Understanding the complex dynamics of financial markets through microsimulation

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Chapter 3

Modern Approaches to Financial Modeling: Heterogeneity, Irrationality and Interactions

As discussed in Chapter 2, the mainstream financial theory has encountered difficulties in explaining many phenomena in real markets. The disagreements between the standard theories and empirical data have stimulated researchers to re-examine the foundation of the traditional theories. This has enabled the development of some alternative theories related to economic or financial systems and phenomena. In the meantime, a few new research fields have accordingly emerged: Behavioral finance, agent-based simulation, and econophysics. In this chapter, we will present a brief overview of these developments.

3.1 Behavioral finance

Many researchers believe that the problems of the mainstream theories discussed above stem from the unrealistic assumptions adopted in the representative agent paradigm, i.e., agents are homogeneous and rational, in the sense that they make unbiased forecasts about the future in response to new information and correctly make decisions to maximize their expected utilities (Hommes and Wagener (2009)). This has tremendously promoted the development of a new paradigm in finance, i.e. behavioral finance.

Behavioral finance proposes psychology-based theories and concerns bounded rationality as well as behavioral heterogeneity. It attempts to understand investors' reasoning patterns and psychological influences on decision-making processes. Behavioral finance argues that people act rationally only to a limited extent and some financial phenomena can be better understood by using models in which agents are not fully rational. It therefore helps in explaining why and how markets might be inefficient. Barberis and Thaler (2003) contended that the field has two building blocks: Psychology and limits to arbitrage.

Psychology

Based on extensive experimental evidence compiled by cognitive psychologists, researchers have identified some specific forms of irrationality, characterized by some systematic biases that arise when people form beliefs and preferences.

Psychologists have learned that, when forming beliefs, people are overconfident in their abilities and judgments (Weinstein (1980), Alpert and Raiffa (1982), Fischhoff et al. (1977)). In addition, once people have formed opinions, they adhere to them persistently, being reluctant to search for evidence that contradicts their beliefs or treating such evidence with excessive skepticism (Lord et al. (1979)).

Traditional models for understanding asset prices are based on the assumption that investors evaluate investments according to their expected utility (EU) values, the weighted sums obtained by adding the utility values of outcomes multiplied by their respective probabilities. Unfortunately, experiments have shown that people systematically violate the EU theory when choosing among risky investments. Researchers in behavioral finance have further argued that some of the lessons we learn from these violations are central to understanding many financial phenomena. Among all the non-EU theories that have been developed, prospect theory is the most successful one in the sense that it can capture experimental results and is promising for financial applications (Barberis and Thaler (2003)). In fact, it won the Nobel price in economics in 2002.

Developed by Kahneman and Tversky (1979), prospect theory describes how people make choices when facing alternatives with uncertain outcomes, of which the probabilities are known. It considers preferences as a function of 'decision weights', and states that people do not always behave rationally, so that the weights do not always match the probabilities. Specifically, people tend to over-weight small probability events but under-react to those with moderate and high probabilities. It also proposes that agents value gains and losses differently and are more sensitive to losses than gains (loss aversion). In addition, agents assign values to gains and losses rather than final assets. The curve of values against gains is normally concave (risk aversion), while the value curve for losses is commonly convex (risk seeking)

Limits to arbitrage

Another debate between the traditional framework and behavioral finance lies in market efficiency. The former asserts that prices already reflect all known information related to the fundamental values of assets and it is impossible to consistently outperform the market except through luck, while the latter argues that asset prices often deviate from their fundamental values, caused by traders who are not fully rational.

Defenders of the traditional theory claim that rational traders can quickly bring prices back to fundamental values through arbitrage (Friedman (1953)). This is refuted by advocates of behavioral finance who argue that even if an asset has been wildly mispriced, strategies designed to correct the mispricing can be both risky and costly, allowing the mispricing to persist. Therefore, the presence of mispricing does not imply that of a profitable investment strategy, i.e., prices can be very wrong without creating profit opportunities.

