

Asset Price Bubble under Behavioral Finance Theory: Based on Log-Periodic Power Law Model

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Abstract. The asset price bubble problem is not only the most concerned topic in the financial circle, but also one of the most important research topics in the financial circle. In history, every time asset prices skyrocketed, bubbles were accumulated, and every asset price crash resulted in a massive shrinking of wealth, bankruptcy of enterprises, and economic recession. This paper is based on the theory of investor behavioral bias in behavioral finance theory, and is based on the log-periodic power law (LPPL) theory of iron ore futures, apple futures, coke futures and stock market indices that is widely used in Chinese financial markets. The market index and bitcoin price are empirically analyzed through the process of bubble accumulation, and the stock market index of China's stock market and the index of China's capital market are predicted and analyzed based on LPPL theory.

Keywords: Bubble; Behavioral finance; Logarithmic periodic power law(LPPL) model.

1. Background and significance of the topic

In recent years, scholars around the world have focused on the issue of asset price bubbles. Especially, the bursting of the GEM bubble in 2015 has had a profound impact on the economic level and even the social level. In addition to the stock market, since 2018, global asset prices have entered a violent volatility situation. Bitcoin dropped 70% from the top, crude oil plunged 43% in just two months, and in December 2018, the volatility of large cap stocks in the United States rarely exceeded that of emerging market countries. That came on the heels of 2019's biggest January gains for the Dow Jones Industrial Average and the S&P 500 in 30 years. In China, due to supply-side reform and environmental protection policies, the supply of upstream bulk raw materials showed sharp fluctuations of more than 30% in 2018. In terms of agricultural futures, the newly listed Apple futures closed with an annual increase of 107% in 2018.

This paper not only expounds the log-periodic Power Law (LPPL) model theory, but also explores the behavioral finance logic behind it. In this paper, the log-periodic Power Law (LPPL) model is applied to all kinds of global assets, and the application scope of the model is clarified by model fitting and superimposing different real scenarios at that time.

2. Literature review

In terms of research on bubble formation and maturation, the model constructed by Ding Xiaogang can point out that irrational traders are the main cause of bubble formation and maturation, and irrational traders and rational traders transform into each other to accelerate the arrival of bubble bursting. Sun Xiujuan found that the factors affecting bubble maturation are extensive, including positive feedback trading behavior, which represents deviation under behavioral finance theory; After the formation of a bubble, some investors will participate in it rationally, while regulators will also sit on the sidelines to some extent. Gong Yusong found in his research that the stock market has the characteristics of rising and falling, and the reason for the drastic fluctuations of the stock market is the main IPO audit system and delisting system. A large number of junk stocks cannot be cleared from the market, making the market unable to allocate resources effectively; If the delisting system can be strictly implemented, the fundamental effect of bubble suppression can be achieved. Chen Daofu put forward that the bubble is a typical unbalanced phenomenon from the economic level; The cause of bubble mainly comes from cognitive deviation, while the cause of deviation comes from

incentive failure, and bubble from in the evolution from formation to maturity, it should be prevented from developing in a bad direction .

3. Paper Research Method

In this paper, we find that the log-periodic Power Law (LPPL) model is the most basic and widely used model to describe foam.

This paper empirically studies Chinese securities and futures markets through the LPPL model, and extends the research to various global assets. On the basis of the empirical conclusion, the paper puts forward some suggestions for the healthy development of future securities and futures markets and individual investors.

4. Investor behavior Deviation in modern behavioral finance theory

Behavioral finance is based on the financial market anomaly caused by the deviation of investors' behavior . Behavioral finance, on the other hand, is based on investors' decisions, which are close to the market reality and more conducive to empirical research . This paper discusses behavioral finance issues from theoretical basis and market vision, listed companies, investment funds, market information and decision-making behavior, etc. .

4.1 Disposition effect

Investors sell earning assets, loss of assets too rapidly for too long tends to be known as the disposition effect, the effect is attributed to the psychology of investors, as investors in order to avoid the loss caused by regret and avoid losses, because once the loss of assets were sold, has proved the investment behavior of investors before failure. Instead, investors tend to sell too quickly when they take a profit, because they want to confirm themselves and justify their decision. The basic result of the disposal effect is that investors are more willing to sell winning stocks and hold on to losing ones. In the process of trading directly caused by disposal, investors are prone to two phenomena: the selling proportion of profitable stocks is higher than that of loss-making stocks; It takes longer to hold a losing stock than a winning one.

