IOSR Journal of Economics and Finance (IOSR-JEF)
e-ISSN: 2321-5933, p-ISSN: 2321-5925.Volume 3, Issue 1. Ver. I (Feb. 2014), PP 44-53
www.iosrjournals.org

Evolutionary Finance Approach:Literature Survey

YosraMeftehRekik[a], YounesBoujelbene[b]
[a]*Department of Financial and Accounting Methods, Tunisia*
[b]*Department of Applied Economy, Tunisia*

Abstract: *The only way to make a major advance in finance modeling is to explore entirely new approaches rather than make incremental modifications to existing models. The purpose of our research is precisely to build models and perform analysis of the economy as a complex system prone to sudden and major changes. This includes the collection of new methods of empirical analysis, and the development of new mathematical and computational tools. This effort will be guided by emerging new conceptual paradigms such as network theory, behavioral economics and agent-based modeling, and empirically grounded by laboratory experiments and micro data. By combining these ideas into a practical simulation and forecasting tool, we aim at building the foundations of a new paradigm within finance.*
Keywords: *Evolutionary Finance; Traditional Theory, Behavioral Finance; Agent-Based Approach*

I. Introduction

The traditional finance paradigm seeks to understand financial markets using models in which agents are "rational". First, rationality means that when they receive new information, agents update their beliefs correctly, in the manner describe by Bayes' law. Second, given their beliefs, agents make choices that are normatively acceptable, in the sense that they are consistent with Savage's notion of subjective expected utility. The world economy is in the midst of a global financial crisis, caused by a mix of a global asset price bubbles, overwhelming irrational exuberance and systemic mistakes of economic agents and financial market participants. Against this background, the standard financial theory, based on the efficient market hypothesis and rational representative agent paradigm, seems to be losing touch with reality.

Simon (1991) has emphasized the importance of bounded rationality, taking into account the limited ability of agents to adapt optimally, or even satisfactorily, to complex environments. Paradoxically, it is hardly rational to attempt being perfectly rational. Indeed a new paradigm based on behavioral models of decision under risk and uncertainty is beginning to crowd out the traditional view based on complete rationality of all market participants. Furthermore, many empirical and experimental works has quite successfully challenged the traditional view of efficient markets and the long-sustained belief in market rationality (Campbell, 2000; Hirshleifer *et al.,* 2002).

Behavioral finance challenges the rationality assumption and aims to improve the understanding of the financial markets by finding that investors' decisions contradict the expected utility theory of Von Neumann and Morgenstern (1944).This theory supposes two important aspects of investors and the market at large. In other Words, behavioral finance in a broad sense is divided into macro behavioral finance and micro behavioral finance (Pompian, 2006). Macro behavioral finance discloses and describes anomalies of efficient market hypotheses that could be explained by models of traders' behavior. Micro behavioral finance analyses behavior and deviations of individual investors', which separates them from rational agents for acting according to stern mathematical statistic models (Jurevieiene *et al.,* 2012).

The traditional and the behavioral finance model, however, share one important feature: They are both based on the notion of a representative agent though this mythological figure is dressed differently. Evolutionary finance suggests a model of portfolio selection and asset price dynamics that is explicitly based on the idea of heterogeneity of investors. Indeed, the hypotheses of rationality and homogeneity are normally invoked so that the agents' individual behavior can be neglected and strategies have all to be equal. The debates in finance about market efficiency and rationality are still unresolved. Hommes (2006) states that the perfect knowledge about the environment in a heterogeneous world implies that a rational agent has to know the beliefs of all other irrational agents. In their paper, "Evolutionary dynamics in markets with many trader types", Brock *et al.* (2005) analyze the dynamical behavior of an asset market as the number of buyer and seller's types tends to infinity. A large type limit result is established in a rigorous mathematical fashion.

As an alternative, taking individual interactions into account, agent-based Artificial Stock Market modeling has developed rapidly over the last 20 years. Since the first agent simulation model used to study financial markets, a growing literature has recently described how to study the price dynamics of markets caused by the investors' behavior via agent-based models. In general, the agents' behavior is time-varying and agents can choose different trading strategies according to some rules. Beginning with the development of the Santa-Fe

Institute agent-based Artificial Stock Market model (Arthur *et al.*, 1997; LeBaron *et al.*, 1999; Ehrentreich, 2006), and the Genoa Artificial Stock Market (Raberto et al., 2001; Cincotti*et al.*, 2005, 2011), theagent-based modeling is developed to facilitate the understanding of some areas that traditional homogeneous models cannot explain very well (LeBaron, 2006; Lux, 2009; Chen, 2012). The paper is organized as follows. A brief standard financial theory literature review is provided in Section 1. Section 2 is devoted to intuitive presentation of the behavioral finance and the principals' behavior bias. In Section 3, we give a general discussion about agent-based financial models as an alternative.

II. Market efficiency and perfect rationality

The proposition that has dominated finance for over 30 years is efficient market hypothesis. There are three basic theoretical arguments that form the basis of this hypothesis. The first and most significant one assumes that investors are rational and by implication securities are valued rationally. The second one is based on the idea that everyone takes careful account of all available information before making investment decisions. The third principle states that the decision maker always pursues self-interest (Nik, 2009). Fama (1965) demonstrates that if market securities are populated by many well-informed rational investors, investments will be appropriately priced and will reflect all available information. In traditional models, rational investors make efficient use of this information; their decision making is based on utility functions with beliefs. Thus, such representative investor holds correct beliefs and is an expected utility maximizer.

