THE EVOLUTION OF COMPLEX SYSTEMS THEORY AND THE ADVANCEMENT OF ECONOPHYSICS METHODS IN THE STUDY OF STOCK MARKET CRASHES

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ABSTRACT. This paper traces the origin and development of the complex systems theory over the course of history, up to its latest advancement in the study of stock market crashes. The trail of the theory's fuzzy evolution is expansive that covers the ground of the complexity epistemology, natural science and computer science. A meticulous review is undertaken to distinguish the complex systems theory from another seemingly overlapping theory of the chaos systems. The paper recounts how researchers from cross-disciplines, particularly from the econophysics have banded together to consolidate and diffuse the application of the complex systems theory in the economics and further discusses the methodological contribution of the econophysics in the area of stock market. To date, the complex systems theory and the methodologies from the econophysics are well-established as the frontier for studies in stock market bubbles and crashes.

Keywords: complex systems, econophysics, stock market crashes
JEL: B5, G1, N2, P4

Introduction

In recent decades, the discipline of economics has experienced its most significant evolution in over a century. This evolution signifies an extensive transformation in the epistemological and empirical direction of the field (Beinhocke, 2006). The paradigm shift is owed mainly to the amalgamation of theories and methodologies originated from the natural sciences. One of the more prominent crossovers is the complex systems theory, which is widely applied in the financial economics of late. The theory is introduced by the interdisciplinary econophysics and such development could be catalysed by the mixed results produced with use of the conventional econometric approaches in resolving issues pertaining to financial economics. This paper aims to trace the history of the complex systems theory and examine the latest methodological innovations brought about by the econophysics, particularly in the study of stock market crashes. An extensive review from the alternative perspective is important as stock market crashes have long been considered as merely outliers from the Gaussian's

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econometric viewpoint (Johansen & Sornette, 1998a; 1998b) albeit their devastating effect on the economy.

According to Merriam Webster (2002), the meanings of complex are as follows: “1) a whole made up of interrelated parts; 2) a group of obviously related units of which the degree and nature of the relationship is imperfectly known; and 3) hard to separate, analyze, or solve.” A system according to the dictionary is defined as follows: “1) a regularly interacting or interdependent group of items forming a unified whole; 2) a group of interacting bodies under the influence of related force; and 3) a group of objects or an organization forming a network.”

Combining the two root words, complex systems can be interpreted as a network of interacting simple units with indistinctive relationships among themselves. These systems are obscure if they are analysed separately; however, when analysed as a whole, the aggregate behaviour of the simple units emerges in an orderly pattern and takes the form of a system. Each of the linked units in the system has its own capacity of self-organising that inaugurates new aggregated behaviours of the whole system. Therefore, the system is continuously evolving to adapt to new environments and has the attribute of involuntary feedback loops.

The theory of complex systems in relative terms is defined as an area of study that is set right at the boundary of chaotic order and deterministic order (Kauffman, 1993). In contemporary terms, the complex systems theory is a system that comprises many individual components that act according to embedded reaction functions, which are usually assumed to be the same for every individual. The components are described as cellular automata. The salient characteristic of such systems is that their dynamic properties cannot be derived analytically from the knowledge of the reaction functions of the components. The only recourse in studying their outcomes is to resort to dynamic simulations, usually conducted with digital computers.

Problems that are concerned with the self-organising individual units that give rise to a system are not easily discernible and hard to solve. Such a system is usually dynamical in order or chaotic in nature, and the structure of the system could be hierarchical due to the emerging behaviour from the micro level of individual units. The intricacy of the emerging pattern often prevents the prediction or forecasting of the systems directly from the simple units’ specification (Wolfram, 2002).

The concept of complex systems can be traced back to the work of Henri Poincare, a mathematical philosopher in the late nineteenth century who introduced nonlinear mathematical solutions after he discovered the fundamental limits of conventional equations. Through nonlinearity, he illustrated how minor effects could cause far-reaching impacts to end results, an idea which years later developed into the chaos theory. He famously worked on the “three body problem,” a simple system that gives rise to unpredictable trajectories that defy analytic description owing to the phenomena of three mutually attracting bodies being in motion together. He discovered that there can be orbits that are bounded and non-periodic and that do not devolve to a stable cycle. This upset some of the presumptions of Newtonian mechanics because he showed that it was mathematically impossible to derive equations to predict the trajectories for even a simple system that contains only three planets interacting in nonlinearity (Taleb, 2007).

