

An Anatomy of Stock Market Bubbles

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Supported by the Humanities and Social Sciences Research Youth Foundation of the Ministry of Education in China (17YJCZH248); Featured Innovation Project of Guangdong University of Foreign Studies (17TS12).

Received 14 March 2018; accepted 8 July 2018
Published online 26 August 2018

Abstract

With the ups and downs of the international financial markets, it is necessary to deepen the understanding of the stock market bubbles. This study does an anatomy of stock market bubbles from different aspects. First, the definitions are roughly bunched into two categories --- the so-called conditional and comparative definitions are mainly based on a deviation from a fundamental value, while the statistical and structural definitions are based on the existence of a strong change of regime. Associated with the review of mechanisms for fueling stock market bubbles, it further presents the varying theoretical models, as well as the detection and prediction methodologies. Finally, three main directions for interdisciplinary and collaborative researches are proposed.

Key words: Bubbles; Stock market; Positive feedback; Super-exponential price

Zhang, Q., & Wu, B. Y. (2018). An Anatomy of Stock Market Bubbles. *Canadian Social Science*, 14(8), 36-44. Available from: <http://www.cscanada.net/index.php/css/article/view/10513>
DOI: <http://dx.doi.org/10.3968/10513>

INTRODUCTION

In recent years, with the ups and downs of the international financial markets, the global economy has

entered a long period of adjustment. The volatility of financial markets under the comprehensive influence of macro-microeconomic factors has become increasingly complicated. As the rapid development of internet technology and the trend of financial mixed operations become more apparent, financial products exhibit diverse and virtualized features. The volatility spillover, linkage and agglomeration effects caused by capital and leverage continue to escalate. Given that the market is imperfect, bubbles can exist even when the stock market is dynamically efficient. In light of this, it is of great importance to develop a credible early warning system to signal the timing of specific countermeasures that could effectively identify the stock market bubbles in such a complex and uncertain environment.

With the rapid development of information technology, a financial eco-system based on the information flows among the market participants is gradually being formed. In this context, their decision-making behaviors exhibit high-frequency and real-time characteristics, and the information flows are becoming more pluralistic with full-period immersive interaction. In the face of the huge volume of macro and microscopic financial data with high flow rates and uncertain correlation, data-driven research can contribute to expand the dimension, measurement, depth, and accuracy of data in the empirical research, even can help to detect the trend of rapid price growth, the strong internal correlation and the spillover effects among different markets. However, limited attention has been paid by the scientific community to create a rigorous and robust framework for exploring the evolutionary characteristic, pattern, micro-foundation and mechanism of stock market bubbles. Hence, this study does an anatomy from different aspects to deepen our understanding of the stock market bubbles.

This paper is structured as follows. Section 2 revisits the definition of a stock market bubble. Section 3 discusses the mechanisms for stock market bubbles and

super-exponential price behavior. Section 4 presents the theoretical models. Section 5 sets out the detection and prediction methodologies. Finally, Section 6 concludes.

1. REVISITING THE DEFINITION OF A STOCK MARKET BUBBLE

I wonder how much it would take to buy a soap bubble, if there were only one in the world.

Mark Twain

Even a dive into the literature invariably ends in a bog of definitions of stock market bubble. As suggested by Sohn and Sornette (2017), now we roughly bunch them into two categories.

1.1 Conditional and Comparative Definitions: Based on a Deviation From a Fundamental Value

A conditional definition refers to a bubble as an “information bubble” and cares more about the information sets on which “true value” is presumably based. For instance, a stock market bubble is defined as price movements which are unjustified by information available at the time (Blanchard & Watson, 1982). Since the intrinsic value of a stock is its value conditioned on information available to all traders, if the price does not reveal all information, or traders have different (pooled) information of their economic world, then it is possible for price to deviate from its intrinsic value and an information bubble exists. More emphatically, this definition is more suitable for the situation where “no reasonable future outcome can justify the price” (Asness, 2014).

