However, whether there were bubble and jump anomalies still requires further quantitative verification. Of course, from Figure 5, it can also be found that the CSI 300 index series is nonstationary. It is necessary to deal with this to a certain extent, that is, to normalize the difference in the values by taking the logarithm of the closing points and then to obtain the rate of return series of the closing points. The specific calculation is shown in equation (1). Figure 6 shows the trend chart of the yield rate of the CSI 300 index. It can be found that the yield rate of the CSI 300 index fluctuates around the value of 0. After the closing points of the CSI 300 index were converted into rates of return, 2569 sample data were obtained. The basic statistical characteristics of the rate of return sequence are shown in Table 1.

Through the analysis of Table 1, it can be found that the mean value of the rate of return series of the CSI 300 index is close to 0, the skewness is less than 0, and the kurtosis is greater than 3. There is a certain phenomenon including left skewness, a high peak, a fat tail, and a jump. Although the difference between the distribution and the normal distribution is large, it does not affect fractal analysis and the construction of the logarithmic accelerated power law model in this paper.

**3.2. Bubble Detection of the Full Sample and Its Fractal Characteristics.** To detect whether there is a bubble in the sample interval, we used  $R/S$  to calculate the Hurst exponent of the full sample data and to test the fractal characteristics and long-term memory of the rate of return series of the CSI 300 index. The specific steps are shown in equations (1)–(5). Table 2 shows the moving average of the Hurst index values, with sequence lengths of 50, 120, and 200, respectively, and Figures 7–9 show the corresponding Hurst exponent change charts.

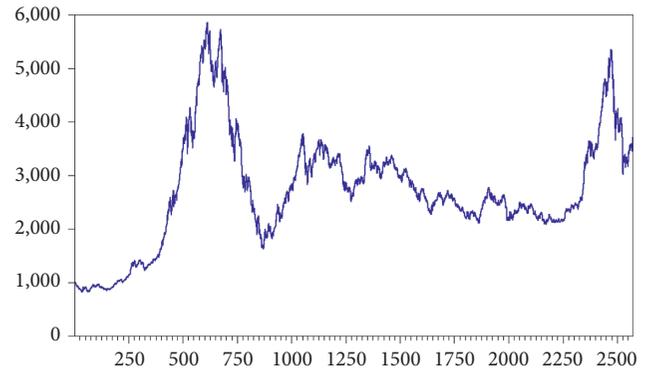


FIGURE 5: Trend chart of the CSI 300 index.

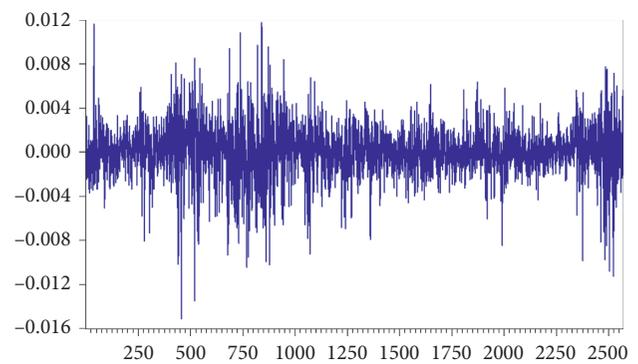


FIGURE 6: Trend chart of the CSI 300 index yield rate jump.

From Table 2 and Figures 7–9, it can be seen that the Hurst exponent of the CSI 300 index is greater than 0.5, the rate of return series has the characteristics of long-term memory and sustainability, and the future increment is positively related to the historical increment, following a biased random walk process with fractal characteristics. Besides, the fractal dimension of the rate of return series calculated by using equation (6) is 1.27, and so the rate of return series of the CSI 300 index has a stable fractal structure. It also satisfies scale invariance and provides evidence for the existence of bubbles in the Chinese stock market.

Based on the above analysis, we can see that, in the above modeling interval, there are jump anomalies and the necessary conditions for bubbles in the Chinese stock market. Furthermore, the bubbles have the potential to greatly harm investors or the whole economy and may lead to the market's collapse and an economic crisis. Therefore, identifying the types of bubble and predicting the collapse of bubbles (mechanism transformation) is of great significance.