The epistemology of deterministic order came under close scrutiny in the 1960s following the translation of Karl Popper's *ogik der Forschung* (*The Logic of Scientific Discovery*) on the falsification of theories into English in 1959. The original work was published in German in 1934 (Popper, 1959). The "Popperian falsificationism" had spurted many ground-breaking explorations by philosophers, scientists and academicians in search of alternative hypotheses and theories to explain the complex phenomena.

Throughout the 1960s, literature by Edward Lorenz (i.e., *Deterministic non-periodic flow, The nature and theory of the general circulation of atmosphere and Three approaches to atmospheric predictability*), the father of the chaos theory who coined the term "the butterfly effect," was widely acknowledged as the impetus to the conceptualisation of the chaos theory. On the other hand, a series of papers by Friedrich A. von Hayek, a Nobel laureate (i.e., *Rules, perception and intelligibility; Kinds of rationalism and The theory of complex phenomena*), laid the foundation for the complex systems theory in the same period (Wible, 2000; Zeidan, 2007). Nevertheless, some literature proposed that the seed of the chaos theory was sown earlier in 1959 by Andrey Kolmogorov, who found the solution to the long-standing conundrum of entropy of the dynamical system in the ergodic theory by applying the thermodynamics approach (Sinai, 2010).

The two themes of complex systems and a chaos system used in the modelling of social and ecological phenomena are axiomatically distinct, but they tend to coalesce. Notably, there was no clear distinction in explaining the phenomena of complex systems and a chaos system in the early literature. Work that gave specifications to the two systems might not have existed when the paradigm shift of non-deterministic order and nonlinear dynamics was in the infancy stage.

As a comparison, works by Lorenz and Kolmogorov were mathematically predominant, whereas works by Hayek were inclined to philosophy and epistemology on complexity. Their works had gone into the book of history as some of the most important contributions to a new branch of knowledge that was almost unfathomable prior to their era. They had brought about a whole new dimension in researching and resolving problems that are seemingly chaotic and highly complex as the theories' namesake.

The subsequent decades of the 1970s and the 1980s saw a significant rise in the acceptance of these theories, especially among mathematicians. Academic courses about these theories were even made available at universities (Hogkin, 2005). In the early 1980s, Stephen Wolfram embarked on research with computer simulation to observe the evolving behaviour of computer systems. This research was based on a very simple configuration of sequences of zeroes and ones, and it was known as cellular automata. He discovered that a simple simulation rule with simple binary values within a system could generate a seemingly chaotic order after many successions of iteration. However, through the extremely complicated outline, regularities of fractal patterns would emerge eventually, forming a similar looking large fractal when combined as a whole. Wolfram named his discovery as the complex systems theory (Wolfram, 1984; 1988). His progressions on the origins of complexity thereafter had helped to establish a solid foundation for the theory to gain recognition and flourish into different fields (Stephen Wolfram, n.d.).

Over the following two decades, more meticulous descriptions of the characteristics of the chaos theory and the complex systems theory had emerged. However, the boundary between the two theories was still very vague. The distinction between the two systems was rather ambiguous, as their specifications often overlapped, but the chaos theory at that juncture was more clearly defined compared to the complex systems theory. As noted previously, Stuart Kauffman, one of the most prominent biologists of the modern era, famously termed complex systems as an order "at the edge of chaos," drawing a clear distinction between the two theories (Kauffman, 1993).

Wolfram (2002) in the synthesisation of his life's works, "A New Kind of Science," treated the chaos theory and the complexity theory as two different entities and used the term complex systems theory and complexity theory interchangeably. On the other hand, other more recent literature considered the chaos theory as a subset of the complex systems theory (Wible, 2000; Kaneko & Tsuda, 2001; Yu, 2006, Cencini, Cecconi & Vulpiani, 2010).

