Behavioral Finance and Agent Based Model: the new evolving discipline of quantitative behavioral finance?

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Abstract

The financial crisis of recent years has called into question the ability of the traditional economic models to help to govern the complexity of the modern financial world. A growing number of scholars, practitioners, and regulators agree that the recurring financial crisis as well as the overwhelming evidence of market anomalies could be explained only by resorting to behavioral finance. Behavioral finance has been able to identify the irrationality of individual investors but proved unable to quantify its total effect on the market in terms of price deviation from fundamental. Quantitative Behavioral Finance (QBF) is an emerging discipline that attempts to model the impact of human cognitive biases over asset prices. The aim of this paper is to provide an overview of the theoretical foundations of QBF and its challenges. The paper is divided in two parts. In the first one, we present a much selected literature review of the key theoretical foundations. Why has this new field of study emerged? What topics does it study? Which disciplines have contributed the most and why? In the second part, the paper sketches an outline and provides a preliminary, set of references about the agent-based model approach as one of the most promising lines of research in quantitative modeling of the behavioral investors' impact on the market. The literature surveyed supports the use of this class of models because of their capability in copying with heterogeneous agents' behavior whether rational or bounded rational, without losing the ability to identify and examine how each operates separately or in interaction. Taken as a whole, the articles reviewed here indicates that many open issues remain both in the theoretical design of agent-based models, due to the modelers' large degree of freedom, and in the empirical use of this class of models for real political economic implications, due to the methodological difficulties for the model validation, calibration and estimation.

Keywords: Literature review**,** quantitative behavioral finance, agent computational finance.

1. Introduction

The traditional economic approach to financial market devised by the American economist Fama with Efficient Market Hypothesis (EMH) has been the fundamental paradigm for Quantitative financial studies. This hypothesis, assuming a rational representative agent and a frictionless market, should result in the observation of a random walk time series of the asset price, i.e. the asset prices are unpredictable[1] (Fama, 1970). Nevertheless, the statistical analysis of asset prices time series showed many empirical regularities of financial data market known as the stylized

[1] In the broadest terms of EMH, there are three types of market efficiency. Firstly, in weak form efficiency, the information set is that the market index reflects only the history of prices or returns themselves. Secondly, in semi-strong form efficiency, the information set includes most information known to all market participants. Finally, in strong form efficiency, the information set includes all information known to any market participant.

facts[2]. During the recent decades these phenomena have drawn the attention of scholars from different disciplines, such as mathematicians and physicists[3], who have sought to produce a different theoretical explanation. Meanwhile Behavioral Finance (BF) scholars investigated individual investors' behavior with techniques derived from experimental psychology and observation, showing how cognitive limitation might lead to anomalies at market level.

BF has gained consensus among professionals and a part of the Academe because of its capability to explain some financial phenomena such as the recurring financial crises. De Bondt et al. reported as examples: the stock market crash of 1987, the bubble in Japan during the 1980s, the demise of Long-Term Capital Management, the Asian crisis of 1997, the dot-com bubble, and the financial crisis of 2008 (DeBondt et al., 2008). *"Most everyone agrees that it is problematical to discuss these dramatic episodes without reference to investor psychology."* (DeBondt et al., 2008) . In spite of the growing attention of academics, practitioners, and regulators, a new coherent alternative market model has not yet emerged. Most BF studies are qualitative and lack discipline. Behavioral finance has been able to identify the irrationality of the individual investor but is unable to quantify its total effect on the market in terms of price deviation from fundamental [4] (DeBondt et al., 2008). Some scholars refer to Quantitative Behavioral Finance (QBF) as a

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[2] Example of stylized facts in financial time series are excess volatility, high trading volume, temporary bubbles and trend following, sudden crashes and mean reversion, clustered volatility and fat tails in the returns distribution . We refer the reader to the seminal work of Bollerslev et al. for a first discussion of the empirical regularities on asset returns volatility (Bollerslev et al., 1986).