It is common to distinguish among three versions of the EMH: the weak, semi-strong, and strong forms of the hypothesis. These versions differ by their notions of what is meant by the term "all available information."The *Weak form efficiency*, in this case, the relevant information set comprises all current and past prices. This version of the hypothesis implies that trend analysis is fruitless. Past stock price data are publicly available and virtually costless to obtain. *Semi-strong form efficiency* asserts that the asset market is efficient relative to all publicly available information. Such information includes, in addition to past prices, fundamental data on the firm's product line, quality of management, balance sheet composition, patents held, earning forecasts, and accounting practices. Finally, the *Strong form efficiency* states that stock prices reflect all information relevant to the firm, even including information available only to company insiders. This version of the hypothesis is quite extreme. Few would argue with the proposition that corporate officers have access to pertinent information long enough before public release to enable them to profit from trading on that information.

Many standard economic models are based on the postulates of the agent who is rational in the full sense of the term. The agent gathers all available information which is relevant to a decision. Baltussen (2009) says that "rationality means that economic agents make the best choices possible for themselves". The efficient market hypothesis is associated with the idea of a "random walk," which is a term loosely used in the finance literature to characterize a price series where all subsequent price changes represent random departures from previous prices. The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow's price change will reflect only tomorrow's news and will be independent of the price changes today. But news is by definition unpredictable and, thus, resulting price changes must be unpredictable and random. As a result, prices fully reflect all known information, and even uninformed investors buying a diversified portfolio at the tableau of prices given by the market will obtain a rate of return as generous as that achieved by the experts.

By the start of the twenty-first century, the intellectual dominance of the efficient market hypothesis had become far less universal. Many financial economists and statisticians began to believe that stock prices are at least partially predictable. A new breed of economists' emphasized psychological and behavioral elements of stock-price determination, and came to believe that future stock prices are somewhat predictable on the basis of past stock price patterns as well as certain "fundamental" valuation metrics. Moreover, many of these economists were even making the far more controversial claim that these predictable patterns enable investors to earn excess risk-adjusted rates of return.

Most criticisms of the "Homo-economics" are based on three underlying assumptions. 1) Perfect rationality, in this context, rationality is not always the first driver of human decision making. As many psychologists believe, the human intellect is subservient to human emotions. 2) Perfect Self-Interest. This assumption is strongly connected with the previous one. Sometimes people are subject of impulses and emotions; hence, they perform volunteering, helping the needy even if it contradicts the wealth maximization objectives. However, that might well fit with utility function integrating this altruistic dimension. Agents are then no longer selfish as they are usually described. 3) Perfect Information. In the world of investment, there is nearly an infinite amount to know and learn because even the most successful investors do not master all disciplines.

III. An alternative behavioral finance

Since the early 1980s, there has been a movement toward incorporating more behavioral science into finance. The proponents of behavioral finance cite several key areas where the reality seems to be most at odds with the efficient market hypothesis. This approach can be viewed as another answer to the extremely unrealistic assumptions of the efficient theory. To provide some suggestion as to how address this deficiency, behavioral theory proposes to employ the insight of behavioral sciences such as psychology and sociology into finance.

Although still being the benchmark of finance, the traditional financial view has been made into question by a new paradigm, the "behavioral finance". Behavioral finance is based on the notion of bounded rationality, in which a person utilizes a modified version of rational choice that takes into account the limitations of knowledge, cognitive issues and emotional factors (Barberis and Thaler, 2003; Ricciardi, 2004).

Hon-Snir *et al.* (2012), in their study, found out that more proficient investors are less affected by the behavior biases. The authors examined five behavioral biases in decision making process in the Stock Market and discussed the differences of possible individual solutions due to these behavioral deviations: Disposition effect, Herd Behavior, Availability heuristic, Gambler's fallacy and hot hand fallacy. Rekik and Boujelbene (2013) show that herding attitude, representativeness, anchoring, loss aversion, and mental accounting all influence the Tunisian investors' perception of their decision making processes. On the other hand, the authors have mentioned the absence of overconfidence bias in the Tunisian Stock Market. In fact, Tunisian investors seem to be under-confident, hesitant and very sensitive to others' reactions and opinions. Their second finding explains the fact that there is an interaction between demographic variables and financial behavioral factors. These results have particularly provided us with the first profile of Tunisian investors' behavior.

A large thread of literature of psychology and behavioral finance instigated by laboratory experiments of Kahneman and Tversky (1973, 1974) suggest that economic behavior is often better explained by simple heuristic rules and irrational biases rather than by dynamic optimization. These are summarized below.

Overconfidence

In their predictions, overconfident people set confidence bands overly narrow, which means they get surprised more frequently than they anticipated (Shefrin, 2000). Overconfidence is a consistent tendency to overestimate skills and the accuracy of one's judgments. People often believe in their own superior knowledge and put much more weight on private information, especially if they are personally involved in gathering and assessing data, rather than on public signals, particularly when these are ambiguous. It is obvious that overconfidence is an extremely relevant topic for financial markets. Investors overconfident about their trading abilities are prone to pursue excessive trading (Odean 1998; 1999; Barber and Odean 2000; 2002), hold under-diversified portfolios (Goetzmann and Kumar 2008), or underestimate risk (De Bondt 1998). All these factors are likely to imply higher transaction costs hand-in-hand with lower returns (Barber and Odean 2000). On the other hand, one of positive implications of overconfident behavior might be the reduced tendency to herd (Bernardo and Welch 2001).