4.2 Anchoring effect

When making decisions, people cannot accurately measure the intrinsic value of everything, so they first set a reference point or "anchor" and compare other things with it to get their relative value, and then adjust only around the "anchor". The typical behaviors of investors under anchoring effect are as follows: investors initially adopt a certain investment strategy and are unwilling to make fundamental changes; Investors like to compare their investment performance with others, so as to affect the investment mood; Investors usually only consider book value, not inflation, when calculating investment returns.

4.3 Overconfidence

Investors tend to overestimate their own cognition, judgment and intuition, underestimate the factors of risk and opportunity, and exaggerate their grasp of the situation. The typical behaviors of overconfident investors include: the more information they get, the more accurate their judgment will be; When an investor buys a stock, he may insist that the investment is correct; Investors often think that they have more information than other investors do.

4.4 Herd Effect

Due to insufficient information, it is difficult for ordinary people to make reasonable expectations about future uncertainties, and they often extract information by observing the behavior of those around them. In this constant transmission of information, many people have roughly the same

information and reinforce each other, leading to convergence in behavior. Under the herding effect, investors' behaviors are as follows: "herding effect" leads people to like to follow the trend and fry stocks; The "herd effect" leads investors to engage in short-term speculation and ignore asset fundamentals.

4.5 Mental Accounts

The human brain tends to process different events separately as if they were separate gains and losses in separate accounts, creating a cognitive illusion that "this money is not that money." Typical behaviors of investors with mental accounts include: the wrong person thinks prudent investing is all about buying low-risk stocks; Defend the loss of stock, but happy to sell the profit of the stock.

4.6 Precipitation cost effect

People like to think about past irreparable costs, and once they have invested money, effort and time in something, they will continue to invest. Under the precipitating cost effect, the typical behaviors of shareholders are as follows: when the price of the purchased stock falls, investors tend to continue to cover the short position to continuously reduce the cost; When investors lose money, they always want to find a chance to recover their money, so they chase higher risk.

5. Theoretical basis and analysis of log-periodic Power Law (LPPL)

The formation of financial market bubbles and the principle of model construction are based on the following points:

- (1) The positive feedback mechanism among investors in the financial market creates bubbles, and rational investors constantly disturb bubbles
- (2) Mutual imitation of investment ideas, investment strategies and even trading behaviors among investors leads to bubbles, in which the proportion of rational investors and irrational investment determines the power index M .
- (3) The continuous positive feedback from investors makes financial assets show obvious power-law growth.

Financial market bubble, performance is asset price rise, fall cycle gradually shorten. The log-periodic Power Law (LPPL) model can quantify the prediction of asset price bubbles. The asset price bubbles are characterized by power-law acceleration of log-periodic fluctuations, and the volatility period becomes shorter as the bubble is closer to the collapse time. From the chart, it can be seen that there is a continuous and regular recurrent cycle with gradually decreasing volatility period. Asset price bubbles can be expressed by the following formula:

$$\ln p(t) = A + B(t_c - t)^m + C(t_c - t)^m \cos[\omega \ln(t_c - t) - \varphi]$$

Due to the large number of unknown parameters, the model contains 7 unknown parameters. There are three linear parameters and four nonlinear parameters. It will be difficult to solve all seven parameters at the same time. The key to predicting the bursting of a bubble is in the model. In order to achieve a better balance between stability and validity of the model, we use the method of dimensionality reduction for reference. The dimensionality reduction process is as follows:

$$\cos(X - Y) = \cos X \cos Y + \sin X \sin Y$$

The log-periodic power-law model can be rewritten as:

$$A + B(t_c - t)^m + C(t_c - t)^m \cos[\omega \ln(t_c - t)] \cos \varphi + C(t_c - t)^m \sin[\omega \ln(t_c - t)] \sin \varphi$$