A phenomenon related to limits to arbitrage is documented by Harris and Gurel (1986) and Shleifer (1986). When stocks were added to indexes, their prices jumped, even seemingly permanently. In this example, on the one hand, obviously there is mispricing because the prices changed even though the fundamental values did not. On the other hand, the mispricing appears to be persistent, threatening arbitrageurs. For more examples from real markets about this issue, see Barberis and Thaler (2003).

Behavioral finance has been applied to explain many regularly occurring anomalies that are inconsistent with standard economic theories. For example, Siegel and Thaler (1997) tried to resolve the equity premium puzzle[1] by employing prospect theory.

Proponents of behavioral finance has responded to some objections offered by supporters of EMH (efficient market hypothesis). Discussions of this issue can be found in, e.g., Subrahmanyam (2007) and Rabin (1998). One of the objections is that behavioral models are designed to explain specific stylized facts. The response is that behavioral models are based on how people actually behave and explain market phenomena in a better way than traditional ones.

Another criticism is about the experimental and survey based techniques which are used extensively in behavioral economics. Many traditional economists are distrustful of results obtained in this manner due to the difficulty of avoiding systemic biases. The response is that the results are reproduced in various situations and markets and they can help reveal some hidden regularities.

There is also an important objection that behavioral finance presents no unified theory unlike the mainstream one. The reaction is that this may well be true at this point, but models of bounded rationality are both possible and much more accurate in describing behavior than purely rational models. In fact, there has already been a burst of theoretical work modeling financial markets with less-than-fully-rational agents (Thaler (1999)). In addition, traditional theories should not be superior to behavioral approaches because the former are not supported by empirical data; specifically, the former discuss how people *should* rather then *actually* behave. Thaler even predicted that in the not-too-distant future, the term 'behavioral' will be a redundant phrase and economists will routinely incorporate as much behavioral factors into their models (Thaler (1999)).

Some of the work of behavioral finance deals with the understanding of the unexpected phenomena observed in financial markets.

[1]Coined in 1985 by Mehra and Prescott (1985), the equity premium puzzle states that historical real returns from stocks are much higher than the real returns from government bonds, and the differences cannot be well explained by the general utility-based theories. This puzzle has attracted extensive research effort in economics and finance, and is still inspiring ongoing debates since a generally accepted solution remains elusive.

3.1.1 Stock markets

Maymin (2009) demonstrated that investors who evaluate risky assets based on prospect theory will often induce high kurtosis, negative skewness, and persistent autocorrelation in return distributions even when the underlying business risk follows a random process and has no extremes. The mere assumptions are loss aversion, i.e., losses are about twice as painful as gains are pleasant, and mental accounting, i.e., evaluating assets based on their past performance. The author therefore suggested that it is investors' trading characterized by psychological bias that is causing the extreme events, not the underlying business risk. Specifically, traders' incorporation of prior gains and losses into evaluations of future prospects may be part of the explanation for the excess-volatility phenomenon observed in real markets, i.e., markets tend to move too much relative to the volatility of the underlying earnings.

McQueen and Vorkink (2004) pointed out that, while much effort has been undertaken to analytically model volatility clustering and the current statistical knowledge of this phenomenon is impressive, our theoretical knowledge of why volatility clusters is very poor. They proposed a preference-based asset pricing model which is claimed to be able to explain many empirical facts in finance. In the model, agents care about wealth changes, experience loss aversion, and keep a mental scorecard that affects their level of risk aversion. They become temporarily more sensitive to news when perturbed by unexpected returns. In addition, their utility increase from gains are smaller than their utility decrease from losses, i.e. loss aversion. It is claimed that the state-dependent sensitivity to news creates volatility clustering and is empirically supported.