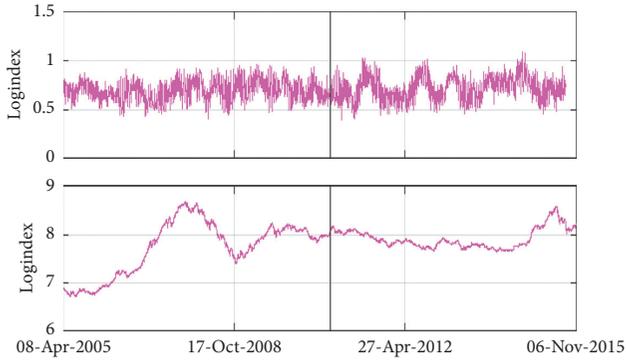
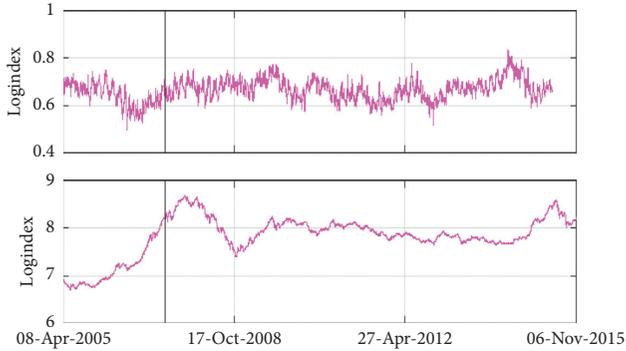
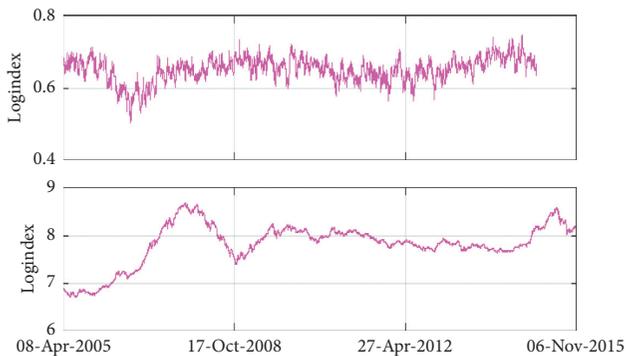
**3.3. Analysis of Stock Market Bubbles under Different Jump Trends.** The phenomenon of jump anomalies in the Chinese stock market is mainly reflected in the corresponding market bubble. The following outlines the use of the LPPL model to identify various bubbles in the Chinese stock market and to further analyze the relative bubble size and the mechanism

TABLE 1: The basic statistical characteristics of the rate of return of the CSI index.

Sample	Mean value	Mid value	Standard deviation	Skewness	Kurtosis	Jarque-Bera	Number
CSI 300 index	0.0000674	0.000128	0.00245	-0.428	6.331	1265.884	2569

TABLE 2: The Hurst exponent results of the CSI 300 index.

Hurst index	CSI 300 index
$N = 50$	0.7284
$N = 120$	0.6836
$N = 200$	0.6714

FIGURE 7: The results of the Hurst exponent when  $N = 50$ .FIGURE 8: The results of the Hurst exponent when  $N = 120$ .FIGURE 9: The results of the Hurst exponent when  $N = 200$ .

transformation time. Besides, the two largest bubbles in the period are compared, and the causes are analyzed.

The stage division in Table 3 is based on the changing trend of the rate of return of the overall market, and it is divided into four types: up jump, down jump, a small jump of the transverse disk, and the transitional stage. The types of stages are shown in Table 4. Among them, the transitional time refers to the initial time when the rate of return begins to move in the opposite direction of the jump trend.

In Table 4, the up jump indicates that the rate of return is positive in a certain period time and the index is in the rising stage; the down jump indicates that the rate of return is negative in a certain period time and the index is in the declining stage; the small jump of the transverse disk indicates that the index has no obvious rising or falling trend in a certain period time; and the transition stage indicates that the index has obvious fluctuations in a certain period time, although the trend cannot be determined. Since the transitional stage does not conform to the characteristics of LPPL model fitting, we select three types of periods for the fitting analysis, i.e., up jump, down jump, and small jump of the transverse disk. The results of the fitted LPPL model are shown in Table 5.

In Table 5,  $t_c$  is the predicted time that the bubble bursts or the jump transformation time. For each stage, the fitting effects are shown in Figures 10–20 which shows a complete fitting diagram, formed by fitting in each stage.