A comparative definition cares more about the difference between the “fundamental value” and the stock price (or stock index). It is commonly defined as large, sustained mispricing of stock (or stock index), in which the price is driven above the fundamental value (Diba & Grossman, 1988b; Garber, 2001; Barlevy, 2007; Brunnermeier, 2008). This kind of definition could be extended to “negative” bubble, where the stock price (or stock index) is allowed to be driven below the fundamental value (Wu, 1997; Michaelides, Tsionas & Konstantakis, 2016). Furthermore, if it allows for under-valuations as well as over-valuations but adds a size requirement, the bubble can be identified as “periods of substantial mispricing” (Temin & Voth, 2004). However, for this definition, some problems stem from the use of “fundamental value”, which is a highly contingent concept of its own, and sometimes is not observable.

1.2 Statistical and Structural Definitions: Based on the Existence of a Strong Change of Regime

A statistical definition focuses on the observable price trajectory, time-horizon or other observables such as trading volume, without reference to theoretical notions (i.e., fundamental value). According to Kindleberger and Aliber (2011), a stock market bubble can be regarded as

an upward price movement over an extended period of fifteen to forty months that then implodes. The bubble is typically associated with an ex post description of a dramatic stock price (or stock index) increases, followed by a reversal of expectations and a sharp decline in price often resulting in financial crisis (e.g., Brunnermeier, 2009). In fact, although most historical notorious stock market bubbles were unsustainable and were followed by sharp price declines after a long maturation process associated with the inflation, it does not require an “implosion” or market crash after the unsustainable price path (Kindleberger & Aliber, 2011).

A structural definition gives a specific explanation for the state of stock market. More specifically, it is easy to see that a stock market has changed structurally when it transfers from the bubble’s expansionary phase that was gradual and protracted to the bubble’s recessionary phase that was sudden and sharp. When the market has entered a completely new regime, it is entirely driven by market sentiment and no longer reflects any real underlying value (Sornette & Cauwels, 2015). But, history shows that not all stock market bubbles are alike. When the bubbles are fueled by credit booms, they increase financial crisis risks. Besides, upon collapse they tend to be followed by deeper and longer lasting recessions and slower recoveries (Jordà, Schularick & Taylor, 2015). In Minsky’s framework, five phases are provided to characterize bubbles and the associated bursts, that is, the evolution is from an initial displacement, to a boom phase, followed by a phase of euphoria, a phase of profit taking, and a panic phase (Brunnermeier & Oehmke, 2013).

2. MECHANISMS FOR THE STOCK MARKET BUBBLES AND SUPER-EXPONENTIAL PRICE BEHAVIOR

Through a literature review, we found that the mechanisms for fueling bubbles have been studied from the technical, instrumental, rational, behavioral and other perspectives (Stiglitz, 1990; Bhattacharya & Yu, 2008; Kaizoji & Sornette, 2010; Hüslér, Sornette & Hommes, 2013; Leiss, Nax & Sornette, 2015; Sornette & Cauwels, 2015; Michaelides, Tsionas & Konstantakis, 2016; Sornette, 2017; Sornette, Cauwels & Smilyanov, 2018). Different strands of literature emphasize different mechanisms, mainly including: the intrinsic financial instability due to the credit expansion cycle (Minsky, 1993), financial accelerators (Corsi & Sornette, 2014), introduction of breakthrough technologies or financial innovations (e.g. Perez, 2009)), agency problems, rational bubbles due to short-sale constraints (Allen, Morris & Postlewaite, 1993) and its interplay with overconfidence (Scheinkman & Xiong, 2003), informational frictions between noise and rational traders (De Long, Shleifer, Summers & Waldmann, 1990) or among rational traders

(Abreu & Brunnermeier, 2003), asymmetric information on hedging strategies, stop-loss orders (Sornette & Cauwels, 2015), heterogeneous beliefs (Harrison & Kreps, 1978; Hong & Stein, 2003; Scheinkman & Xiong, 2003; Xiong, 2003), psychological biases and over-optimism (Shiller, 2009; Kindleberger & Aliber, 2011), breakdown of “psychological galilean invariance”, imitation and herding (De Marzo, Kaniel & Kremer, 2008), speculating (Scheinkman & Xiong, 2003; Greenwood & Nagel, 2009), riding (Abreu & Brunnermeier, 2003; Temin & Voth, 2004), greed (Kindleberger & Aliber, 2011), mimetic contagion and convention (Orléan, 1995; Johansen & Sornette, 1999).