[3] We have seen as the famous Mandelbrot's study of as well as the recently development of Econophysics.

[4] There is a lot of controversy in regard to the fundamental of an asset price. Let's take Keynes that underlined how difficult it is to define the "fundamental price" . He stated that it is not clear what the 'correct' fundamental variables are, and fundamentals can be relevant only when enough traders agree on their role in determining asset prices (Keynes, 1936). .

new multidisciplinary approach that attempts to model the prediction of asset prices using quantitative methods to measure the impact of human cognitive biases over asset prices.[5] Hence, research in behavioral finance has to rely on complementary methodologies (DeBondt et al., 2008). One of the most known approaches for studying financial markets with a quantitative (computational) approach is the agent-based model and the derived models of the artificial stock markets recently surveyed by LeBaron (LeBaron, 2006). Artificial financial markets are models to study the link between individual investor behavior and financial market dynamics. The heterogeneous bounded rational agents' model (Hommes, 2006) focuses on small type models with only a few different kinds of traders who may apply an evolving set of rather sophisticated trading strategies (Westerhoff, 2008). These models make it possible to virtually replicate the stylized facts of asset price returns (Hommes, 2006) . They could also enable the study of heterogeneous bounded rational agents market and the analysis of cognitive biased agent impact upon the market.

The term "quantitative behavioral finance" is widely used but, as an emerging field of study, it has a variety of meanings[6]. This paper has been inspired by a recent Conference[7] on this field of study. It begins by briefly introducing, in section 2, the traditional economic approach to asset pricing. Section 3 presents the behavioralist approach and the need to use complementary

[5] As for any emerging field of study a precise definition of the field is not yet available: We have chosen this one as the most useful for the present work.

[6] This work is not aimed to be a systematic review of all the methodologies proposed in regard to quantitative approach Behavioral Finance. A relevant example, not reviewed in this study, is the work by Gudrun Caginalp (Caginalp & DeSantis, 2011)

[7] The Conference on Quantitative Behavioral Finance, Nice Dec. 8-11, 2010.

quantitative methodologies. Section 4 and 5 presents the Computational economic and the agent- based model approach for studying financial markets. Section 6 is the conclusion.

2. Modern Neoclassical quantitative financial Approach

In the last fifty years the Efficient Market Hypothesis (EMH) (Fama, 1970) has been the theory that has dominated the analysis of financial economics. EMH states that market prices fully reflect all available information. This hypothesis is rooted in the traditional neoclassical economic approach. The theory "has more been challenged by economists who stress psychological and behavioral elements of stock-price determination and by econometricians who argue that stock returns are, to a considerable extent, p*redictable"* (Malkiel, 2003). There are many other critics, among them; the agent computational economic researchers rooted in Simon's bounded rationality theory.

2.1 The Rational behavior assumption

"Rational behavior has two related but different aspects (e.g. Sargent, 1993). Firstly, a rational decision rule has some micro-economic foundation and is derived from optimization principles, such as expected utility or expected profit maximization. Secondly, agents have rational expectations (RE) about future events, that is, beliefs are perfectly consistent with realizations, and a rational agent does not make systematic forecasting errors." (Hommes, 2006)

Rational expectations happened to offer a smart and mean way to disregard genuine market psychology study and proper forecasting regulations when dealing with economic modeling. The rational expectations hypothesis has dominated mainstream economic thought with the expectation formation paradigm right from its introduction by Muth in the 60s and its popularization in economics by Lucas; Milton Friedman, who defended the rational agent approach, declared that investors', consumers' and firms' behavior may be understood as if it was rational (Egidi, 2005).

2.2 Efficient Market Hypothesis and APT

Fama (Fama, 1970) claimed that market efficiency is a further relevant topic when discussing rational against boundedly rational behavior. If markets were not efficient, the resulting over-looked profit opportunities would remain in rational arbitrage traders' hands. Then, by means of under or overpricing, they would take asset prices back to the fundamental value. There cannot be a structure to forecast asset returns because such a structure would disappear faced with rational arbitrageur's exploitation. According to Fama's Efficient Markets Hypothesis (EMH), rational traders never miss unexploited profit opportunities; within the traditional scheme, in which there are no market frictions, security's price equals its fundamental value. That is to say, those prices are right in the sense that they are fixed by sensible agents with knowledge of Bayes' law.