By comparing  $t_c$  in Table 5 with the actual transformation time in Table 3, it can be found that the critical time of the 10 stages given by the LPPL model is very close to the actual transformation time. The average error of the 7 stages of the bubble in terms of days is not more than 10 days, the minimum error is 0, and the maximum error is 16. The accuracy of the critical time  $t_c$  is very important. To a certain extent, it represents the validity of the LPPL model. In particular,  $t_c$  is the estimated time for the termination of the positive bubble (negative foam) or the beginning of the reversal bubble (reverse negative bubble).

From Figures 10–19, we can see that Figures 10 and 18 both show positive bubbles; Figure 19 shows a negative bubble; Figures 11, 14, and 16 exhibit reverse bubbles; and Figure 12 shows a reverse negative bubble. That is, there are four types of bubbles in the Chinese stock market, which is a significant multiple bubble market. This also reflects the fact that, to a certain extent, China's market is less mature. We also apply the LPPL model to the Dow Jones industrial index and the UK FTSE 100 index in the same period. We find that these two indices have only two bubbles: a reverse bubble and a reverse negative bubble (the calculation process is the same as the calculation in the paper, so please contact the corresponding author if necessary), and these two indices have large differences from the Chinese stock market. Among them, the Dow Jones industrial index from April

TABLE 3: Jump transformation time of CSI 300 index returns.

Time quantum	Transformation time	Time quantum	Transformation time
2005/4–2007/10	2008/1/14	2012/1–2012/4	2012/5/7
2007/11–2008/10	2008/11/5	2012/5–2012/11	2012/12/3
2008/11–2009/7	2009/8/3	2012/12–2013/6	2013/6/27
2009/8–2009/11	2009/12/7	2013/7–2014/5	2014/6/6
2009/12–2010/6	2010/7/5	2014/6–2015/5	2015/6/11
2010/7–2010/10	2010/11/8	2015/6–2015/11	—
2010/11–2011/12	2012/1/5	—	—

TABLE 4: Unit root test of price return of metal futures.

Up jump	Down jump	Small jump of transverse disk	Transition stage
2005/4–2007/10	2007/11–2008/10	2009/8–2009/11	2012/1–2012/4
2008/11–2009/7	2009/12–2010/6	—	2012/5–2012/11
2010/7–2010/10	2010/11–2011/12	—	2013/7–2014/5
2014/6–2015/5	2012/12–2013/6	—	—
—	2015/6–2015/11	—	—

TABLE 5: LPPL model fitting of the rate of return of CSI 300 index.

Time quantum	$\alpha$	$\bar{\omega}$	$\phi$	$A$	$B$	$C$	$t_c$	Bubble morphology
2005/4–2007/10	0.0293	1.8975	-197.806	7.7938	-0.0530	0.7707	2008/1/8	Bubble
2007/11–2008/10	0.5807	-13.313	-39.9702	7.1852	-0.0599	-0.0048	2008/11/14	Reverse bubble
2008/11–2009/7	0.7520	-17.968	6.7555	8.2478	-0.0156	-0.0014	2009/8/3	Reverse-negative bubble
2009/8–2009/11	0.4599	-35.915	35.430	18.792	-23.903	-0.3169	2009/12/23	—
2009/12–2010/6	0.7557	9.6010	-286.34	8.3643	-10.076	-1.3509	2010/7/11	Reverse bubble
2010/7–2010/10	0.3495	-4.9952	11.372	8.4486	-0.1240	-0.0124	2010/11/18	—
2010/11–2011/12	0.3331	12.362	-52.269	7.6212	-0.0750	0.0068	2012/1/6	Reverse bubble
2012/12–2013/6	0.3769	4.5453	-19.081	8.0244	-0.8004	-0.2039	2013/7/2	—
2014/6–2015/5	0.5504	11.520	-20.875	9.2901	-0.0740	0.0039	2015/6/14	Bubble
2015/6–2015/11	0.0563	-0.4777	339.04	13.263	-24.062	5.3505	2015/12/08	Negative bubble

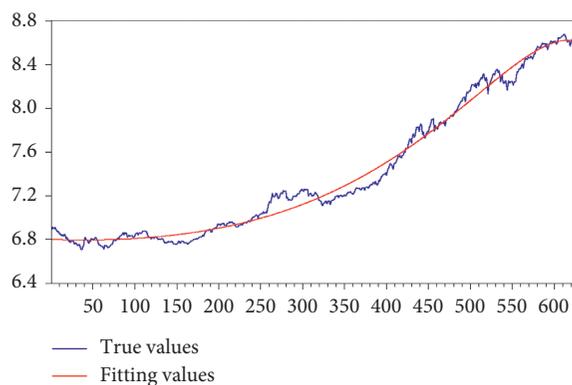


FIGURE 10: Fitting results from 2005/4 to 2007/10.