Daniel *et al.* (1998) present a model of securities over and under-reaction based on overconfidence which is defined as the overestimation of private signals precision. In their work, they reveal a tendency of overconfidence to impact market prices and increase market volatility. Overconfidence in its simplest way could be defined as "an inopportune belief toward a witnessed reasoning, judgment and the person's cognitive abilities" (Sadi, *et al.*, 2011, Chou and Wang, 2011).

Herd Behavior

Herding behavior in financial markets has attracted increasing attention over the past decade. The literature defines herding as an obvious intent by investors to ignore their personal information and copy the behavior of other investors leading them to trade in the same direction and thus moving in and out of markets as a group (Nofsinger and Sias, 1999; Bikhchandani and Sharma, 2001). Even though such behavior among investors can be driven by rational or irrational motives, it can clearly lead to market stress by pushing asset prices away from their fair values as supported by the economic fundamentals, hence driving up market volatility (Blasco *et al.*, 2012).

Herding is sometimes considered as an opposite tendency to overconfidence regarding information efficiency. In this context, Bernardo and Welch (2001) argues that thanks to overconfident individuals, information "that would be lost if rational individuals instead just followed the herd" is preserved. Herd behavior is the tendency individuals have to copy the actions of a large group irrespective of whether or not they would make the decision individually.

Starting with Christie and Huang (1995) on U.S. equities, a number of studies in the literature have utilized a measure of cross-sectional dispersion of stock returns and examined the relationship between return dispersions and market return in order to make inferences on whether herding behavior exists. Later, the testing methodology by Christie and Huang (1995) was modified by Chang *et al.* (2000) and this modified methodology has been employed in a number of papers including Gleason *et al.* (2003) on commodity futures traded on European exchanges, Gleason *et al.* (2004) on exchange traded funds, Demirer and Kutan (2006) and Tan *et al.* (2008) on Chinese stocks, and more recently Demirer *et al.* (2010) on Taiwanese stocks and Chiang and Zheng (2010) on global stock markets.

Anchoring and adjustment

The anchoring effect was first introduced by Tversky and Kahneman (1974) and is described as the heuristics implemented when making judgments under uncertainty. In numerical prediction, when a relevant value is available, people make estimates by starting from an initial value that is adjusted to yield the final answer. The anchor may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient. The anchoring effect has attracted much attention and has been applied in several research works. However, few research studies have taken a look at the anchoring effect in the financial markets. Fisherand (2000) used forecasts based on P/E ratios and dividend yields to discuss the anchoring bias in market forecasts.

Törngren and Montgomery (2004) examined the differences between performance and the confidence of professionals and lay people in the stock market. They concluded that persons are usually influenced by the historical price movements of stocks, implying that past movements serve as anchors for their expectations. In addition, Kaustia *et al.* (2008) explored the effect of anchoring bias on long-term stock return expectations. Based on their experiments, they concluded that, whether participantsare students or professionals, their estimates are affected by an initial value. More recently, Cen, *et al.* (2013) explore the role of anchoring bias in analysts' earnings forecasts. It was found that the forecast median industry EPS serves as an anchor, showing that analysts' earnings forecasts for firms with a low forecast EPS vis-à-vis the industry median are more optimistic than firms with a high forecast EPS.

Representativeness

The representativeness heuristic is a psychological bias which means that, under uncertainty, investors are prone to believe that a history of a remarkable performance of a given firm is “representative” of a general performance that the firm will continue to generate into the future. Investors subjects to this heuristic overreact, thus, to salient and similar information about firms past performance such as similar consecutive earnings surprises. According to Shefrin (2000), representativeness heuristic is a judgment based on stereotypes. Representativeness is high when an observation fits the pattern (Goldberg and Nitzsch, 2001).

To validate the behavioral models with representativeness heuristic, one needs to examine the long-run survival of traders with such heuristic.

Although there are few studies exploring the contribution of the representativeness to explain the investor behavior, their empirical results are mixed. Some psychological and experimental studies show that this concept is not convenient to detect the individual behavior in real economic states (Charness *et al.,* 2010). In contrast, other studies which lie within the behavioral finance approach find that this heuristic affects the investor's decision when evaluating stocks (Barberis, *et al.,* 1998; Bloomfield and Hales, 2002; Frieder 2004, 2008; Kaestner, 2006; Alwathainani, 2012). Boussaidi (2013) tried to explain the investor overreaction by the representativeness heuristic. However, the behavioral literature refers to two other biases which can account for it: the self-attribution and the overconfidence. The authors suggest that investors overreact to their private information and under-react to public information. Thus, it would be appropriate to explore this perspective. Recently, Guo (2013) constructs an analytical model of a competitive securities market to examine the survival of representativeness heuristic traders in competition with rational traders. Guo (2013), show that without the presence of noise traders, heuristic traders will be driven out of the market by rational traders due to their representativeness heuristic. However, with the presence of noise traders, heuristic bias gives heuristic traders an advantage over rational traders when exploiting the misevaluations through the impact of their up dated mean and variance on their relative profitability to rational traders. Consequently, heuristic traders can make more expected profit than rational traders. If the traders' types replicate according to the profitability of their strategies, heuristic traders can survive or even drive out rational traders

Mental Accounting

Another bias entering into investing is the so called mental accounting, referring to the tendency for people to separate their money into separate accounts based on a variety of subjective criteria such as the source of the money and the purpose for each account (Thaler, 1985, 1989). Thaler (1999) note that mental accounting includes three components. The first compartment of mental accounting captures how outcomes are perceived and experienced, and then how decisions are made and subsequently evaluated. The second part of mental accounting assigns the activities to specific accounts. It keeps track of inflow and outflow of funds from each specific activity. The third component is concerned with the frequency with which accounts are evaluated. Accounts can be balanced on a daily, weekly, monthly, or yearly basis.