3.1.2 Options markets

In option pricing theory, the future value of any security is obtained by integrating its payoff function with respect to the risk-neutral density function. Shefrin (2008) pointed out that the traditional risk-neutral approach to option pricing has led to the view that option prices are independent of investors' beliefs. However, as options are naturally structured as contingent payoffs, they are inevitably impacted by investors' beliefs. In particular, since sentiment measures the degree of bias in the representative investor's probability density function, it acts as a proxy to explain how investors' behavioral and psychological factors influence option prices in equilibrium. In particular, pessimists overestimate volatility and underestimate expected returns, while optimists underestimate the former and overestimate the latter. In addition, the overestimate of volatility associated with pessimists dominates prices of out-of-the-money puts, and the underestimate of volatility associated with optimists dominates prices of out-of-the-money calls. Importantly, Shefrin (2008) presented a behavioral counterpart to the BS formula with a closed-form solution, and illustrates that the volatility smile is a feature of the behavioral framework.

Shefrin (1999) and Shefrin (2008) took a specific example to illustrate how investors' sentiment can influence option prices and induce smile patterns. The implied volatilities of the options traded in the period from November to December 1996 were studied. In this period, the investors' sentiment, which is represented by some indexes, experienced a process from being highly positive to being very negative.

This study stated that disagreement among investors is pervasive. Having seen a price trend, some investors predict continuation, while others predict reversal. Some investors overreact, while others underreact. The disagreement causes markets to be inefficient. Options markets are particularly vulnerable in this respect and the volatility smile is one manifestation of the inefficiency. Through an event investigation by combining information collected from option prices with other information about market sentiment, the study assessed the impact of heterogeneous beliefs on market efficiency. The conclusion was that, when investors are sharply different in the level of optimism, bullish ones tend to take long positions in calls and bearish ones tend to take long positions in puts. This difference gives rise to the volatility smile; the sharper the difference, the stronger the smile.

3.2 Agent-based simulation

Traditional analytical approaches in finance and economics to study aggregate phenomena either are purely macroscopic, or rely on top-down construction based on a number of unrealistic assumptions mainly for the sake of analytical tractability. Interactions between traders play no role in the explanation of the phenomena (Tesfatsion (2002), Hommes (2006)). In fact, financial markets are decentralized systems comprising of large numbers of autonomous, adaptive and interacting agents. Their behavior and interactions give rise to macroeconomic regularities, including the patterns observed in financial time series. The macro-dynamics in turn feeds back to influence or determine the microscopic behavior and interactions. A market is therefore a network of many highly nonlinear causal chains, and its operation and behavior can hardly be studied analytically. The avoidance or omission of treating economic systems as complex systems may mainly account for the failure or deficiency of the mainstream economic theory's explanations of many market phenomena.

As stated by Tesfatsion (2002) and Hommes (2006), economics and finance are witnessing an important paradigm shift from the neoclassical modeling approach towards an agent-based approach based on computational models where markets are viewed as complex evolving systems with many autonomous, heterogeneous, interacting agents. Researchers of agent-based simulation (ABS) rely on computational laboratories to study the evolution of economic systems under controlled experimental conditions. In this paradigm, a financial market is constructed as a multi-agent system, of which the components, i.e. the agents are realistically modeled. In experiments, the initial attributes of the agents are first specified and the artificial market is then left to evolve over time without further intervention. Time series of some variables of the model, which may represent certain economic factors such as price and volume, are generated in this process. According to Hommes (2006), the following observations and developments have contributed to this paradigm shift,

- No trade theorem: If all agents are rational and each agent knows that other agents are rational, there will be no trade. The reason is that rational agents will not sell assets to any other rational agents when the latter want to buy, because the former think that the latter have superior private information. This is in odd with the large daily trading volume observed in real markets.

- Stock prices exhibit excess volatility, i.e., movements in stock prices are much larger than those in underlying economic fundamentals. In particular, it is difficult to explain the stock market crash in October 1987 by models with representative, rational agents.

- The traditional financial theories concern agents with perfect information about the environment and with unlimited computing abilities. This cannot be realistic because, in a heterogeneous world, a rational agent cannot know the beliefs of all other non-rational agents.

- A evolutionary approach has been advocated in the ABS paradigm, which can plausibly represent the process in which bounded-rational agents select from a large class of possible forecasting and trading strategies. The story is that agents select strategies according to how well they perform and how much they are used by others.

- Economists have applied new developments in nonlinear dynamics and complex system theory to study financial markets, which are almost always highly nonlinear and adaptive systems.