According to Kaneko and Tsuda (2001), the cause of ambiguity in the definitions of complex systems is attributed to its wide appeal across many fields of studies because the characterisations for the theory are conceived rather arbitrarily in each respective field based on the needs and interests of each field. It was noted that some researchers even perceived that assigning a set of unequivocal specifications for the complex systems theory would inhibit the development of their studies. On the contrary, other researchers advocated the need for clearer specifications to the theory, as not all systems with complicated orders are complex systems.

Meyer (2011) concurred and stipulated that over the years, the features used to describe the complex systems theory have been expanding owing to its wide application across research disciplines. Taken from different contexts, such as biology, physics, computer science, sociology and economics, the combination of features for complex systems are becoming more diverse, suited accordingly to the respective subjects.

Onnela (2006) also underscored the growing acknowledgement of the complex systems theory as a discipline that bridges the gaps between various well-established sciences, such as chemistry, physics and biology, and its increasing influence that transcends the boundaries of natural science into areas such as economics, psychology and social science.

In the early days, the complex systems theory was generally more prevalent in the areas of computer science and biology and to a lesser extent in sociology and economics, whereas the chaos theory was more widely applied in mathematics, physics and, to some extent, economics. Of late, the complex systems theory has established a firm footing in economics, particularly in financial economics (apart from maintaining its inherent influence in natural sciences and mathematics).

1. Complexity Economics

It is prevalent for economic theories and hypotheses for empirical studies to be derived on the notions that the economy is of a deterministic order, linear and founded upon a static equilibrium system bounded by a restrictive set of assumptions. The contradictions between economic theories and the reality of the economy could not be argued any more meticulously than by Beinhocker (2006) and Sornette (2003).

The divergence is ironic in the fact that the view of economics complexity, not dissimilar to the complex systems theory, is not something novel and has been deeply entrenched in the very early works of some very prominent philosophers in economics. For example, Karl Popper, who served as a professor at the London School of Economics in the 1940s and is widely acknowledged as one of the greatest philosophers in the twentieth century, had advocated academia to gain insight into the non-deterministic order in economics (SEP, n.d.) through his work with the problem of induction. Similarly, Friedrich A. von Hayek, a recipient of the Nobel Memorial Prize in Economics and a former professor at the London School of Economics, deliberated rigorously on the need to adopt a holistic approach for economic analysis in a series of papers (Nobleprize.org, n.d.).

Hayek (1964), in his defining forethought on the nature of complexity, articulated that "the phenomena of life, of mind, and of society" are much more complex than that of the natural sciences. The emerging patterns from the complex interactions of the irregular phenomena in economics and social sciences have a higher degree of complexity compared to the patterns that emerged from the complex combination of elements with constant relationships within a deterministic structure in fields like physics. The very fact that economics has to impose the ubiquitous *ceteris paribus* restriction in the construction of theories and the frequent irregularity of outcomes that defy empirical predictions demonstrate that economics is essentially a field of complex phenomena.

Colander (2000) chronicled that economic thoughts initially evolved from informal stories of the political economy in the era of Adam Smith to classical economics, which assigned values for theories. It later progressed to neo-classical economics, which advanced theories in the form of general equilibrium. In the course of time, economics has gradually progressed into the path of natural sciences. Research is focused on simplifying complicated hypotheses into structural mathematical equations, or statistical models and theories are tested on the empirical modelling of historical data.

According to Colander (Ibid.), econometric modelling using macroeconomic variables has in fact accentuated the fallibility of modern economic analyses because most microeconomic and general equilibrium hypotheses do not conform to empirical findings, albeit they share a common theoretical framework.

The economy is much more complex than as perceived by standard economics because the conventional assumption of "far-sighted rationality" of individuals does not hold. In reality, individuals could not rationally handle all aspects of the economy on their own. Institutions were formed to prepare policies to deal with economic issues. These institutions in turn would influence the behaviours of individuals in the economy. Thus, the intervention of institutions on the market, which rarely conform to the rational expectation from the micro level, renders the proposition that the outcome of economy is based on the rational expectation of individuals invalid.