Using the idea of least squares, we set the objective function as:

$$F(t_c, \omega, \varphi, A, B, C_1, C_2) = \sum_{i=1}^m [\ln p(t_i) - A - B(t_c - t_i)^m - C_1(t_c - t_i)^m \cos[\omega \ln(t_c - t_i)] - C_2(t_c - t_i)^m \sin[\omega \ln(t_c - t_i)]]^2$$

Then:

$$(\hat{t}_c, \hat{\omega}, \hat{\varphi}) = \underset{t_c, \omega, \varphi}{\operatorname{argmin}} F(t_c, \omega, \varphi)$$

$$F_1(t_c, \omega, \varphi) = \underset{A, B, C_1, C_2}{\min} F(t_c, \omega, \varphi, A, B, C_1, C_2)$$

6. Empirical analysis and forecast of trading based on LPPL model

The concept of BitCoin was originally put forward by Satoshi Nakamoto in 2009. According to the idea of Satoshi Nakamoto, the open source software and P2P network on it are designed and released. Bitcoin is a peer-to-peer form of digital currency. Bitratio is a typical consensus currency, which does not have any fundamental support and regulatory endorsement, and completely depends on the consensus of participants. The structure of investors is stable, the transaction friction cost is low, there are no trading restrictions, and the trading time is 7*24 hours without breakpoints. The above points have great advantages for testing the reliability of LPPL model. This paper selects 224 data of Bitcoin against USD from March 26, 2017 to November 6, 2017. Take March 26, 2017 as the starting point of the bubble, because the price of bitcoin fell from \$1360 to \$896 on March 5, 2017, a decline of 34% in 19 trading days. It fits the general definition of a bubble bursting. Hence March 26 as the start of the bubble. Bitcoin hit \$19,891 on December 15, 2017, a 22-fold increase in 269 trading days. As of February 6, 2018, it fell to \$6,487, a decline of 67.08% in 52 trading days, which meets the definition of a bubble bursting.

First of all, the currency against the dollar on March 26, 2017 to November 6, 2017, until 224 data fitting, and then to forecast the point to bubble burst. So the graph looks like this,

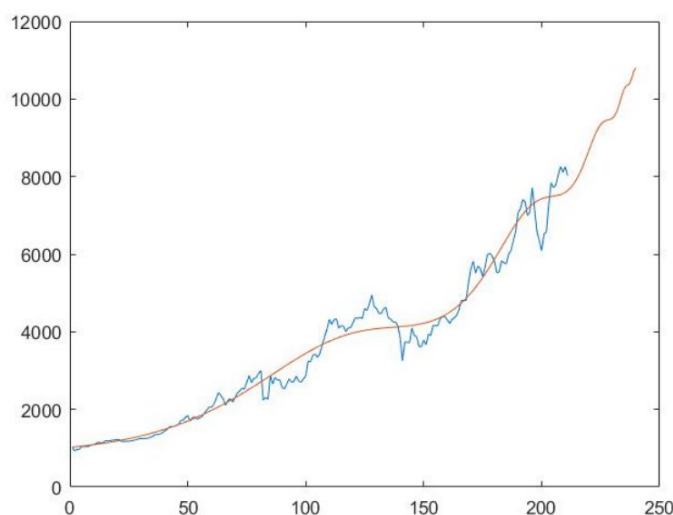


Figure 1. LPPL model for Bitcoin price prediction

As can be seen from Figure 1, the price of bitcoin climbed slowly in the initial stage, and the main logic behind it was the loose global liquidity combined with the general distrust of great power politics after Trump took office. Anarchism and the transnational development of large technology companies constantly promoted the price of bitcoin. With the Chicago Mercantile Exchange planning to launch bitcoin commodity futures in December, expectations for bitcoin's use as a currency have soared. And bitcoin's top collapsed amid China's crackdown on bitcoin exchanges and a continuing contraction in global liquidity.

In addition, the simulation results show that the tc bubble burst time 265 days, the currency actual collapse time was 269 days. Thus LPPL model can well fit the currency price fluctuations, for tc bubble point prediction is more accurate.

7. Iron ore futures trading empirical analysis based on LPPL

This paper selects the data of 66 trading days of iron ore index from March 23, 2019 to July 3, 2019. March 23, 2019 as the starting point of the bubble accumulation is because of the dam break in Brazil in March 2019, which caused a significant contraction of iron ore supply, and the 110 trading days after that, the rise of 40%. The rising process obviously conforms to the characteristics of LPPL model.