- Laboratory experiments have shown that individuals often do not behave rationally and this type of experiments have reinforced theoretical studies of markets with heterogeneous, non-rational agents.

- Empirical data showed that financial practitioners use different trading and forecasting strategies. In addition, some techniques can generate significantly positive returns, suggesting extra structure above and beyond the benchmark of efficient market hypothesis.

- Both in research and teaching, computational tools have become widely available and tremendously stimulated the development of numerical simulation of financial markets.

By nature, ABS is suitable for studying financial markets which are inherently multi-agent systems. ABS researchers can investigate how large-scale effects in financial markets arise from the behavior and interactions among many agents.

Specifically, as stated by Axelrod and Tesfatsion (2006), ABS researchers pursue four specific goals: Empirical, normative, heuristic, and methodological.

- The goal of empirical understanding focuses on the explanation of the emergence and persistence of global regularities despite the absence of top-down planning and control, specifically the governing causal mechanisms grounded in the repeated agent interactions.

- The normative goal centers on the application of agent-based models in the designs of desirable economic or financial systems, processes, and policies, in order to achieve higher efficiency of the entire systems despite continuous attempts by privately motivated agents to gain individual advantages.

- The heuristic goal is for the exploration of the deeper insights attained about the fundamental causal mechanisms in a wide range of economic systems.

- The methodological goal focuses on the discovery and development of general methods and tools need to undertake the rigorous study of economic systems through controlled computational experiments.

At present, however, most ABS research in finance focuses on understanding the empirically observed characteristics of financial markets. To achieve this objective, many agent-based models of financial markets have been developed during the last decade.

3.2.1 Stock markets

In view of the fact that financial prices exhibit some universal attributes that resemble the scaling laws characterizing physical systems in which large numbers of units interact, Lux and Marchesi (1999) questioned whether scaling in finance emerges in a similar way — from the interactions of a large ensemble of market participants. For this purpose, they developed a multi-agent model of financial markets consisting of two groups of traders: Fundamentalists and noise traders. Fundamentalists buy (sell) the asset when its market price is below (above) its fundamental value. Noise traders attempt to identify price trends and patterns, and imitate the behavior of other traders. The group of noise traders are further differentiated into optimists and pessimists. The former believe in a rising market and buy the asset, whereas the latter believe in a declining market and sell. The crucial point of this model is that agents may move to the other group or subgroup when they believe that the traders in that (sub)group are more successful. Price changes are modeled as endogenous responses of the market to imbalances between demand and supply. Although the news-arrival process in the model lacks both power-law scaling and any temporal dependence in volatility, fat tails and volatility clustering are generated through the interactions between the agents. Based on the results, the authors challenge the prevalent efficient market hypothesis which assumes that the movement of financial prices are an immediate and unbiased reflection of incoming news about future earning prospects, and support the idea that scaling arises from mutual interactions of market participants. A detailed description of this model and its simulation results can be found in Wang (2005).

Cont and Bouchaud (2000) presented a model of a speculative market to examine how the existence of herd behavior among market participants gives rise to large fluctuations in the aggregate excess demand reflected by a heavy-tailed non-Gaussian distribution, and how the excess kurtosis of returns and the average order flow are related. The agents in the model face three alternatives at each time period: To buy a unit of a financial asset, to sell a unit of the asset, or not to trade. They form coalitions through independent binary links between each other. The resulting market structure is then described by a random graph whose connected components (or clusters) correspond to groups of investors who act together, independently from other groups, to buy or sell. Each cluster of agents decides, independently from other clusters, whether to buy, to sell, or not to trade. Albeit its simplicity, the model can generate a probability distribution with heavy tails and finite variance, similar to empirical distributions of asset returns. In addition, analytical results based on the model indicate that the volumes of the order flow and the fluctuations of the asset price are negatively related, in line with the empirical facts that large price fluctuations are more likely to occur in less active markets and larger order flows enable market makers to more easily balance supply and demand. In brief, the model demonstrates a quantitative link between the two issues observed in financial markets: The heavy tails of return distributions and the herd behavior of financial traders. A detailed description of this model and its simulation results can be found in Wang (2005).