Over the decades, the proliferation of academic writings based on various simplified premises in explaining the complex world has drawn many criticisms. Carroll (2001) in his assertion on *The Epidemiology of Macroeconomic Expectations* echoes the flaw of rational assumption and argues that elaborated mathematical models parametrised with the rational expectation assumption are ineffectual and should be replaced with more realistic and explicit models that capture the dynamism of the economy as a whole. No single set of variables in a model could consistently produce an accurate forecast in the long run. Beinhocker (2006) concurred and noted that early economic theories are too intertwined with the mathematics of equilibrium, requiring the contrivance of highly restrictive assumptions. Such developments have increasingly detached theoretical economics from the real world.

The *Lucas Critique* famously argued that forecasting results derived from econometric models would immediately become obsolete and ineffectual when the optimal decision rules are negated by the policies enforced based on the model itself. Subsequently, the outcome would also systematically feed back into the model and change its original structure (Lucas, 1978).

Echoing the proposition of the *Lucas Critique*, Arthur (1995) argued that the complexity of the economy and financial markets are due to many reasons, and the underlying causes that perpetuated the failure of conventional forecasting are due to the following explanation:

> "Actions taken by economic decision makers are typically predicated upon hypotheses or predictions about future states of a world that is itself in part the consequence of these hypotheses or predictions. When we attempt to model how such predictions might be generated we become stymied: the predictions some economic agents might form depend on the predictions they believe others might form; and the predictions these might form depend upon the predictions *they* believe the original group might form. Predictions or expectations can then become self-referential and deductively indeterminate. This indeterminacy pervades economics and game theory."

One of the classic examples of the *Lucas Critique* is the flawed interpretation that the Phillip curve (i.e., the empirical evidence that showed an inverse relationship between inflation and unemployment) could be capitalised to calibrate the economy to a desired outcome. The structure of the model would change if there was an attempt to artificially perpetuate inflation through monetary policy, as the market would alter the employment decisions based on the inflation expectation (Ljungqvist, 2008).

Another example that illustrates the complexity of the economy is a scenario where the deliberate attempt by the Federal Reserve to prevent the stock market from an overdue correction through monetary easing could instead exacerbate the inflation the market bubble and increase the level of speculation (Vines, 2009). Such an instance would create a chained action-reaction feedback loop between the Federal Reserve and investors. On the one hand, the Federal Reserve would adopt monetary measures to support the market. On the other hand, investors would take advantage of the measures to maximise their return. The emerging behaviour of the stock market would continue until it reaches a tipping point and falls like an avalanche.

2. Evolution of the Complex Systems in Economics

In one of the earliest pieces of literature in this area, Hayek (1964) suggested that the simplification of an abstract pattern with the general statistics methodologies overlooks the actual complexity of phenomena. By addressing problems from an elevated view, the general modelling approaches have a tendency to disregard the changes of the fundamental dynamism of relationships among elements and the organization of structure within a system that occurs over time. Nevertheless, the development of economics took a very different direction, and the seed of complexity epistemology did not gain a footing into mainstream economics until many decades later.

In the mid-1980s, a group of renowned scientists from interdisciplinary sciences came together and established one of today's foremost research centres in complexity sciences, the Santa Fe Institute. The establishment had created a very important foundation for the diffusion and cross sharing of ideas based on the complex systems theory from across disciplines such as physics, chemistry, biology, computer science and economics. Eventually, the institute helped to produce considerable literature that offered alternative theories and quantitative methods in resolving problems based upon the general principle of "inclusiveness and broad perspective, one that comprehends the components of a system but views those elements as actors in a large, interconnected, often unpredictable world" (SFI, n.d.). The Santa Fe Institute compiled some of the most important literature on economics in the context of complex systems, namely the three volumes of "The economy as an evolving complex systems" (2015).

According to Sornette (2003), a complex system must be scrutinised at the appropriate level of specification to capture the essence of the phenomena. Thus, when such a system is being examined, the decomposition of stages or the disintegration of some parts may be required to exclude some details until the right level of conception is achieved. Similarly, Arthur (1995) suggested that all research on complex systems should consider the complexity resulted by the multi-faceted components that adapt or react to the behaviour that emerges within the system. These components would adjust continuously to form a cumulative pattern; on the other hand, a pattern would feed back to the components in a continuous loop. With the exception of the emergence of an asymptotic state or equilibrium, the evolution of the dynamical complex systems would continue perpetually.