At a higher level, above mechanisms might lead to the positive feedbacks. And the dynamics of stock price (or stock index) are the outcomes of amplifying (or pro-cyclicality) in cumulatively positive feedbacks and dampening (or counter-cyclicality) in cumulatively negative feedback among traders. Positive feedback is the dominant mechanism for the dynamical signature of stock market bubbles, which is generated by traders that create nonlinear positive feedback in the valuation of assets and unsustainable growth (Koutmos & Saidi, 2001). Moreover, the positive feedbacks can also lead to “negative bubbles” in the form of the transient accelerating price falls.

As inspired by the dynamics of positive feedback, many historical stock bubbles were started with a phase of price growth or decay faster than exponential, thus being referred to as “super-exponential” (Sornette & Cauwels, 2015). Besides empirical observations, a controlled price formation experiment also demonstrates with high statistical significance that laboratory bubbles have a tendency to show super-exponential price behavior, resulting from the existence of positive feedback amplifying past price increases into even faster growth rates. This behavior seems particularly relevant to markets where stock prices are only loosely connected to fundamentals (Hüsler, Sornette & Hommes, 2013).

Due to the super-exponential price growth constitutes a transient deviation from a long-term trend, it provides a clear signature of a non-sustainable regime whose growing return at the same time embodies and feeds over-optimism and herding through various positive feedback loops. This feature allows the association of these transient super-exponential regimes with what is usually called a “bubble” (Kaizoji & Sornette, 2010). The end of bubble signals the end of the transient super-exponential growth, and the transition to a different regime, with unspecified characteristics. Consequently, when positive feedback is involved and the rise of returns is faster than linear, the super-exponential acceleration of price is even more pronounced. It also corresponds to the market expectations of super-exponential growth until the irrationally exuberant market typically precedes a crisis and the risk attitudes in the market are totally changed (Leiss, Nax & Sornette, 2015).

3. THEORETICAL MODELS

Associated with above mechanisms, it may instead be useful to model the stock market bubbles and present the interpretation.

3.1 Rational Models

The theory of rational bubbles provides an elegant and powerful way to think about real-world bubbles. As the workhorse model of bubbles in macroeconomics, the rational models assume that there can be rational deviations of the stock price from intrinsic value. The market price is equal to the discounted flow of future dividends plus an additional bubble term reflecting extrapolative price behavior.

Samuelson (1958) started the theory of rational bubbles by showing that, in an endowment economy with overlapping-generations, rational bubbles could offer a remedy to the problem of dynamic inefficiency. Tirole (1985) extended these insights to the classic Diamond’s (1965) neoclassical growth model, asserting that a rational bubble can be present with an infinite succession of overlapping generations of asset holders with finite planning horizon, as long as the growth rate of the economy is greater than or equal to the required rate of return. In the spirit of Blanchard and Watson (1982) or Tirole (1985), the main approaches of empirical studies that seek to test for the presence of rational bubbles rely crucially on an infinite horizon setting. Weil (1987) studied the existence of stochastic bubbles in general equilibrium, extending to the case of bubbles that have a constant, exogenous, probability of collapsing. Within this overlapping-generations framework but infinite planning horizons, the particular solution to the linear expectational difference equation is defined as the market fundamental component of the stock price, while the rational bubbles component can be represented as a general solution (Diba & Grossman, 1988a). However, some models of rational bubbles with infinite horizon are irrelevant or simply cannot represent reality because the bubble exists only because there is a non-zero payment at infinite time (Schatz & Sornette, 2018). In other words, these models are completely artificial, even if they have been studied a lot.

Early works regarding the rational bubbles focused on deterministic bubbles, which rely on the explosive feature of the (conditional) bubble path, display a very predictable behavior and never burst. The new generation of rational models attributes the existence of bubbles to various incentive problems faced by key economic agents. Using Bayesian methods and modeling recurrent bubbles in an infinite-horizon Dynamic Stochastic General Equilibrium (DSGE) framework, stock market bubbles can also be treated as a latent variable and emerge endogenously through a positive feedback loop mechanism supported by self-fulfilling beliefs (Miao, Wang & Xu, 2015). Along this direction, bubbles can be regarded as pyramid schemes, whose contributions are voluntary and entitle

the contributor to receive next period's contribution (Scherbina & Schlusche, 2014).