2.3 Joint hypothesis problem

It is not possible to test Market Efficiency in itself, but only together with an equilibrium model such as the Capital Asset Pricing Model or the Arbitrage Pricing Model.

One of Hayward's papers published in 2005 described the principal features of the modern neoclassical approach or "*Autonomous Representative Agents' Approach*" (Hayward, 2005). Hayward's representation of the model with its building blocks is shown in figure 1.

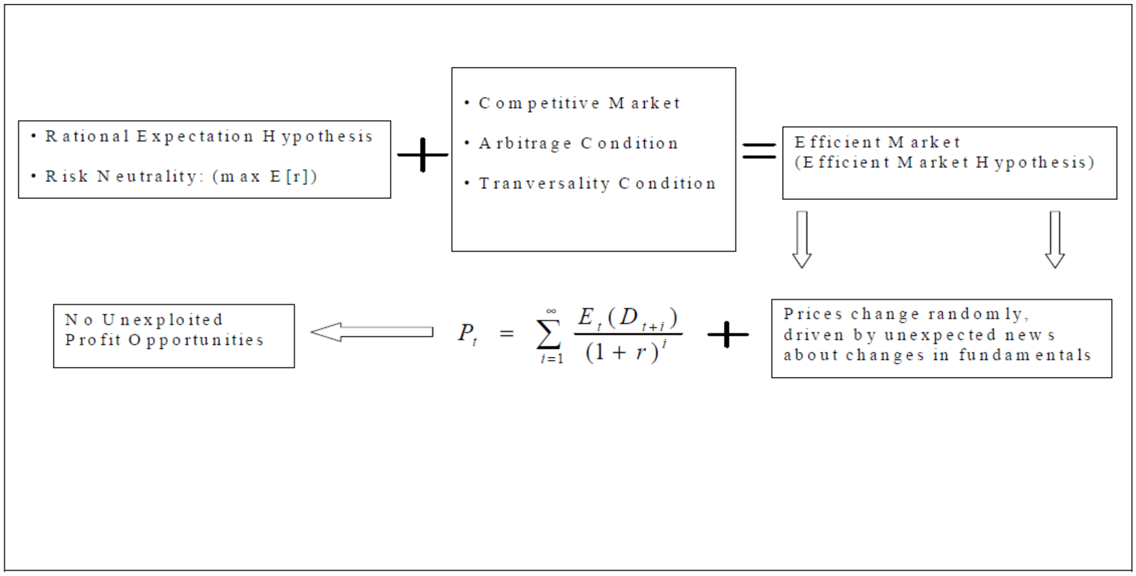

Figure 1. The Autonomous Representative Agents' Approach and Assets Pricing.

3. Behavioral finance and Quantitative Behavioral finance

The BF roots can be found in the Tversky's and Kahnemann's work on prospect theory (Kahneman & Tversky, 1979), studies on decision-making, and the bounded rationality of Herbert Simon (Simon, 1991). Tversky and Kahneman, the pioneers of heuristics and biases literature focused on cognition; exploring how people think or how they decide. At present cognitive based studies are ongoing with further works on emotion and social psychology, with especial interest in herding behavior. [8]

Since the 1950's the normative interpretation of decision-making theory has been called into question and some scholars have resorted to positivist approach through observation and experi-

[8] New disciplines like Neuroeconomics and Social psychology studies are contributing to behavioral economics and finance. We refer to the studies of Camerer and Nowak.

ments to understand "how decisions are truly made" (DeBondt et al., 2008). Their starting point is "bounded rationality" (Egidi, 2005).