Approaches used in research that are based on the complex systems theory are distinctive and wide ranging. The diversity in these approaches is attributed to the wide espousal of the theory by different fields of studies. Methodologies conceived by research that examined their problems from the lens of the complex systems theory depart significantly from the conventional methodologies for all of the respective fields. This put into perspective Hayek's (1964) criticism on the general treatment of complex problems and the importance to rectify such deficiency. Among some of the methods are network models (i.e., Small-World Networks, Random Boolean Networks and Neural Networks), Markov processes (i.e., Levy's Flight and Brownian Motion), bifurcations and diffusion and fractal and cellular automata (Gros, 2008).

In summary, the methodologies used for complex systems research generally allow the information of individual units to be retained as much as possible and permit the dynamism within the structure and the correlation among units to change as required. Some methodologies (e.g., network graphs and fractal and cellular automata) are not developed for the purpose to prove or reject hypotheses like the conventional statistical approaches. On the contrary, predictive patterns are allowed to emerge freely from their initial abstract forms. The main objective is to observe how the complex systems unfold into patterns that allow for some extent of generalization and predictability rather than fitting observations into a predetermined framework or simplifying a phenomenon that is inherently not simple. The flexibility in applying the complex systems theory, albeit not necessarily straightforward, has enabled research problems to be scrutinised from a wider perspective. Methodologies can be developed hierarchically or in stages through simulations or exploratory trials and errors as the observations move along.

3. Complexity of Financial Market and Stock Market Crash

A financial market crash depicts a meltdown of a financial institution, and a stock market crash is commonly described as a brief but abrupt and sharp drop in the price of stocks or stock market indices. These two events commonly occur simultaneously, and the causality could be either way. A stock market crash specifically is caused by panic that sets into the market resulting from overwhelming sell orders all at once. Market crashes have great adverse impacts on the economy and devastating social implications.

A crash that is caused by the inherent market mechanism, such as a speculative bubble, is categorised as endogenous. The most typical definition to a speculative bubble is the prices of stocks (or prices of assets in general) being overvalued due to unreasonable market demand. A crash could entail a prolonged decline in the market that lasts for months or years (Johansen & Sornette, 2008). For centuries, the world had witnessed numerous endogenous crashes, some more devastating than others. Among the most severe and well-documented crashes include the seventeenth century "Tulip Mania," the eighteenth century "South Sea Bubble," the "Great Depression" in the 1930s, the "Black Monday" in 1987, the "Dot Com Bubble" in the late 1990s and the "Subprime Financial Crisis" in the late 2000s (Malkiel, 2007; Pele & Mazurencu-Marinescu, 2012; Vines, 2009). Throughout the course of history, random events created shock to the market, such as the 9/11 tragedy and the breakout of war (i.e., World War I). Such isolated non-economic events that triggered crashes are categorised as exogenous (Fry, 2012; Johansen & Sornette, 2008).

Therefore, a healthy economy rarely triggers a financial crisis or a stock market crash. This perfectly logical and almost universally accepted postulation, nevertheless, contradicts the efficient market hypothesis (EMH) of which most financial literature was built upon. According to Cooper (2008), the EMH assumes that asset prices are always in equilibrium and mirror the asset value correctly at any time, adjusted based on all available information in the market.

Thus, the hypothesis is ignorant to the fact that in most times, a market rally occurs even when stock prices have reached an overly inflated and unsustainable level due to speculative herding (Shiller, 2005). Shiller (2002) and Cross et al. (2005) argued that the widely accepted notion of the EMH is fundamentally flawed because it fails to capture the critical attributes of the market behaviour in reality, and the shortcomings "manifests itself most clearly in the real-world phenomena of non-Gaussian market statistics such as fat-tails, excess kurtosis and volatility clustering (and the corresponding market bubbles and crashes)."