3.2 A Phenomenological Langevin Equation Model

The Langevin equation model is based on an identification of the different processes influencing the demand and supply. This kind of mathematical transcription emphasizes the importance of feedback effects of price variations onto themselves. Risk aversion is responsible for the sudden collapse of speculative bubbles and crashes when it leads to self-reinforcing "panic" and an "up-down" symmetry breaking (Bouchaud & Cont, 1998).

3.3 Behavioral Models and Agent-Based Models

Behavioral finance theory, in contrast to the efficient markets theory, places the emphasis on explaining the empirical evidences related to the rise and deflation of stock market bubbles, such as, attributing them to cognitive biases that lead to groupthink and herd behavior. Using the freedom of departing from perfect rationality and behavioral agent-based model, the financial phenomena and anomalies can be comprehensive through two buildings blocks: limits to arbitrage and psychology (Barberis & Thaler, 2003).

Behavioral models capable of capturing bubbles can be roughly classified into four categories. The first class of models incorporates the influence of short sale constraints in the presence of diverging investor beliefs. The second class assumes that a group of feedback traders form their trading demands based on the past price movements. The third class assumes that traders suffer from the self-attribution bias, pay attention to public signals that confirm their priors, and dismiss that contradicted signals as noise, which leads to an overreaction in prices (Daniel, Hirshleifer & Subrahmanyam, 1998; Gervais & Odean, 2001). The fourth class combines the representativeness heuristic that leads them to overreact to potentially uninformative but attention-grabbing news, with the conservatism bias that lead them to underreact to update their faulty models with relevant signals (Scherbina & Schlusche, 2014).

Among many theoretical models, the minority game model established by Challet and Zhang (1997) can capture the characteristics of adaptability, heterogeneity and feedback, and thus became an important paradigm for studying complex adaptive systems. The adaptive belief system proposed by Brock and Hommes (1997; 1998) can describe the process of interaction and co-evolution between the price and investors' trading rules. Chiarella and He (2003), Anufriev and Panchenko (2009) constructed a model composed of bounded rationality and heterogeneous agents, which exhibited complex nonlinear dynamics that can explain stylized facts. In 2012, Chen, Chang and Du (2012) reviewed 50 agent-based models and found that there was no model that could explain all "abnormal" phenomena in the market,

and believed that heterogeneity, learning mechanisms, and interaction mechanisms were the three basic elements for the construction of such models. Agent-based models are particularly well-suited to describe bubbles and crashes and to analyze the role of herding among some market participants. However, the adoption and the generalization of the agent-based models are drastically hindered by the absence of general reliable operational calibration methods (Fievet & Sornette, 2018).

3.4 Experimental Tests on Bubbles

Because of the difficulty in measuring the fundamentals in field data, some empirical analysis of stock market bubbles are carried out in experimental studies. These studies set up artificial markets with finitely lived stocks and observe that price bubbles arise frequently. A main advantage of laboratory experiments is that they allow the researchers to isolate and test specific mechanisms and theoretical arguments, while some uncertainties are eliminated. For example, multiple agents can be endowed with stocks that are defined to have a finite lifespan and a known probability distribution of dividends. One main line of researches in this area is concerned with backward induction (Sunder, 1995). The experiments are even designed with agent-based modeling for computer simulations and/or analytical theory (Smith, Suchanek & Williams, 1988; Huang, 2015). At present, the well-known computational experimental platforms such as Swarm, Repast, Ascape, Mason, Netlogo, and Starlogo have been successively established in the world. This fact lays a solid foundation for simulating the evolution of the artificial stock market. However, the major results are the discovery of very strong bubbles or show diverse emergent properties of the laboratory stock markets.