With reference to the theory, individuals assign different functions to each asset group, which often has an irrational and detrimental effect on their consumption decisions and other behavior. The mental accounting bias also concerns investing. For example, some investors divide their investments between a safe investment portfolio and a speculative portfolio in order to prevent the negative returns that speculative investments may have from affecting the entire portfolio. The problem regarding such practice is that despite all the work and money that the investor spends to separate the portfolio, his net wealth will be no different than if he had held one larger portfolio.

Loss aversion bias

Loss aversion is a pervasive phenomenon in human decision making under risk and uncertainty, according to which people are more sensitive to losses than gains. It plays a crucial role in Prospect Theory (Tversky and Kahneman, 1974, 1992). A typical financial example is in investors' difficulty to realize losses.

Behavioral explanations, in particular loss aversion, have been used to explain why a high equity premium might be consistent with plausible levels of risk aversion. Loss-averse decision makers have preferences over gains and losses relative to a reference point rather than overall wealth. Typically, such preferences display a kink at the reference point, with the slope of the utility function over losses being steeper than the slope of the utility function over gains. For a given absolute loss or gain, this implies a first-order difference between the decrease in utility due to a wealth loss and the increase inutility due to a wealth gain of equal magnitude. Thus, this non-differentiability of the utility function at the reference point is loosely analogous to locally high risk aversion. This type of loss-averse utility provides a possible explanation why investors may prefer safer bonds with low returns to riskier equities with high returns. Shefrin (2000) calls this phenomenon *"get-evenitis,"* that is, people hope that markets will work in their advantage and that they will be able to terminate their investment without incurring any losses.

Engelhardt (2003) investigates the effects on household mobility. Using data from the NLSY on household moves across multiple metropolitan areas in the U.S., Engelhardt finds that nominal loss aversion significantly restricts household mobility, while low equity because of fallen house prices does not. Ferreira *et al.* (2008) find similar results using data from the American Housing Survey. More recently, Paolo (2014) study equilibrium trading strategies and market quality in an economy in which speculators display preferences consistent with Prospect Theory (Kahneman and Tversky, 1979, 1992). Loss aversion induces speculators to trade less (more), and less cautiously (more aggressively), with their private information, but also makes them less (more) inclined to purchase private information when it is costly, in order to mitigate (enhance) their perceived risk of a trading loss. The author demonstrate that these forces have novel, nontrivial, state-dependent effects on equilibrium market liquidity, price volatility, trading volume, market efficiency, and information production.

Disposition Effect

The disposition bias is the anomaly that investors seem to hold on to their losing stocks to a greater extent than they hold on to their winning stocks (Schlarbaum *et al*., 1978; Shefrin and Statman, 1985; Weber and Camerer, 1998). Grinblatt and Han (2005) propose a model which incorporates disposition effect, the tendency of investors to hold onto their losing stocks and sell their winners, leads to stock return momentum. Empirically, the capital gains overhang variable designed to capture the role of disposition effect in momentum is able to explain away the predictive ability of past returns. A key implication of the Grinblatt and Han model is that the predictability of capital gains overhang would be stronger for stocks with greater proportion of disposition prone investors.

Newton *et al.* (2013) examines whether investing experience can dampen the disposition effect, that is, the fact that investors seem to hold on to their losing stocks to a greater extent than they hold on to their winning stocks. To do so, the authors devise a computer program that simulates the stock market. They use the program in an experiment with two groups of subjects, namely experienced investors and undergraduate students. As a control procedure, they consider random trade decisions made by robot subjects. Newton *et al.* (2013) finds that though both human subjects show the disposition effect, the more experienced investors are less affected.

Availability bias

The availability heuristic (Tversky and Kahneman, 1973) describes how a person evaluates the probability of events by the ease with which relevant instances come to mind. Faced with thousands of stocks to choose from and assimilating large amounts of information, individual investors are forced to rely on cognitive shortcuts and heuristics. Another example is the repurchasing of stocks previous owned and sold for a gain (Strahilevitz *et al.,* 2011). Strahilevitz *et al.* (2011) find that individual investors frequently repurchase a stock previously sold for a gain. They argue that this comes from a simple form of learning whereby investors repeat actions that previously resulted in pleasure while avoiding actions that previously led to the pain of regret.

IV. The new paradigm - Agent based systems

Much of the mainstream underlying the financial theory draws upon the efficient market hypotheses and the rational representative agent paradigm. The conflict of traditional models calls for new approaches which allow for the particular properties of financial markets and facilitate a deeper understanding of financial dynamics. Agent-based modeling represents such an approach (Tesfatsion and Judd, 2006). Agent-based models of financial markets simulate financial markets by replicating the behavior of individual agents and their interaction. They enable the implementation of findings from the field of behavioral finance and, thus, can account for irrational motives (LeBaron, 2006; Hommes *et al.* 1998; Lux *et al.* 2000; Hommes, 2006; Chiarella 2009; Kefan *et al.*, 2010; Hachicha *et al.*, 2011; Manahov *et al.*, 2013).

Table: The comparison of Standard theory and Agent-Based approaches

Neoclassical economics	Agent-Based Models
Fully-informed	Limited access to information
Market participant are rational	Participant has bounded rationality
Participant interact only indirectly through markets	Participant interact directly with one another
Focus on equilibrium outcomes	Focus on dynamics The ability to learn about one's environment From gathered information, past experiences, social mimicry.