First for iron ore index on March 23, 2019 to 2019 on July 3 until 66 data fitting, then the bubble point to predict get graphics as shown in the figure below:

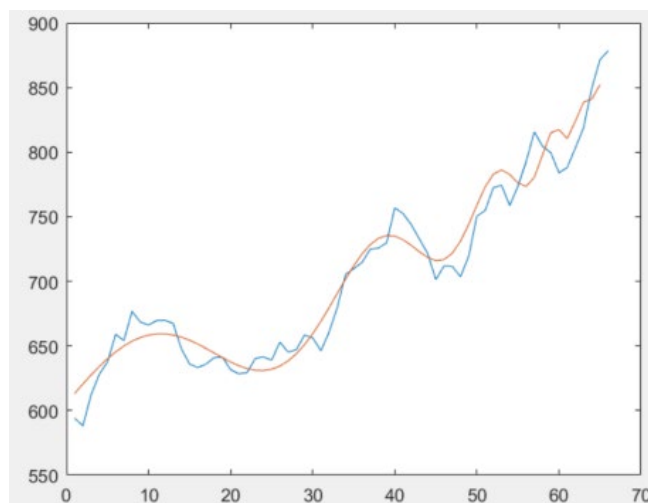


Figure 2. LPPL model for iron ore futures price forecast

As shown in Figure 2, through the simulation results show that the tc bubble burst time 63 trading days, but the reality is iron ore futures futures trading in 67 an adjustment in the future, produce 34% decline, thus LPPL can model a good fitting price fluctuation. Similarly, iron ore I2001 contract is selected, with 66 data from March 23, 2019 to July 3, 2019. March 23, 2019 was taken as the starting point of the bubble accumulation because of the dam break in Brazil in March 2019, which caused a significant contraction of iron ore supply, and the following 110 trading days i2001 rose 71%.

First for iron ore index on March 23, 2019 to 2019 on July 3 until 66 data fitting, then the tc bubble point to predict get graphics as shown below:

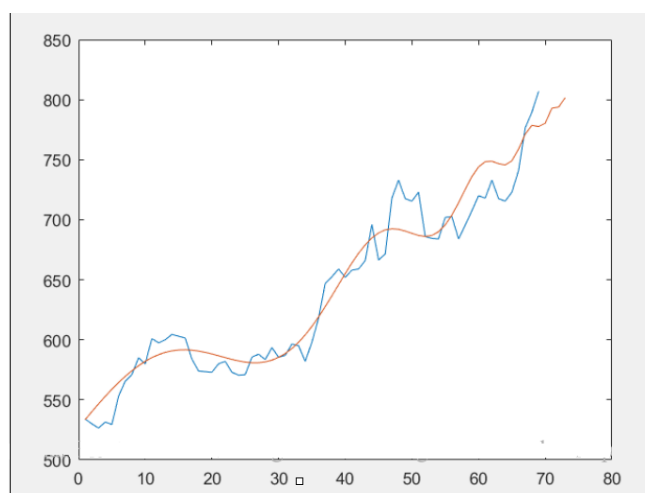


Figure 3. LPPL model for iron ore futures I2001 price forecast

8. Conclusion

This paper finds the scope of application of the LPPL model through the calculation of different types of assets around the world. Through the empirical research comparing Bitcoin and GEM (2015), it is found that assets with fewer transaction restrictions, better transaction consistency, and no repeated policy disturbances are more suitable for LPPL Model. Through the empirical research of the CSI 300 Index in 2017 and the empirical research of the CSI 1000 in 2018, it is found that the model is more suitable when the investor structure is stable. Collapse after bubble formation is not the only outcome. After applying dozens of assets around the world, it is found that the formation of bubbles does not necessarily burst. A "solid" bubble effect can be achieved by changing the

fundamentals. Through empirical research on apple futures, we found that although the typical LPPL model features appeared during the rise, natural disasters led to production reductions, and apples were supported by fundamentals. After the bubble burst, there was no sharp decline, but a long-term sideways move.

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