3.5 Log-Periodic Power Law Singularity (LPPLS) Model

From the perspective of physics, the Johansen-Ledoit-Sornette (JLS) and the Log-Periodic Power Law Singularity (LPPLS) models (Johansen & Sornette, 1999; Jiang et al., 2010) do not rely on the assumption of traditional financial models for the fundamental value, but define the bubble as unsustainable growth over a period of time. The bursting of bubbles is regarded as a phase change experienced by stock markets, while the dynamics of stock price (stock index) characterized by a power law decorated with log-periodic oscillations, leading to a finite-time singularity at a critical time. It not only considers the faster-than-exponential growth in stock prices decorated by accelerating oscillations as the main diagnostic of bubbles, but also embodies a positive feedback loop of higher return anticipations competing with negative feedback spirals of crash expectations. In fact, the LPPLS model has been applied successfully to predict a large variety of historical bubbles in many different stock markets, which breaks the traditional consensus that bubbles can only be tested afterwards (Jiang et al., 2010).

4. DETECTION AND PREDICTION

4.1 Econometric Tests of Rational Bubbles

When examining the existence of stock market bubbles, most econometric methodologies that rely on rational expectations theories are differentiated by varying testing techniques.

4.1.1 Variance Bounds Tests

Variance bounds tests for equity prices were initiated by Shiller and LeRoy and Porter in 1981. Shiller's test (1981) only generates point estimates of variances so statistical significance cannot be tested, whereas LeRoy and Porter (1981) treat equity prices and dividends as a bivariate process, constructing estimates of variances with standard errors. Although a violation of the variation bound might be due to the presence of bubbles, this kind of tests is a test of the present value model and rejection (even when there are no econometric problems) may be due to any assumption or failure of the model. And they need aggregated data (i.e. indices) over a long period of time to avoid small sample bias. Having such problems in implementation make these tests unsuitable for bubbles.

4.1.2 West's Two-Step Tests

West's two-step test has explicitly put a bubble in an alternative hypothesis, and would "find" a bubble by eliminating all other alternatives by appropriate specification tests, based on Euler's equation of no arbitrage process and the autoregressive process of dividends that governs the market fundamental stock price. It is designed to tackle the simultaneous test of model specification and bubbles problem by testing the model and no-bubbles hypotheses sequentially. But due to factors other than a bubble, there still exists the issue about the interpretation of the rejection of the no-bubbles hypothesis. Again, it might exhibit significant size distortions in small samples (West, 1987).

4.1.3 Integration/Cointegration Based Tests

A way to test for the existence of a bubble from the data is to see whether stock prices are stationary when they are differenced the number of times required to make dividends stationary. When one or both conditions are rejected, a bubble is deemed present. This kind of analysis defines a rational bubble to be a self-confirming divergence of stock prices from market fundamentals in response to extraneous variables, and the simulation results supports the conclusion that stock prices do not contain explosive rational bubbles (Diba & Grossman, 1988b). However, Evans (1991) criticized the test by arguing that it was unable to capture a periodically collapsing bubble.

4.1.4 Intrinsic Bubbles

Some researchers measure the bubble component in the price by excluding the intrinsic value of the stock. These include the dividend discount model, the free cash flow model, and the macro econometric model. However, as

the definition in section 2.1, most of these test models regard the part of the stock price that deviates from a fundamental as a "bubble" and cannot avoid assuming a fundamental. However, because these test methods are essentially a joint test, the defined fundamental model may be biased. Even if the hull hypothesis is rejected, the detection of bubbles cannot be achieved with a satisfactory degree of certainty.

Bubbles may or may not be correlated with fundamentals. If they are uncorrelated with fundamentals, they must grow exogenously at an expected rate per period to be arbitrage free. Froot and Obstfeld (1991) suggested a different formulation of bubbles, in which the bubble was identified as a deterministic function of dividends and real price. They qualified a bubble when a nonlinear relationship between prices and dividends is found statistically significant, while assuming that the log-dividends follow a martingale.

4.1.5 Bubble as an Unobserved Variable

The problem with above econometric bubble detection tests is the difficulty of evaluating whether the implied properties of the bubble are reasonable or not, due to some tests do not produce a statistically significant of a bubble component or a bubble process. They may simply diagnose a misspecification of the model itself and not the genuine presence of a bubble, or be vulnerable to the criticism on the assumed process. Wu (1997) took the "bubble as a deviation from the presented value model" detection scheme seriously and presents estimated values of the bubble under this interpretation. By using the recursive Kalman filter method on a model where price differences are regressed against a number of present and lagged dividend differences, a bubble can be estimated as a non-directly observable component of the price.