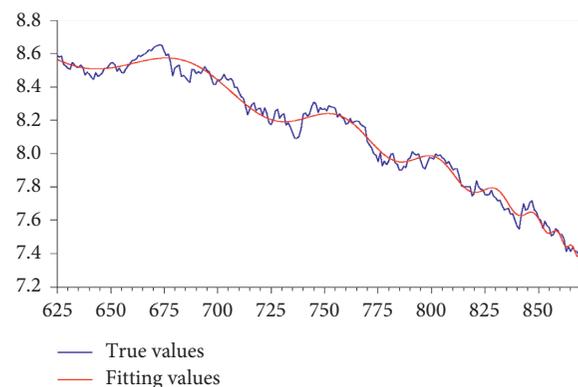


FIGURE 11: Fitting results from 2007/10 to 2008/10.

2005 to July 2007 and March 2009 to November 2015 was in a reverse negative bubble, and from August 2007 to February 2009, it was in a reverse bubble. The FTSE 100 was very similar, with the index lagging by one month. From April 2005 to August 2007 and from April 2009 to November 2015, it was in a reverse negative bubble, and from September 2007

to March 2009, it was in a reverse bubble. Furthermore, through comparison, we find that the fluctuation range of the Dow Jones industrial index is far less than that of the CSI 300 index (in terms of the average relative fluctuation), while that of the FTSE 100 index is slightly larger than that of the Dow Jones industrial index, but it is also far less than that of

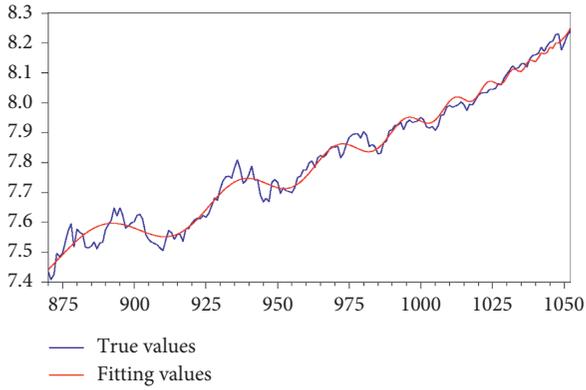


FIGURE 12: Fitting results from 2008/11 to 2009/7.

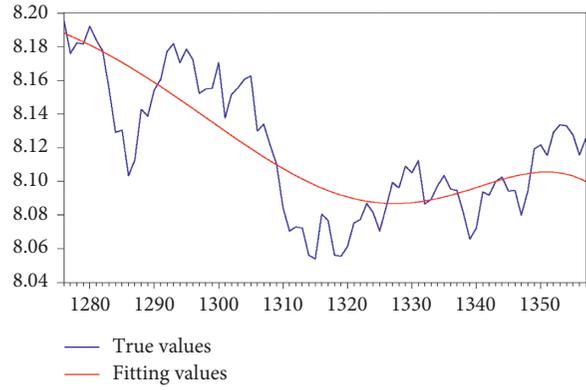


FIGURE 15: Fitting results from 2010/7 to 2010/10.

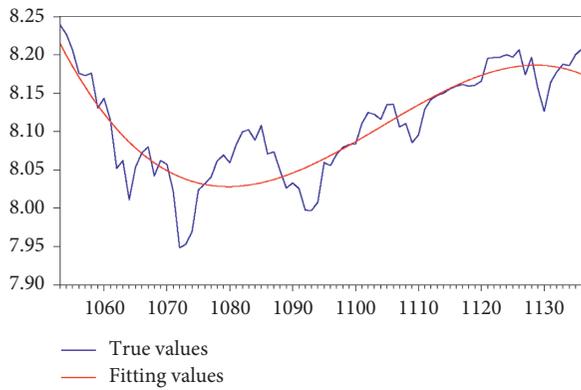


FIGURE 13: Fitting results from 2009/8 to 2009/11.

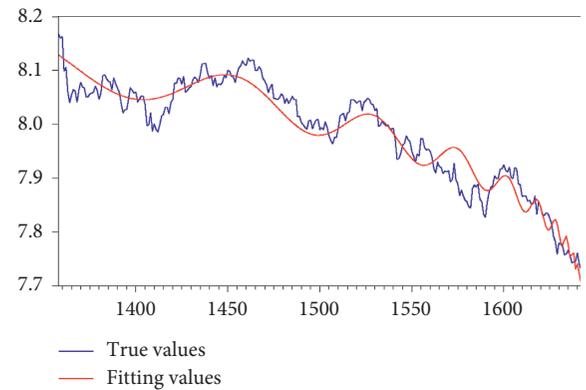


FIGURE 16: Fitting results from 2010/11 to 2011/12.