In recent academic financial literature, the representative agent approach and the Efficient Market Hypothesis (Fama, 1970) together with the Rational Expectations Hypothesis (Muth 1961; Lucas, 1978), which have dominated the field in the past, are being replaced by more realistic agent-based computational approaches. The desire to build financial theories based on more realistic assumptions lead to the application of computational approaches that allow traders' heterogeneity, irrationality and market non-equilibrium dynamics to financial problems. New so-called computational paradigm bridges the gap between a human and computer systems. These disciplines use different computational techniques, such as artificial life, fuzzy logic, collaborative intelligence, neural networks, instant-based techniques, agent-based modeling Chen *et al.* (2007), Lacay and Peffer (2010) and other areas of artificial intelligence to solve complex financial problems.

In this section, we give an overview of a number of existing agent-based models of financial markets, and explain them in terms of the proposed conceptual model. Even though most agent-based models incorporate some behavioral aspects into the agents' implementation, the last two examples given in this overview are interesting because they have explicitly accounted for a number of behavioral finance topics. Overviews of artificial financial markets from different perspectives can also be found in LeBaron (2006), Levy *et al.* (2000) and Boer *et al.* (2005).

Adaptive Belief Systems (Brock and Hommes (1989))

Brock and Hommes (1989) investigate market dynamics in a simple present discounted value asset pricing model with heterogeneous beliefs. The authors investigate possible bifurcation routes to complicated asset price dynamics, by using a mixture of bifurcation theory and numerical methods. A few simple belief types are considered in the experiments. Brock and Hommes (1989) present numerical evidence of chaotic attractors when the intensity of choice to switch prediction strategies is high. The paper shows how an increase in the intensity of choice to switch predictors can lead to market instability and the emergence of complicated dynamics for asset prices and returns. This includes irregular switching between phases where prices are close to the fundamental value, phases of optimism where traders extrapolate upward trends, and phases of pessimism where traders are causing a sharp decline in asset prices (Brock and Hommes, 1989).

Switching model (Lux (2000))

Lux (2000) describes a financial market with a fixed number of fundamentalist and chartists. Fundamentalists' trading is based on fundamental value. They buy when the current market price is below the fundamental value. Chartists or technical traders pursue a combination of imitative and trend following strategy. The author presents a possible explanation for volatility clustering in multi-agent framework using a switching principle in strategy choice. To summarize, Lux's model generates all of the mentioned stylized facts of financial markets endogenously through the interaction of the agents. The author argues that the source of volatility clustering and leptokurtotic return distributions is the switching between chartist and fundamentalist strategies. Statistical investigation of the simulated time series showed that the main stylized facts can be found in the artificial market modeled by Lux (2000).

Microscopic Simulation (Levy et al. (2000))

Levy, Levy, Solomon's model is a prominent model of the financial market based on the microscopic simulation approach which has roots in physics. It is a numerical model developed in the framework of expected utility maximization. In this paper, we have focused on the variant of the model presented in Levy *et al.* (2000).
One of the main results of the simulations is that investors who use past information create cyclic bubbles and crashes which can be related to the size of their memory window. This happens in the case when investors are homogeneous with respect to their memory lengths. When investors are heterogeneous in memory lengths, the market dynamics becomes more realistic in the sense that it does not display such prominent and semi-predictable bubbles. Levy *et al.* (2000) have also applied this model to investors who are characterized by Prospect Theory type of preferences.

Investment Systems Based on Behavioral Finance (Takahashi and Terano (2003)

Although various behavioral aspects of agents, including investor biases, have been studied in earlier literature, the model of Takahashi and Terano (2003) is to our knowledge one of the first agent-based models that explicitly studied a number of investor biases proposed in the behavioral finance literature. When the market consists of the same number of fundamental and technical traders, the market price correlates with the fundamental price. However, when there is a large fraction of technical traders in the market, the market price deviates largely from the fundamentals and fundamentalists are eventually eliminated from the market. There are also deviations from the fundamental price in the case of overconfident investors and when non-fundamentalists act asymmetrically towards losses.

SimStockExchange Model (Hoffmann et al. (2007)

Following the tradition of Takahashi and Terano (2003), the paper of Hoffmann *et al.* (2007) is another study that combines a number of behavioral phenomenawithin an agent-based simulation of the financial market. Hoffmann *et al.* (2007) focus especially on the social aspects of investor behavior and studyconsequences of two distinct network topologies. The results of the simulations indicate that the structure of the social network of investors influences the dynamics of the prices. When investors were forming a Barabasi and Albert scale-free network, there was no indication of volatility clustering in the market, but when they were forming a torus network, such evidence was found. The authors speculate that networks of investors may behave more like networks with respect to information diffusion, and that information may sometimes take longer to travel to distant parts of the networks, allowing the old shocks to influence the presence for a considerable period of time (Hoffmann *et al*., 2007).