4.2 Regime-Switching Tests

Considering the expanding and collapsing periods of the bubble as different regimes, as the definition in section 2.2, the bubble detection can be shifted to test the regime-switching behavior, such as, a change from a random walk to an explosive process by Chow-type break test (Homm & Breitung, 2012). In these regime switching tests, they are designed to detect the existence of transient regimes of market growth characterized by strong returns, followed by "collapsing" phases of negative returns. However, the problem of these empirical implementations is that they fail to reject the null hypothesis of no regime switching (and therefore of no bubble) (Van Norden, 1996; Van Norden & Vigfusson, 1998), especially for the detection of a bubble requires it to be followed by a change of regime to the "collapsed" state.

4.3 Sup ADF Test and the Generalized Sup ADF (GSADF) Test

To identify the stock market bubbles and give an early warning, a number of approaches that of detecting a

transition from a stationary process are mapped to a unit root process, or even to a “mildly explosive” process (Phillips, Wu & Yu, 2011; Phillips, Shi & Yu, 2015), and then back to a stationary process. Specifically, the conventional augmented Dickey-Fuller (ADF) unit root test, involving scanning different time windows with reduced variables associated with a mildly explosive process, provides a method to construct early warning indicators (Taipalus, 2012).

A sup ADF (SADF) test provides a method for bubble detection based on sequence of forward recursive right-tailed ADF unit root tests. The generalized sup ADF (GSADF) method extends the sample coverage by using the double-sup criteria of recursion over a feasible range of flexible windows, which is able to detect potential multiple bubbles and thus overcomes the weakness of the SADF test. The SADF and GSADF tests for the existence of speculative bubbles provide a kind of appealing statistical method for determining when a stock price is exhibiting explosive behavior, and measure the probability that bubble behavior is present (Phillips, Wu & Yu, 2011; Phillips, Shi & Yu, 2015).

4.4 LPPLS Fitting Technique and Probabilistic Forecasts

Sornette and his collaborators have proposed that stock market bubbles can be identified as “super-exponential” price processes, punctuated by bursts of negative feedback spirals of crash expectations, which can be parametrised by the so-called Log-Periodic Power Law Singularities (Johansen, Sornette & Ledoit, 1999; Hüsler, Sornette & Hommes, 2013; Leiss, Nax & Sornette, 2015; Sornette & Cauwels, 2015; Sornette, 2017). Based on the LPPLS model, the explosive bubble detections can be performed by detecting the log-periodic behavior with Lomb spectral analysis of detrended residuals and (H,q)-derivative of logarithmic indexes. By sampling many intervals as well as by using bootstrap techniques, the inherently probabilistic predictions reflect the intrinsic noisy nature of the underlying generating processes, and provide probabilistic estimations on the time intervals of bubble end and the change of bubble regime (Jiang et al., 2010).

4.5 Historical and Implied Volatility

Some studies declared that the historical volatility of stock price time series tend to increase before a crash (Jarrow, Protter & Shimbo, 2010; Jarrow, Kchia & Protter, 2011; Protter, 2013). Vogel and Werner (2015) suggested that the implied volatility leads historical volatility and that a rise in the implied volatility foreshadows a bubble or crash condition. However, by investigating the dynamics of volatility during the individual forty historical bubbles and its aftermath, Sornette, Cauwels and Smilyanov (2018) found that the volatility is not a reliable indicator of the maturation towards the end of a bubble and of its impending crash, due to the inconsistent behavior of the volatility.

4.6 Algorithm and Data-Driven Prediction Model of Financial Time Series

Data-driven prediction models, concerning the noisy, dynamic, complex, and high-dimensional data structures in stock markets, are mainly based on data mining and artificial intelligence algorithms, such as hidden Markov models, artificial neural networks, fuzzy logic, evolutionary algorithms, and machine learning. De Oliveira and Ludermit (2016) proposed a hybrid algorithm by combining the exponential smoothing, ARIMA model, the artificial neural network model and the support vector machine. The empirical results showed that the hybrid algorithm has certain accuracy and effectiveness in predicting financial time series. Similarly, although evolutionary algorithms are often used in the prediction models of financial time series, most of them are combined with other algorithms to improve the accuracy and stability of the prediction results. Deep learning can even help to discover intricate structure in large data sets by using the backpropagation algorithm, and allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction (LeCun, Bengio & Hinton, 2015).