Behavioral finance emerged as a field in the early 1980s with contributions, among others, from David Dreman, Robert Shiller, Hersh Shefrin, Meir Statman, Werner De Bondt, and Richard Thaler (DeBondt et al., 2008). Psychologists and behavioral scientists have reported systematic violations of principles of the rationality assumption due to the cognitive characteristics of choice processes that are becoming more and more important for the explanation of investment decisions. De Bondt et al (DeBondt et al., 2008) underlined: "Behavioral finance endeavors to bridge the gap between finance and psychology. Now an established field, behavioral finance studies investor decision processes which in turn shed light on anomalies, i.e., departures from neoclassical finance theory." Hence Behavioral Finance deals with nature and quality of financial judgments, individual economic agents' choices, and the consequences arising for institutions and markets as a whole.

Among its many definitions we can say that Behavioral finance is the study of the way in which psychology influences financial decisions in households, markets and organizations; BF research questions are about what people do and how they do it. As for its research methods, most of them are (but not exclusively) inductive. Facts regarding individual behavior are collected by means of experiments, surveys and field studies, all these behavioral researchers will finally be classified into "super facts" (DeBondt et al., 2008).

3.1 Bounded rationality decision making theory

Herbert Simon (Simon, 1978) emphasized that individuals are limited in their knowledge about their environment and in their computing abilities. Moreover, he claimed that they face search costs to obtain sophisticated information in order to pursue optimal decision rules. Simon argued that, because of these limitations, bounded rationality with agents using simple but reasonable or satisfying rules of thumb for their decisions under uncertainty is a more accurate and more realistic description of human behavior than perfect rationality with fully optimal decision rules.

3.2 Computational bounded rationality

To make decisions involves reasoning. Complex problems require computational power, like for example, solving an assignment problem in Operations Research. Some agents may be able to solve larger problems more quickly than others. If we push the computational limit even further, making rational decisions may involve solving combinatorial optimization problems for which no known NP algorithms are available, like job shop problems or the traveling sales-man's problem with thousands of cities. "Whether rational agents exist is therefore questionable; the best thing one can do (in general cases) is to find approximations. Given a limited amount of time, some algorithms will be able to find better approximations than others will. Given the same algorithm, the faster a computer is the more potential it can have to find better solutions. Therefore, when serious computation is involved, how 'rational' an agent is depends on what algorithms it uses, and what computing power it has access to." (Tsang & Martinez Jaramillo, 2004)[9]

[9] See also from the same author (Tsang, 2008) where he formalizes the "Cider Theory".

3.3 Human cognitive bounded rationality

Behavioral economics is rooted on the psychological studies on judgmental heuristics, cognitive biases, and mental frames (DeBondt et al., 2008). Behavioral finance builds itself upon two pillars: psychology, and limits to arbitrage (Barberis and Thaler, 2003). Psychology lists a number of deviations from rationality due to cognitive biases; the limits to arbitrage have tried to explain the phenomena of mispricing. If noisy traders, irrational investors, prevailed in the market determining a price different from fundamental values[10], rational investors might not be able to correct this mispricing through the arbitrage. According to Barberis and Thaler such examples of inefficiencies may continue for a long time on the actual financial markets because the rational investors would avoid the high costs and risks emerging when applying arbitrage strategies (Barberis & Thaler, 2003). To cite Westerhoff: “A huge body of experimental evidence (Simon 1955, Kahneman, Slovic and Tversky 1986, Smith 1991) supports the notion that human agents are boundedly rational” (Westerhoff, 2008).

3.4 Heuristics and frames

A heuristic can be understood as a “rule of thumb”, a simplified way to achieve decision making by applying a general rule to a specific situation. This heuristic procedure benefits our decision making process, improving its speed and possibilities of a correct, or near as, answer. Nevertheless, when dealing with situations which are more complex or involve probability, heuristics can lead us to incorrect answers or results. Examples of relevant heuristics in analysts’ and inves-

[10] Equal reasoning upon the fundamental price can hold here.

tors' decision making are: anchoring, overconfidence and conservatism. Being a relevant concept in BF literature, "anchoring" defines how people choose values based on certain deviation from a determined threshold (anchor) instead of assessing them in an independent way. It has proved to hold even in cases in which the anchor applied is fairly related to the asked question. Needless to say, this affects financial markets as it happens to be widely used by analysts for their predictions – so far from assessing from the bottom up, they will assess from an anchor such as the industry average pricing.