Genoa Artificial Market (Cincotti et al. (2011)

In their paper, a multi-assets artificial financial market populated by zero-intelligence traders with finite financial resources is presented. The market is characterized by different types of stocks representing firms operating in different sectors of the economy. Zero-intelligence traders follow a random allocation strategy which is constrained by finite resources, past market volatility and allocation universe. Within this framework, stock price processes exhibit volatility clustering, fat-tailed distribution of returns and reversion to the mean. Moreover, the cross-correlations between returns of different stocks are studied using methods of random matrix theory. The probability distribution of eigen-values of the cross-correlation matrix shows the presence of outliers, similar to those recently observed on real data for business sectors. It is worth noting that business sectors have been recovered in our framework without dividends as the only consequence of random restrictions on the allocation universe of zero-intelligence traders. Furthermore, in the presence of dividend-paying stocks and in the case of cash inflow added to the market, the artificial stock market points out the same structural results obtained in the simulation without dividends. These results suggest a significant structural influence on statistical properties of multi-assets stock market.

In short, making strong assumptions in standard financial models may have been about the only way to make theoretical generalizations about the market behavior. But now that the growing computing power and advancing computational methods have enabled researchers to relax some of those assumptions, economics and finance are witnessing an important paradigm shift towards a behavioral, agent-based approach. According to this approach, markets are seen as complex dynamical systems consisting of heterogeneous learning, irrational heterogeneous agents.

V. Conclusion

Financial market regulation is based on the classical theoretical paradigm of individual rationality, which requires, among other things, that investment choices are made after acquiring and processing all the available information, on the basis of pre-existent, stable and consistent preferences and by using a cognitive process of utility maximization. Global economic and financial problems caused by the disorderly unwinding of imbalances that had been accumulating over decades cannot be easily reconciled with the efficient market paradigm based on rational expectations and perfectly rational representative agent assumptions.

However, individuals do not act rationally, nor do they seem able to acquire and correctly process the available information. Vice versa, when choosing under uncertainty, they seem inclined to apply rules of thumb that allow simplifying problems. Moreover, preferences do not appear stable and well-defined since they may change depending on whether prospects of loss or gains prevail and according to the presentation format. These factors lead to systematic evaluation errors as well as violations of the assumption of rationality. Paradoxically, it is hardly rational to attempt being perfectly rational. Moreover, a large thread of literature of psychology and behavioral finance suggest that economic behavior is often better explained by simple heuristic rules and irrational biases rather than by dynamic optimization.

While psychology studies behavioral biases in order to understand how they arise and manifest themselves, behavioral finance aims to understand how they aggregate across individuals, whether they have impact on the market dynamics and ramifications for investor performance. In order to study such implications of investor biases, it is important to understand the most relevant aspects of investor behavior as well as the environment in which they are operating. Although there is a significant body of literature on those topics, not much attempt has been made to conceptualize and give more structure to this body of knowledge. In this situation there is actually a growing need to look for a replacement for financial and macroeconomic models based on heroic assumptions.

This paper advocates the view that agent-based financial modeling, which models financial markets as complex dynamical systems consisting of interacting heterogeneous agents, can potentially become a viable alternative. This agent models inspired by cognitive ability, personality traits and culture are concerned with mechanisms which generate human decision and behaviors, and which have to a large extent and for a long time been considered as a black box.

References

[1]. Alwathainani, A. (2012), "Consistent winners and losers", International Review of Economics and Finance, Vol. 21, pp. 210-220.
[2]. Arthur, B., Holland, J., LeBaron, B., Palmer, R., Tayler, P., (1997), "Asset Pricing Under Endogenous Expectations in an Artificial Stock Market", The Economy as an Evolving Complex System II, pp. 15-44.
[3]. Baltussen, G., (2009), "Behavioral Finance: an Introduction", SSRN Working Paper.
[4]. Barber, B. and Odean, T. (2002), "Online Investors: Do the Slow Die First", Review of Financial Studies, Vol. 15, pp. 455-488.
[5]. Barberis, N., Shleifer, A. and Vishny, R. (1998), "A model of investor sentiment", Journal of Financial Economics, Vol. 49, pp. 1-53.
[6]. Bernardo, A. and Welch, I. (2001), "On the Evolution of Overconfidence and Entrepreneurs", Journal of Economics and Management Strategy, Vol. 10, pp. 301-330.
[7]. Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992), "A theory of Fads, Fashion, Custom and Cultural Change as Informational Cascades", Journal of Political Economy, Vol. 100, pp. 992-1026.
[8]. Blasco, N., Corredor, P. and Ferreruela, S. (2012), "Does Herding Affect Volatility? Implications for the Spanish Stock Market", Quantitative Finance, Vol. 12, pp. 311-327.
[9]. Bloomfield, R. and Hales, J. (2002), "Predicting the next step of a random walk: experimental evidence of regime-shifting beliefs", Journal of Financial Economics, Vol. 65, pp. 397-414.
[10]. Boussaidi, R. (2013), "Representativeness Heuristic, Investor Sentiment and Overreaction to Accounting Earnings: The Case of the Tunisian Stock Market", Procedia Social and Behavioral Sciences, Vol. 81, pp. 9 -21.
[11]. Brock, W. and Hommes, C. (1998), "Heterogeneous Beliefs and Routes to Chaos in a Simple Asset Pricing Model", Journal of Economic Dynamics and Control, Vol. 22, pp. 1235-1274.
[12]. Campbell, J. (2000), "Asset Pricing at the Millennium", Journal of Finance, Vol. 55, pp. 1515-1567.
[13]. Cen, L., Hilary, G. and Wei, J. (2013), "The Role of Anchoring Bias in the Equity market: Evidence from Analysts' Earnings Forecasts and Stock Returns", Journal of Financial and Quantitative Analysis, Vol. 48, pp. 47-76.
[14]. Chang, E., Cheng, W. and Khorana, A. (2000), "An Examination of Herd Behavior in Equity Markets: an International Perspective", Journal of Banking and Finance, Vol. 24, pp. 1651-1699.
[15]. Charness, G., Karni, E. and Levin, D. (2010), "On the Conjunction Fallacy in Probability Judgment: New Experimental Evidence Regarding Linda", Games and Economic Behavior, Vol. 68, pp. 551-556.
[16]. Chen, S. (2007), "Computationally Intelligent Agents in Economics and Finance", Computational Intelligence in Economics and Finance, Vol. 2, Springer-Verlag Berlin Heidelberg, pp. 143-176.
[17]. Chiang, T. and Zheng, D. (2010), "An Empirical Analysis of Herd Behavior in Global Stock Markets", Journal of Banking and Finance, Vol. 34, pp. 1911-1921.
[18]. Chou, R. and Wang, Y. (2011), "A test of the different implications of the overconfidence and disposition hypotheses", Journal of Banking and Finance, Vol. 35, pp. 2037-2046.
[19]. Christie, W. and Huang, D. (1995), "Following the Pied Piper: do Individual Returns Herd Around the Market?", Financial Analyst Journal, pp. 31-37.
[20]. Cincotti, S., Ponta, L. and Pastore, S. (2011), "Information-Based Multi-assets Artificial Stock Market with Heterogeneous Agents", Nonlinear Analysis: Real World Applications, Vol. 12, pp. 1235-1242.
[21]. Demirer, R. and Kutan, A. (2006), "Does Herding Behavior Exist in Chinese Stock Market?", Journal of International Financial Markets", Institutions and Money, Vol. 16, pp. 123-142.
[22]. Demirer, R., Kutan, A. and Chen, C. (2010), "Do Investors Herd in Emerging Stock Markets? Evidence from the Taiwanese market", Journal of Economic Behavior and Organization, Vol. 76, pp. 283-295.
[23]. Ehrentreich, N. (2006), "Technical Trading in the Santa Fe Institute Artificial Stock Market Revisited", Journal of Economic Behavior and Organization, Vol. 61, N°4, pp. 599-616.
[24]. Engelhardt, G. (2003), "Nominal loss aversion, housing equity constraints, and household mobility: evidence from the United States", Journal of Urban Economics, Vol. 53 ,pp. 171-195.