While emphasizing on the presence of non-linearity in bubbles, it can employ artificial neural networks and many algorithms for the accurate and early detection of bubble formation, which is structured upon a rigorous and robust mathematical and econometric framework (Michaelides, Tsionas & Konstantakis, 2016).

CONCLUDING REMARKS

Through the literature review, we found that the evolutionary behavior of stock market bubbles has the typical characteristics of complexity, such as long memory, positive feedback and fluctuation accumulation. When the growth or decay of stock prices (stock indexes) caused by positive feedback mechanism is not sustainable, the external disturbances will trigger the system’s inherent instability and cause a phase change or a self-correction of market. The resulting market’s self-correction often manifests itself as the bursting of the bubble or the crash (Sornette & Cauwels, 2015). Most collapse of stock prices (or stock indexes) and the moment of crisis are the turning points of the market transition from prosperity to recession. These phenomena essentially embody the endogenous dynamic mechanism of the system that develops from stability to instability.

Based on above discussions, in order to mine real-time information flows to explore the evolutionary rules of stock market bubbles and detect the possible critical times, it is necessary to propose corresponding solutions through interdisciplinary and collaborative researches (Battiston et al., 2016). We thus propose three main directions as below.

A. Studies Related to “The Micro-Foundation of Stock Market Bubbles Formation”

From the complex system perspective, stock market bubbles can be regarded as one kind of financial anomalies. Agent-based modeling method widely advocated by computational finance is an important method of applying the theory of complex systems to financial practices. The model it constructed portrays the behavioral characteristics of micro agents, which can simulate and reproduce a variety of financial anomalies and explain the macro-market behaviors (including the stock market bubble phenomenon). However, although a number of models and empirical tests have examined the micro-foundations of the formation of stock market bubbles, they have not included the common evolutionary rules and lack the analysis of the out-of-sample prediction capabilities of existing models. Therefore, it is necessary to further examine the changes in decision-making behaviors and cognitions of agents in the new era (such as the psychological alienation, the changes of their learning mechanisms and interaction mechanisms, etc.), so as to enhance the learning efficiency of this kind of models for real market operations. Ultimately, the framework can be improved with the gain of the capability of generalization and reliability.

B. Studies Related to “the Test on Stock Market Bubbles and Detection of Critical Times”

Many scholars have applied the theory and tools of multiple disciplines to the quantitative research of stock bubbles and have made many useful explorations. But most studies are to test the existence of bubbles in specific stocks with different analytical frameworks of various methods. While few studies are data-driven to identify the evolutionary states of bubbles, it is difficult to give an early warning of the critical time of bubble bursts, or to provide a strong support for the risk management in the stock markets. Therefore, it is necessary to grasp the changes in the internal logic of the market from the perspective of macro-prudential supervision, clearly put forward the evolutionary mechanism of bubbles, explore multiple theoretical paradigms in-depth and use a variety of methods for cross-validation. It would be helpful to provide more accurate way to dynamically monitor the accumulation of systemic risks caused by stock bubbles.

(3) Studies related to “the data-driven prediction model of financial time series”

Under the background of the rapid development of informatization, the wide application of “data paradigms” has become an important change in modern scientific researches. In view of the trend of different types of data fusion, how to select suitable models and algorithms needs further exploration. A single statistical method is more suitable for the processing of stationary univariate time series, while the intelligent computing technology exhibits relatively superior performance when dealing with multivariate high-dimensional financial data. If the

stock market is treated as a complex system, the price time series is the discrete data generated by this system. Then the analysis of the underlying laws cannot just rely on a certain model, but should increase the dimensions, granularity and accuracy of the data. Besides, new model frameworks and systems for early warning should be built by data driven methods, while the attention should be transferred from the significance of parameters to the structure and dynamic characteristics of them. Furthermore, corresponding policy suggestions should be proposed to improve the speed of market information transmission and the transparency of market transactions, promoting the sound operation of the price mechanism and achieving effective allocation of resources in the stock market.

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