Cellular automata (CA) have been widely applied to study complex phenomena in different fields such as physics, chemistry, biology, and social and economic sciences, etc. (Talia and Sloot (1999)). Recently, some researchers have used cellular automata to model financial markets for studying their complex dynamics.

Iori (2002) employed a random field Ising model to describe the trading behavior of agents in a stock market. In the model, the agents are represented as the nodes of a square lattice connected to four nearest neighbors. At each time step, a given trader can take one of the three actions: Buying one unit of the stock, selling one unit, or remaining inactive. The decision making is driven by idiosyncratic noise and the influence of the nearest neighbors. A trade friction is further assumed which can be interpreted as a transaction cost. This friction is modeled as an individual activation threshold, only if exceeding which an agent's signal can trigger a trade. There is also a market maker who clear the orders and adjust prices. Three ingredients: Imitation, adjusting thresholds and variable rate of price adjustment, play a crucial role in generating volatility clustering. While the first ingredient can generate a large spike in trading volume, the second and third help propagate it through time. They together creates volatility clustering along with a positive volatility-volume correlation. This work supported the idea that power law fluctuations of asset prices are caused by the inherent interaction among market players and the trading process, rather than merely reflecting the probability distributions of exogenous shocks hitting the market.

Some agent-based models have been developed to explain the similar characteristics observed in some other types of financial market. For example, Chatagny and Chopard (1997) presented a microscopic agent-based model of the foreign exchange market. Two types of agent are included in the model: Market makers and speculative traders (chartists). The model is promising because it captures many of the qualitative features of the real markets.

However, researchers in this field have not yet reached an agreement on explaining the complex dynamics of financial markets. In addition, as recently pointed out by Cont (2005), due to the complexity of the existing (agent-based) models, it is often not clear which aspects of the models are responsible for generating the stylized facts and whether all their ingredients are indeed required for explaining empirical observations.

3.2.2 Options markets

Recently some agent-based studies have been undertaken to investigate the origin of the volatility smile phenomenon observed in option markets. Levy et al. (2000) pointed out the drawback of the BS model and most of its extensions is that the volatility of the underlying is assumed to be known and agreed about by all investors. They argued that if this is the case, there will not be any trading in options and that, in reality, however, the volatility is not known and investors have different and uncertain estimations of its value. Based on these ideas, the authors developed a MS model in which investors have some uncertainty about the volatility and may disagree about its distribution. Through the BS formula, this translates to uncertainty and disagreement about the values of options. Each investor believes that the volatility is distributed according to a probability distribution and thus the option price at the future time is a random variable. In order to maximize utility based on their distributions, the investors hold different numbers of an option and the equilibrium price of the option is the price for which the excess demand is zero. Due to the convexity of the plot of BS price against volatility, uncertainty of estimated volatility will induce higher option prices. The higher the convexity, the more significant the overpricing. The levels of convexity of in-the-money (ITM) and out-of-the-money (OTM) options are higher than those of at-the-money (ATM) and near-the-money options[1], therefore ITM and OTM options will be overpriced and their IVs are higher, indicating a volatility smile.

[1] An in-the-money, at-the-money, and out-of-the-money option would give the holder respectively a positive, zero, and negative cash flow if it were exercised immediately. Therefore, a call option is in the money, at the money, and out of the money when the price of the underlying asset is respectively greater than, equal to, and smaller than the strike price, while a put option is in the money, at the money, and out of the money when the former is respectively smaller than, equal to, and greater than the latter.

Platen and Schweizer (1998) presented a method for constructing diffusion models for stock prices explicitly incorporating the technical demand induced by hedging strategies. The price processes are with a stochastic volatility and imply option price distortions. Consequently, a U-shaped IV surface is obtained from the expected payoffs of the options with different strike prices. The important argument of this work is that the existing literature has predominantly focused on directly modeling volatility as a stochastic process in order to explain such option price distortions. But the description of the volatility process is typically ad hoc, i.e. based on the assumption that the stock or option prices cannot be affected by the trading of agents. It excludes the feedback process in which a substantial use of hedging strategies affects the dynamics of the underlying stock. In other words, the demand for a stock can be determined by the evolution of the stock price itself.