[25]. Fama, E. (1965), "The Behavior of Stock Market Prices", Journal of Business, Vol. 38, N°1, pp. 34-105.
[26]. Ferreira, F., Gyourko, J. and Tracy, J. (2008), "Housing busts and household mobility", NBER
[27]. Fischer, P. and Verrecchia, R. (1999), "Public Information and Heuristic Trade", Journal of Accounting and Economics, Vol. 27, pp. 89-124.
[28]. Frieder, L. (2004), "Evidence on Behavioral Biases in Trading Activity". Working paper, University of California, Los Angeles.
[29]. Frieder, L. (2008), "Investor and price response to patterns in earnings surprises", Journal of Financial Markets, Vol. 11, pp. 259-283.
[30]. Gleason, K., Lee, C. and Mathur, I. (2003), "Herding Behavior in European Futures Markets", Finance Letters, Vol. 1, pp. 5-8.
[31]. Gleason, K., Mathur, I. and Peterson, M. (2004), "Analysis of Intraday Herding Behavior among the Sector ETFs", Journal of Empirical Finance, Vol. 11, pp. 681-694.
[32]. Goetzmann, W. and Kumar, K. (2008), "Equity Portfolio Diversification", Review of Finance, Vol. 12, pp. 433-463.
[33]. Grinblatt, M. and Han, B. (2005), "Prospect theory, mental accounting, and momentum", Journal of Financial Economics, Vol. 78, pp. 311-339.
[34]. Guo, L. (2013), "Can representativeness heuristic traders survive in a competitive securities market?", Journal of Financial Markets, Vol. 16, pp. 152-164.
[35]. Hachicha, N., Jarbouib, B. andSiarryc, P. (2011), "A fuzzy Logic Control Using a Differential Evolution Algorithm Aimed at Modeling the Financial Market Dynamics", Information Sciences, Vol. 181, N°1, pp. 79–91.
[36]. Hirshleifer, D., Lim, S. and Teoh, H. (2002), "Limited Investor Attention and Stock Market Misreactions to Accounting Information", Oxford JournalsEconomics and Social SciencesReview of Asset Pricing Studies, Vol. 1, N°1, pp. 35-73.
[37]. Hoffmann, W. and Eije, E. (2007), "Social Simulation of Stock Markets: Taking it to the Next Level", Journal of Artificial Societies and Social Simulation, Vol. 10, N°2.
[38]. Hommes, C. (2006), "Heterogeneous Agent Models in Economics and Finance", Handbook of Computational Economics, Vol. 2, pp. 1110-1186.
[39]. Jureviciene, D. Kristina, J. (2012), "The Impact of Individuals' Financial Behaviour on Investment Decisions", Electronic International Interdisciplinary Conferenc, pp. 3-7.
[40]. Kaestner, M. (2006), "Anomalous Price Behaviour Following Earnings Surprises: Does Representativeness cause Overreaction?", Revue de l'AssociationFrancaise de Finance, 27, 5-31
[41]. Kahneman, D. and Tversky, A. (1973), "Availability: A Heuristics for Judging Frequency and Probability", Cognitive Psychology, Vol. 5, pp. 207-232.
[42]. Kahneman, D. Tversky, A. (1979), "Prospect Theory: An Analysis of Decision Under-Risk", Econometrica, Vol. 47, pp. 263-291.
[43]. Kaustia, M., Alho, E. and Puttonen, V. (2008), "How much does expertise reduce behavioral biases? The case of anchoring effects in stock return estimates", Financial Management, Vol. 37, pp. 391-412.
[44]. LeBaron, B. (2006), "Agent-Based Computational Finance", Handbook of Computational Economics, Vol. 2, pp. 882-892.
[45]. LeBaron, B., Arthur, B. and Palmer, R. (1999), "Time Series Properties of an Artificial Stock Market", Journal of Economic Dynamics and Control, 23:1487-1516.
[46]. Llacay, B. and Peffer, G. (2010), "Realistic Agent-Based Simulation of Financial Crises: the 1998 Turmoil", In Computational Intelligence in Business and Economics, Vol. 3, pp. 189-197.
[47]. Lucas, R. (1978), "Asset Prices in an Exchange Economy", Econometrica, Vol. 46, pp. 1429-1445.
[48]. Lux, T. and Marchesi, M. (2000), "Volatility Clustering in Financial Markets: A Micro-simulation of Financial Agents", International journal of theoretical and applied finance, Vol. 3, pp. 675-702.