Cooper (Ibid.) highlighted that the brink of stock market crashes throughout history was often marked by the occurrences of sharp increases in market volatility. From a behavioural finance viewpoint, the severe volatility at this juncture is caused by the continuous feedback loop of actions and reactions between cautious traders looking for indicators to pull out from the market and the monetary authority (i.e. the Federal Reserve and central bank) strategizing to keep the market afloat based on the traders' manoeuvres. The market fluctuation, which is based on closely scrutinised information, naturally creates a perception of EMH conformity until the "crash-triggering" information bursts the bubble. Thus, as noted by Arthur (1995), a financial meltdown or a stock market crash is merely the tipping point of the underlying complex phenomena that occur throughout an extended course of time.

White (2008) concurred and noted that in almost all financial crises in history, the overpricing of assets was largely due to the credit expansion measure that follows a crash. The excessive flow of credit into the market enhances the market's optimism and increases risk-taking endeavours among investors. In progression, the asset prices would deviate from the intrinsic asset values and the fundamentals of the economy due to artificial market sentiment. The distortion of economic fundamentals would then manifest in the change of the consumption-investment pattern. At the critical point when the market has transcended the psychological threshold where the realization of an unrealistic level of asset prices catches up with the market expectation, "the whole endogenous process would go into reverse."

When the speculative bubble burst, the economy would be the collateral damage, and adversity would be exacerbated by strain in the financial market due to the prior credit expansion. The feedback loop is once again set in motion but in the reverse direction. White (Ibid.) stressed that most of the forecasting models only describe a section of the whole occurrence. Due to the complexity of the market, a qualitative assessment would seem to be the more appropriate option.

From the angle of econophysics (Sornette, 2003), a stock market crash is similar to the business cycle where the market goes through a cyclical transition over time from a stable state to an unstable state before finally crashing. There are five common stages to the building up of a bubble that leads to an imminent stock market crash: displacement, takeoff, exuberance, critical stage and crash. A stock market crash is caused by the gradual evolvement of the market towards the state of instability due to the progressive ascendance of market price over an extended period of time.

The inherent herding nature of traders in the market, especially during the market's upward trend, reinforces market optimism and creates a loop that further inflates the market bubble. Therefore, the explicit cause that triggers a market collapse is merely superficial. When the market passes the instability threshold, any minor exogenous disruption would catalyse a meltdown. As such, the market is essentially a complex system that encompasses a network of individual systems that are dynamic and exhibit resembling behaviour. The interactions among large integrated units in the overall system usually exhibit self-organizing and sometimes emerging patterns.

4. Latest Development of the Complex Systems Theory in Stock Market

Since the late 1990s, the interest of mathematical physicists in researching economic phenomena has been on a rise. The proliferation of cross-disciplinary research with the application of solutions originated from the physics epistemology has entailed a gradual paradigm shift in the theoretical articulations and methodological approaches in economics, primarily in financial economics. The development has resulted in the emergence of a new branch of discipline, namely "econophysics," which is broadly defined as a cross-discipline that applies statistical physics methodologies (which are mostly based on the complex systems theory and the chaos theory) for economics analysis (Mantegna & Stanley, 2000).

Mandelbrot, a distinguished mathematical physicist who ventured into the discipline of quantitative financial economics, was one of the independent pioneers who developed the random walk theory that stipulates that the movement of stock has no memory (Mandelbrot, 1966, 1968). He then famously contradicted his own ground-breaking theory years later and, through econophysics approaches, provided evidence that the stock market indeed has a long memory in the form of a self-similarity pattern, which he coined as "fractal" (Mandelbrot, 1999a). Mandelbrot's works in the area of fractal and scaling in finance (pioneering literature, i.e., 1997a, 1997b, 1999a, 1999b, 2000, 2001a, 2001b, 2001c, 2001e and 2004) had laid a very important methodological foundation that has become an integral part of most contemporary econophysics research, particularly in the application of the complex systems theory in financial economics.

The conundrum of bubbles and stock market crashes eventually becomes the focal point of econophysicists, leading to a remarkable expansion of the complex systems theory in the study of the stock market. Many novel methodologies from mathematical and mechanical physics were introduced into the economics discipline. Among the novel methodologies that completely departed from conventional econometrics include scale invariance, hierarchical systems, 1/f-noise and the use of a hazard rate in modelling the build-up of a bubble prior to stock market crashes (Johansen, 1997; Stanley et al., 1999). The fundamentals for most of these methodologies were heavily influenced by the fractal concept introduced by Mandelbrot.