People's tendency to overestimate their own opinions while setting error bounds too low is psychologically described as "overconfidence". In financial theory, in regard to limited arbitrage, overconfidence implies that an investor will set a higher value to assets while reckoning to get a higher return, thus leading to stock market over-valuation[11]. Any decision taken can be seriously affected by the frame in which it has been originally presented. This has been widely documented through several examples of how people consider the framing of the decision more than the 'expected' approach when making a financial decision. Tversky & Kahneman, (Tversky & Kahneman, 1992) provides a remarkable experiment. In this case students were supposed to answer two essentially identical questions about vaccination policy: One was framed so that it saved a fraction (x) of lives, and the second question frame accepted the death of the (1-x) fraction. The students' answers showed great inconsistency across the two choices in spite of the essentially identical questions, so proving that framing is highly influential in decision making.

[11] (Lovric, 2011) pag.58.

Framing is also applied in the explanation of the Equity Premium Puzzle through the Myopic Loss Aversion model created by Bernartzi and Thaler (Benartzi & Thaler, 1993).

3.5 Risk, a normative versus a positive theory approach

The crucial concept for investments and decision making in general is the concept of risk. Yet, there are many definitions of risk with its meaning varying across different domains. In standard decision theory, a risky prospect is expressed as a set of events and event-contingent outcomes, with probabilities assigned to each event. The most influential theories for decisions under risk and uncertainty are the “Expected Utility Theory” and the “Prospect Theory”. There have been many definitions of decision maker’s attitude towards risk. From the Expected Utility Theory, the classical economy risk attitude is defined as a preference between a risky prospect and its expected value through the method of revealed preference[12]. The risk could be measured through the curvature of utility function and can be characterized as risk neutrality, risk-aversion, and risk-seeking. There are many other theories used to study and measure risk in decision theory[13], among them one of the most used in economics is the loss aversion based on Kahneman’s and Tversky’s empirical work (Kahneman & Tversky, 1979) on Prospect Theory. ”Losses loom larger than gains, and while people are typically risk-averse for gains, they are risk-seeking in the domain of losses” (Kahneman and Tversky, 1979).

[12] For a clear description of the theory we refer to (Mas-Colell et al., 1995) chapter 1.

[13] We refer to Lovric (Lovric, 2011) for a short list of theories for dealing with uncertainty, ambiguity, or vagueness .

3.6 Financial market anomalies

Econometricians have recognized some empirical regularity of time series not congruent with the EMH, the so called stylized facts. By the end of the last century researcher had documented many more anomalies through empirical research. Malkiel's work (Malkiel, 2003) analyzed the hypothesis that stock prices are partially predictable and described the major statistical findings as well as their behavioral underpinnings. He also described the crash of 1987, the dotcom 'bubble', and other specific irrationalities often mentioned by critics of efficiency. Malkiel argues against BF theories, maintaining that the stock markets "are far more efficient and far less predictable than some recent academic papers would have us believe". Hence from his stand-point the evidence is that whatever "anomalous behavior of stock prices may exist, it does not create a portfolio trading opportunity that enables investors to earn extraordinary risk adjusted returns ".

While there is no theoretical evidence[14] of the lasting effects of irrational investors' behavior on the market price, many surveys[15] have documented analysts' and investors' common practice of relying on investment strategies such as technical trading[16] whose assumptions are the opposite of the Malkiel's conclusions. Technical trading rules aim to derive trading signals out of past price movements; fundamental trading rules bet on a reduction of the mispricing in the markets. Agents rely on both technical and fundamental trading rules when determining their

[14] This proof is a real challenge for the behavioral finance theory, for the technical issues we refer to Caginalp (Caginalp & DeSantis, 2011).