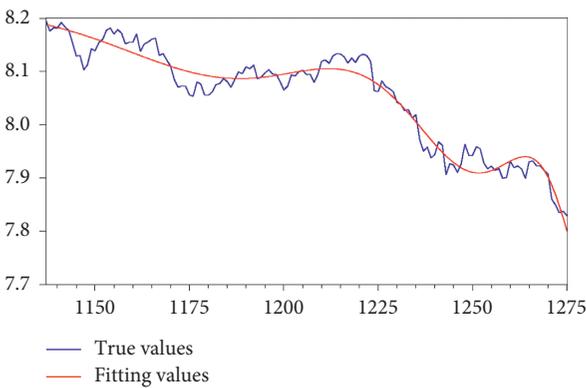


FIGURE 14: Fitting results from 2009/12 to 2010/6.

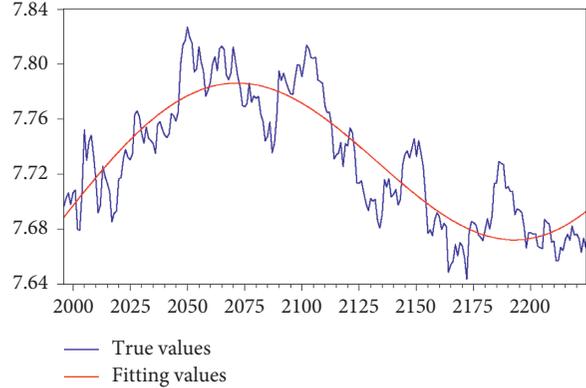


FIGURE 17: Fitting results from 2012/12 to 2013/6.

the CSI 300 index. The fluctuation range of the CSI 300 index is 38.9%, that of the FTSE 100 index is 14.8%, and that of the Dow Jones industrial index is 12.2%.

Furthermore, from Figure 20, we can see that from 2005 to now, there are two bigger skyrocketing jumps in the Chinese stock market, corresponding to Figures 10 and 18, respectively, and the periods 2005/4–2007/10 and 2015/6–2015/11, which are two serious stages of bubble generation and the jump anomaly in the Chinese stock market. From

April 2005 to October 2007, the CSI 300 index rose from 1003.5 to 5862.38, up as much as 500%, with the rate of return of the stock market ranking first in the world at that time. From June 2014 to May 2015, the CSI 300 index rose from 2134.28 to 5353.75, up as much as 150%. Combining the values of  $\alpha$  and  $\omega$  in Table 5, we can find that there was an obvious market bubble in the Chinese stock market during this period, which is a reflection of the market jump anomaly.

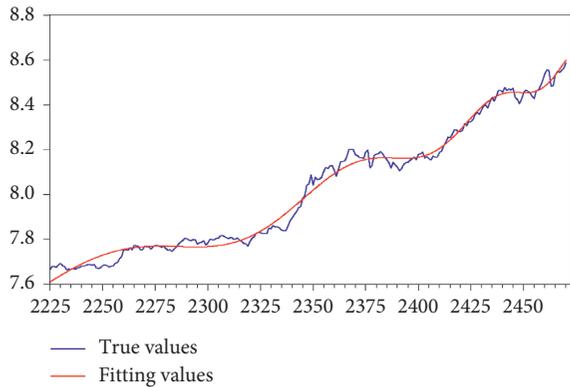


FIGURE 18: Fitting results from 2014/6 to 2015/5.

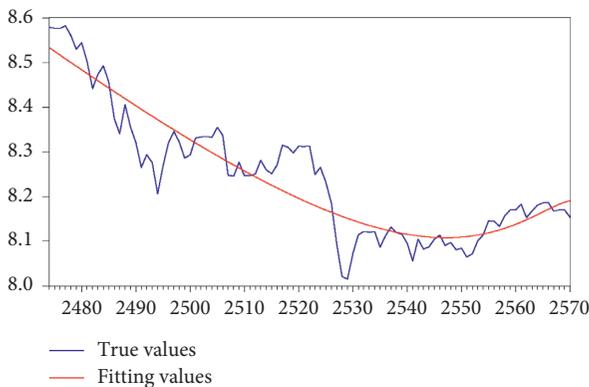


FIGURE 19: Fitting results from 2015/6 to 2015/11.