Over the last decade, one of the most dominant complex systems methodologies in financial economics is the application of log periodic power law (LPPL) formulae as used in the Johansen-Ledoit-Sornette (JLS) model to predict the building up of financial bubbles. The JLS model (and its variations) is able to capture the signature of an impending bubble-induced crash and estimate the risk of the crash along the timeline with a hazard rate (among the earliest literature, see Johansen, Sornette & Ledoit, 1999; Sornette, Johansen & Bouchaud, 1996; Sornette & Johansen, 1997; 1998).

Johansen, Sornette & Ledoit (Ibid.), the pioneers of the JLS model, interpret the stock market as a trend-chasing system that leaves a trail of positive feedback. In some measure, traders in the market based their trading decision on others' decisions, and the loop of such interactions determines the prices of stocks. Such interactions also lead to the formation of self-similar clusters of traders, which could result in the creation of a market bubble. Therefore, the stock market is considered an epitome of self-organizing complex systems that resembles nature's other "dynamically driven out of equilibrium systems such as earthquakes, avalanches and crack propagation."

The JLS model, which adopts the assumptions of the rational expectation theory (one of the mainstream economic foundations) for its theoretical framework, categorises the traders in the market into the following two groups: rational traders and noise traders. Rational traders are defined as traders who make sound and informed decisions based on market fundamentals, whereas noise traders are defined as irrational traders who collectively imitate the trading decisions of others (i.e., herding behaviour) (Fantazzini & Geraskin, 2013; Johansen, Sornette & Ledoit, Ibid.).

The intricate technicalities (e.g., assumptions, equations and algorithms) of the LPPL frontier are well elucidated in literature by Fantazzini & Geraskin (Ibid.); Johansen, Sornette & Ledoit (Ibid.); Pele (2012) and Pele & Mazurencu-Marinescu (Ibid.). Criticisms of the method can be found in Chang & Feigenbaum (2008a, 2008b), Fantazzini & Geraskin (Ibid.), Feigenbaum (2001) and van Bothmer & Meister (2003);

some of the pioneers responded to these criticisms (Sornette, Woodard, Yan & Zhou, 2013).

Conclusions

A conventional theory in financial economics has evolved over the decades from an Austrian-style of methodological individualism and critical rationalism into a mathematically elegant and technically advanced logical empiricism discipline. Being rooted in the qualitative foundation that strives to explain social phenomena through the assumption of rational behaviour, the development of financial economics has never been able to fully depart from the general economics endeavour of mapping mathematical solutions to phenomena in the market that are rigidly tied up with the constraints of the rational assumption of interacting agents and the *ceteris paribus* assumption of the economic condition.

In general, behavioural finance argued that agents are not always rational when dealing with financial matters in a highly intense market. Volumes of contradicting empirical evidence on the behaviour of the financial market over time suggested that the only constant in the market is change. Thus, it is difficult to assimilate these arguments with the generalization of market efficiency.

One illustration to underscore the argument is that there is no plausible explanation of the conundrum of who buys a share when someone sold it in the market. If everyone has the same rationale and shares the same information, transactions could almost never occur in a market deemed to be "efficient." In addition, the overgeneralization of the financial market has led to the wide espousal of the Gaussian distribution, which is oblivious to outliers when the most devastating events that could happen in the financial market are outliers (i.e., financial crisis and stock market crashes).

Econophysics edges out conventional economics because of its highly efficient nonlinear dynamics methodologies, which are rooted in statistical mechanics, and the common application of hierarchal processes, which is very sensitive in diagnosing problems. The quest of econophysics is to seek answers to problems, emphasising precision without dwelling on a plausible explanation at every phase as characterised by the chaos and complex systems theories, also introduced a new dimension to the field of financial economics.

Of late, econophysics is gradually bridging the gaps between mathematical technicalities and the conventional economic assumptions as shown through the considerable attempts to assimilate the theoretical foundation of economics with econophysics approaches. One such attempt was seen in the development of the JLS model and its subsequent variations. Despite the fact that some of these attempts could be construed as afterthoughts, such efforts are nevertheless commendable, as the synthesis of strength from both disciplines would be beneficial to the continuous evolution of the field.

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