[15] Ibidem, pag.18.

[16]Westerhoff (Westerhoff, 2008) cites: Taylor and Allen 1992, Menkhoff 1997, Lui and Mole 1998.

investment position. For short term trading both strategies have been judged equally important (Westerhoff, 2008).

3.7 BF critique and the QBF

Behavioral finance has been for the most part a qualitative discipline, able to identify the individual investor irrationality, but unable to quantify the total effect on the market in terms of price deviation from fundamental. It is also questionable if this deviation is temporary and unique as underlined by Malkiel (Malkiel, 2003). The term QBF is often used as synonym of BF, while some authors refer to QBF as the discipline that quantifies the market effects of the bounded rational investors' decisions, hence a discipline that has to rely on mathematical, statistical or simulation models. The need to resort to complementary methodologies (economic decision making modeling, human subject experiments, and quantitative studies) for behavioral finance has been underlined, among others, by De Bondt et al. (DeBondt et al., 2008). Many approaches have been developed in recent years to precisely quantify the effects of behavioral biases on the market. In a recent work Caginalp and De Santis (Caginalp & DeSantis, 2011) clearly states the reasons for a more structured approach of behavioral finance studies. They also underline the technical issues to quantify the effect of irrational investors on the assets markets and propose a new paradigm based on a structured statistical approach to measure behavioral effects, as for example over- and under-reaction. The suggested method is among those based on the analysis of large available prices' data set, methods beyond the scope of the present work.

4. Agent Computational Economics

The financial crisis of recent years has call into question the ability of the economic sciences to help to govern[17] the financial complexity of the modern world. The ECB's governor Trichet, in the introductory speech given at Central Banking Conference on November 2010, suggested the need "to develop complementary tools to improve the robustness of our overall framework"[18]. He indicated resorting to the Agent Based Model approach[19] as one of the most promising lines of research.

4.1 Reasons for ACE

"Agent-based computational economics (ACE) is the computational study of economies modeled as evolving systems of autonomous interacting agents." (Tesfatsion, 2006). The complicated dynamic system of recurrent causal chains connecting agent behaviors, interaction networks, and social welfare outcomes and two-way feedback between microstructure and macrostructure has long been recognized within economics (Tesfatsion, 2003).

The traditional deductive and inductive models available to economists did not allow modeling this feedback quantitatively in its real complexity. Hence, they had to resort to externally imposed coordination, fixed decision rules, common knowledge assumptions, representative agents,

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[17] *"As a policy*-maker during the crisis, I found the available models of limited help. In fact, I would go further: in the face of the crisis, we felt *abandoned by conventional tools."*(Trichet, 2011)

[18] Ibidem

[19] *He explained further: "*The atomistic, optimizing agents underlying existing models do not capture behavior during a crisis period. We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. We need to entertain alternative motivations for economic choices. Behavioral economics draws on psychology to explain decisions made in crisis circumstances. Agent-based modeling dispenses with the optimization assumption and allows for more complex *interactions between agents."* (Trichet, 2011).

and market equilibrium constraints. Only the highly stylized game could be used to analyze the interactions among economic agents (Tesfatsion, 2003). In the second half of last century the development of the scientific “Complexity” [20] theory and of the computational approach as a tool[21] for the science has allowed the economists to build much more complicated bottom-up system.

4.2 Main ACE Research areas

This new approach required ACE scholars to resort to many areas of research. Particularly relevant for both Economic and Finance[22] are the mechanisms for modeling agents and markets: The modeling of Agents plays an important role in an agent-based model. The theory of learning and decision making and their computational model[23], whether mathematical or derived from the growing studies of artificial intelligence, are at the center of these models research.