Very recently, Buraschi and Jiltsov (2006) reported both theoretical and empirical studies of a simple general equilibrium economy with two sets of risk-averse agents that are with rational learning capabilities but have different beliefs on expected returns and are uncertain about the stochastic drifts of some risk factors. In maximizing utility, their difference in expectation creates natural demands for insurance: Optimistic traders act as insurers of pessimistic agents writing out-of-the-money (OTM) puts in exchange for OTM calls. The model derives the optimal portfolio holdings in the underlying asset and the options as a function of the differences in belief. Then, in general equilibrium, a downward sloping IV skew is generated. Specifically, among many other findings, they conclude that changes in the difference of belief affect the level and steepness of the smile: The greater the difference, the higher and steeper the IV smile. In addition, the extent of most arbitrage violations are correlated with abnormal changes in the difference of belief. Furthermore, current levels of belief difference have positive and statistically significant predictive power for the future realized volatility

While these studies have clearly demonstrated the potential of MS-based approaches for studying the origin of the smile phenomenon, they have not reproduced or realistically explained IV curves of options on underlying assets of different types, such as the upward sloping skew observed in the commodity options market. In addition, they have not confirmed the dynamical properties of the smile.

3.3 Econophysics

The traditional view in economics characterized by agent rationality and market equilibrium has been challenged severely in recent years. Behavioral economists have advocated bounded rationality and presented evidence of frequent market anomalies; agent-based approaches have manifested the importance of agent heterogeneity and interactions for the dynamics of financial markets. However, as posed by Farmer (1999), is there a statistical mechanics that can explain some of the statistical properties of the market?

The complexity of financial markets has attracted a growing number of physicists and a new research community has emerged (Mantegna and Stanley (2000)). This field of research is known as *econophysics*, coined in 1995 by Eugene Stanley. Econophysicists argue that the empirical data can be studied by using the tools and methodologies developed in statistical physics and the stylized facts of financial markets are best understood as emergent properties of a complex system (Rickles (2008)). Specifically, the research activity in this field puts its emphasis on the empirical analysis of economic data. It is characterized by the concepts developed in statistical physics, such as scaling, universality, and self-organization, etc.

The minority game (Challet and Zhang (1997)) is one of the most successful econophysics models (Gallegati et al. (2006)). It was originally motivated by the El Farol bar problem (Arthur (1994)), in which a fixed number of agents face the question of whether or not to attend the bar. If less than half the agents turn up, the agents attended win. If the bar is too crowded, those agents who stayed home win. Agents make decisions based on the recent record of total attendance at the bar. The bar is analogous to a financial market in which those wining traders are generally in minority; in addition, traders try to forecast the aggregate because if everyone uses the same strategy it is guaranteed to lose. The minority game is a mathematical formulation of the El Farol problem.

At each time step, a fixed number of agents independently choose between two possibilities and the attendance is recorded. Each agent has a set of strategies, and at any given time plays the one that has been most successful up until that point in time, representing a simple learning mechanism. The minority game is characterized by agents' heterogeneity, bounded rationality, and adaptation. In addition, the minority rule forces the agents to choose the strategies that makes them singular in the community. Driven by switching between strategies, the attendance record fluctuates aperiodically. The standard deviation of the historical attendance record serves as a measure of the efficiency of the market: Higher variance corresponds to lower predictability hence higher efficiency, vice versa. When the memory of the agents (measured by the number of previous time steps) is low, the market is efficient. However, as the memory increases, the market gradually becomes inefficient.

Briefly, in contrast to the standard view in economics which considers that markets are efficient and prices only change due to the arrival of news regarding the fundamental value of the asset, the minority game points out that a market with many traders is inefficient by nature and the price fluctuates even in the absence of any new external information (Challet and Zhang (1997)).

The EL Farol market model was also formulated and parametrized by Johnson et al. (2003). Through simulations, they showed that the statistical features of the model are consistent with the stylized facts observed in real financial markets. The authors also qualitatively and quantitatively described the essential interactions driving the variation in volatility in the minority game.