[49]. Manahov, V. and Robert, H. (2013), "Herd Behavior Experimental Testing in Laboratory Artificial Stock Market Settings: Behavioral Foundations of Stylised Facts of Financial Returns", Physica A: Statistical Mechanics and its Applications, Vol. 392, N°19, pp. 4351-4372.
[50]. Newton, J., Marco, G., Cesar, C., Jurandir, M. and Sergio, S. (2013), "The Disposition Effect and Investor Experience", Journal of Banking and Finance, Vol. 37, pp. 1669-1675.
[51]. Nik, M. and Maheran, N. (2009), "Behavioral Finance vs Traditional Finance", Advance Management Journal, Vol. 2, pp.1-10.
[52]. Nofsinger, J. and Sias, R. (1999), "Herding and Feedback Trading by Institutional and Individual Investors", Journal of Finance, Vol. 54, pp. 2263-2295.
[53]. Odean, T. (1998), "Are Investors Reluctant to Realize Their Losses?", Journal of Finance, Vol. 53, pp. 1775-1798.
[54]. Odean, T. (1999), "Do Investors Trade Too Much?", American Economic Review, Vol. 89, pp. 1279-1298.
[55]. Paolo, P. (2014), "Prospect Theory and market quality", Journal of Economic Theory, Vol. 149, pp. 276-310.
[56]. Pompian, M. (2006), "Behavioral Finance and Wealth Management: Building Optimal Portfolios that Account for Investor Biases". John Wiley and Sons.
[57]. Raberto, M. Cincotti, S., Focardi, SM. and Marchesi, M. (2001), "Agent-Based Simulation of a Financial Market", Physica A, Vol. 299, pp. 319-327.
[58]. Rekik, Y. and Boujelbene, Y. (2013), "Determinants of Individual Investors' Behaviors: Evidence from Tunisian Stock Market", IOSR Journal of Business and Management, 109-119.
[59]. Sadi, R., Ghalibaf, H., Rostami, M., Gholipour, A. and Gholipour, F. (2011), "Behavioral Finance: The Explanation of Investor's Personality and Perceptual Biases Effects on Financial Decisions", International Journal of Economics and Finance.
[60]. Schlarbaum, G., Lewellen, W. and Lease, R. (1978), "Realized Returns on Common Stocks Investments: The Experience of Individual Investor", Journal of Business, Vol. 51, pp. 299-325.
[61]. Shefrin, H. (2000), "Beyond Greed and Fear - Understanding Behavioral Finance and the Psychology of Investing", Harvard Business School Press.
[62]. Shefrin, H. and Statman, M. (1985), "The Disposition to Sell Winners too Early and to Ride Losers too Long: Theory and Evidence", Journal of Finance, Vol. 40, pp. 777-790.
[63]. Simon, A. (1991), "Bounded Rationality and Organizational Learning", Organization Science, Vol. 2, pp. 125-34.
[64]. Strahilevitz, M., Barber, B. and Odean, T. (2011), "Once Burned, Twice Shy: How Naïve Learning, Counterfactuals, and Regret Affect the Repurchase of Stocks Previously Sold", Journal of Marketing Research, Vol. 48, pp. 102-120.
[65]. Tan, L., Chiang, C., Mason, J. and Nelling, E. (2008), "Herding Behavior in Chinese Stock Markets: An Examination of A and B shares. Pacific-Basin Finance Journal, Vol. 16, pp. 61-77.
[66]. Thaler, R. (1985), "Mental Accounting and Consumer Choice", Marketing Science, Vol. 4, N°3, pp. 199-214.
[67]. Törngren, G. and Montgomery, H. (2004), "Worse than Chance? Performance and Confidence Among Professionals and Laypeople in the Stock Market", Journal of Behavioral Finance, Vol. 5, pp. 148-153.
[68]. Tversky, A. and Kahneman, D. (1974), "Judgment Under-Uncertainty: Heuristics and Biases", Science, pp. 1124-1131.

[69]. Tversky, A. and Kahneman, D. (1992), "Advances in Prospect Theory: Cumulative Representation of Uncertainty", J. Risk Uncertainty, Vol. 5, pp. 297-323.
[70]. Weber, M. and Camerer, C. (1998), "The Disposition Effect in Securities Trading: An Experimental Analysis", Journal of Economic Behavior and Organization, Vol. 33, pp. 167-184.
[71]. Working Paper, (No. 14310).