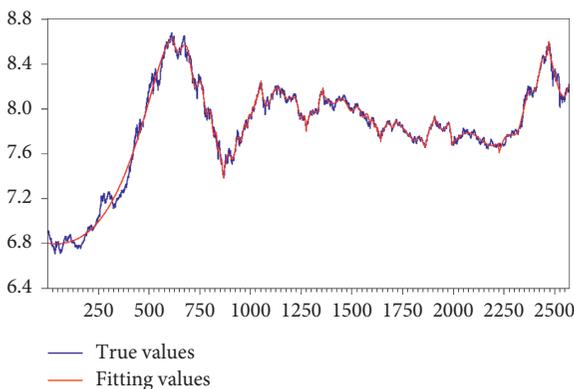


FIGURE 20: Fitting results from 2005/4 to 2015/11.

This study confirms that from April 2005 to October 2007, thanks to the improvement of macroeconomic policies, the Chinese stock market experienced a continuous rise/jump, which eventually led to the jump anomaly in the stock market. Before this round of gains, the China Securities Regulatory Commission issued a “notice on issues related to the pilot reform of nontradable shares of listed companies,” announcing the launch of the pilot reform of

nontradable shares, which eliminated the differences between tradable shares and nontradable shares. To a certain extent, this solved the problem of balancing the interests among the relevant shareholders in the A-share market and ushered in a brand new period in the development of the Chinese stock market. Following this, the stock market flourished, the rate of return increased unceasingly, and market speculation and irrational investment increased massively. The market had entered the phase of the jump anomaly. Finally, the bubble burst in January 2008, and the CSI 300 index fell sharply, from 5699.15 points to 1627.76 points. After approximately 7 years of jumps up and down, in June 2014–May 2015, there was a new upward trend. At this stage, both the uptrend and the height were at least as good as those of the previous phase. Figures 3 and 11 show the details. The reason for this phenomenon may be abundant short-term liquidity and large amounts of capital inflow. In particular, abundant short-term liquidity manifested itself in a sharp fall of the short-term SHIBOR interest rate and a flood of short-term liquidity in the financial industry. A large amount of capital inflow was reflected in China’s economic recession, and many real economic indicators declined to a large degree. Investors then chose to invest capital in the stock market, which led to another jump anomaly in the Chinese stock market. The above analysis also corresponds to and verifies the empirical conclusion of this paper.

#### 4. Conclusions and Suggestions

Taking the CSI 300 index as a research object, we have used the  $R/S$  analysis to detect the fractal characteristics of the rate of return and then obtained evidence of bubbles in the Chinese stock market. We also have used the LPPL model to identify the types and sizes of bubbles in different stages of the stock market and the predicted mechanism reversal time. The results showed that there are four types of bubbles in the Chinese stock market, namely, positive bubbles, negative bubbles, reverse bubbles, and reverse negative bubbles. According to the analysis of the two largest fluctuations in the stock market, we found that there have been significant jump anomalies in the Chinese stock market. Additionally, by comparing the bubble types and the fluctuation ranges of the Dow Jones industrial index and the British FTSE 100 index in the same period, it is found that only reverse bubbles and reverse negative bubbles have occurred in both indices, and the Chinese stock market has fluctuated to a larger extent than these mature international markets. This also shows that the Chinese stock market is not yet mature and requires further improvement. Moreover, its multiple bubble characteristics have often led to the appearance of market jump anomalies.

These jump anomalies in the stock market are not only related to the rise and fall of the stock market, but they can also have a large impact on the national economy. Our findings suggest that the relevant departments in China should introduce a mechanism for stock market bubble detection, identification, prevention, and treatment and then

effectively measure and respond to stock market bubbles and jump anomalies. It is noted that there are also some limitations to this study. The researches of this paper were primarily focused on the fractal and periodic power law measures of stock market bubbles, and there is no analysis of the causes of stock market bubbles. Furthermore, the methods on how to deal with an uncontrollable stock market bubble and the market over-jump anomaly have not been discussed in this paper. Therefore, further studies on such issues could be important and interesting [33–36].

## Data Availability

The data used to support the findings of this empirical study can be downloaded at <http://www.wind.com.cn>. If required, the entire data can be obtained by contacting the corresponding author.

## Conflicts of Interest

The authors declare no conflicts of interest.

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