Some researchers in econophysics deal with the statistical characterization of the stochastic dynamics of asset prices, empirically-consistent derivatives pricing, portfolio optimization, and income distribution of firms and statistical properties of their growth rates, etc. (Mantegna and Stanley (2000)). In addition, a group of econophysicists concerns the development of models that are able to encompass all the essential features of real financial markets. Below we summarize some models that have clear links to statistical physics.

Bak et al. (1997) reported an extremely simple, but completely defined, economic model of many agents. There is only one type of stock and each agent can own at most one share. The agents are of two types: (1) noise traders whose choice of price to buy or sell may imitate choices of other traders and whose current volatility may depend on recent changes in the market; (2) rational agents who optimize their own utility functions, based on the expected dividends of the stock, and their degrees of risk aversion. In the simplest case, a single agent is chosen who updates price, randomly looks into the market, and chooses the most favorite price (if there is one) advertised by another trader to transact. If the noise traders are independent of other traders and the stock price, the model is equivalent to a reaction-diffusion model where two types of particle, A particles and B particles, are injected at different ends of a tube. These systems have been studied extensively by physicists. Surprisingly, the resulting price variations based on the diffusive behavior of the independent noise traders follow the power law. If the noise traders are allowed to adjust their current price towards the current market price and mimic other traders in the market, the price variations become much more dramatic and qualitatively look a lot more like the variations observed in a real stock market. When the information on the volatility of the markets is fed back to the agents, i.e., the strength of the drifting of each noise trader is proportional to recent price variation, the effect of volatility clustering is generated. This work was motivated by the observations in statistical physics that distributions with fat tails naturally occur in systems with very many interacting components, and economics clearly deals with many interacting agents. A detailed description of this model and its simulation results can also be found in Wang (2005).

A stochastic CA model for simulating the dynamics of stock markets was introduced in Bartolozzi and Thomas (2004). The agents of the market are represented by cells on a two-dimensional grid and each agent at each discrete time step is characterized by three possible states or spin orientations: 1 is associated with the purchasing of a stock, -1 with the selling, and 0 with being inactive. Through a direct percolation process, active traders form a hierarchy of clusters and the traders in each group share information and have identical spin states, representing traders' herding behavior. The trading dynamics is governed by the synchronous updating of the spins of the active traders. The simulation shows that the returns show a type of intermittent behavior and their distribution is characterized by power-law tails. In addition, long time correlations are present in the volatility. The key element of this model is the formation of the hierarchy of clusters of active traders, mimicking the process in which traders are associated with professional investors. Large price changes, including crashes and bubbles, can be interpreted as a chronization of the spin orientation of the more influential clusters.

The boundaries between these new research fields: Behavioral finance, agent-based simulation, and econophysics are by no means clear cut. Many models of behavioral finance are comprised of numerous heterogeneous agents; many agent-based models deal with human intelligence and psychology; and many models in econophysics are based on agent behavior and interactions. Nevertheless, through theoretical and experimental explorations from different angles, the research activity in these fields have greatly promoted our understanding of the complexity of financial markets and they have become complementary to the traditional approaches of economics and finance.

The current financial turmoil evokes the strong advice that policy makers should adopt behavioral and agent-based approaches. As stated by Buchanan (2008), none of the economic models being used by government regulators anticipated the crisis, while the academic economics profession remains reluctant to embrace new computational approaches. If we want to avoid crises, we need something more imaginative, starting with a more open-minded attitude to how science can help us understand how markets really work. Computer simulation can enable us to discover relationships that the unaided human mind, or even the human mind aided with the best mathematical analysis, would never grasp. Farmer and Foley (2009) pointed out that agent-based simulations potentially present a way to model the financial economy as a complex system and can handle a far wider range of nonlinear behavior than conventional equilibrium models. Policy makers can thus simulate an artificial economy under different policy scenarios and quantitatively explore their consequences. Buchanan (2009) went further to suggest that agent-based computer models, when applied properly, could prevent another financial crisis.