4.3 Evolving Agents and market microstructure

The type of agents can vary from no-minded agents, so called zero intelligent agents, with only very simple computational methods like in the agent-based model of financial markets; the zero intelligence (ZI) agents of Gode and Sunder (Gode & Sunder, 1993), to the very sophisticated

[20] (Arthur et al., 1997)

[21] (Miller & Page, 2007).

[22] ACE has been used in many traditional fields of study of economics surveyed in the Handbook of Ace computational economics of L. Tesfatsion and K. Judd).

[23] ACE researchers and other computationally oriented social scientists have used a broad range of representations for the learning processes of computational agents. These include reinforcement learning algorithms , neural networks, genetic algorithms , genetic programming , and a variety of other evolutionary algorithms that attempt to capture aspects of inductive learning .(Tesfatsion, 2003) pag. 3.

learning agents modeled using artificial intelligence techniques like in the seminal Artificial Stock Market (ASM) from the Santa Fe Institute (Arthur et al., 1997). Many techniques derived from artificial intelligence research are used to design the learning mechanisms e.g. : neural networks, genetic algorithms, learning classifier systems, genetic programming, etc.. The study of Market Microstructure is another research field that could take advantage of the flexibility of ABM. Examples are the study, cited in the Computational Economics review of the Tesfatsion, of the simple Walrasian tatonnement or the study of the continuous double auction (Tesfatsion, 2003). The characteristic bottom-up technique allows the modeler an ample freedom even if this feature could also be seen as one of the limits of this class of models (LeBaron, 2006).

4.4 Computational finance and ABM

Advances in computing have given rise to a whole new area of research in finance and economics, e.g.: Computational and Intelligent Finance, Agent Computational finance, Econophisics, Financial Engineering. From an academic point of view, many of these disciplines lack a precise definition, that is, a shared view of their contents and boundaries, as for example artificial intelligence (Tsang & Martinez Jaramillo, 2004). Tsang et. al. were among the first to survey "Computational Finance" (Tsang & Martinez Jaramillo, 2004). They used a working definition of Computational Finance as "the study of investment decisions, trading strategies and risk management using computational simulations". We report their attempt at classification to outline the scope of the Computational Finance using examples of the main research areas. They tried to classify the area of interest as follows:

- Challenges to Fundamentals in Economics and Finance: Rationality and EMH.

- Understanding Financial Markets: Agent-based as in Artificial Markets and the role of evolving agent study, Market microstructure, Computational approaches to game theory.
- Forecasting in computational finance: Neural Networks in forecasting, Evolutionary Computation in forecasting, using data with richer information content, using high frequency data, exploiting arbitrage opportunities, portfolio selection.

In the following sections we will focus on the agent-based Computational Finance as a highly promising line of research in quantitative economic modeling.

5. Agent based computational finance

Artificial financial markets, recently surveyed by LeBaron (LeBaron, 2006), are models for studying the link between individual investor behavior and financial market dynamics (Tesfatsion, 2003). These models are mathematical and computational models of financial markets, usually comprised of learning and evolving heterogeneous and boundedly rational agents, which interact through some trading mechanism. They are built for the purpose of studying agents' behavior, price discovery mechanisms, the influence of market microstructure, or the reproduction of the stylized facts of real-world financial time-series. LeBaron synthesizes the appeal to study these type of markets with ABM under four reasons: 1) Market efficiency and rationality in financial markets are still disputed. 2) Many puzzles remain unexplained. 3) The availability of large data sets permits validation of models. And finally, 4) an evolutionary analysis can benefit from available good fitness measures like wealth or return performance (LeBaron, 2006).

5.1 Designing Artificial Stock Market

Designing of ASF requires addressing key issues related to the Agents and market design. The main agents' features are: decision making, information gathering, learning, and endowments. The key market's design choices are the number and types of securities traded and the clearing system. According to LeBaron (LeBaron, 2006) we can classify these design options into: preferences, price determination, evolution, and learning information representation, social learning, and benchmarks. LeBaron clearly explained these model central insights and limits: "*Since the behavior of agents is completely under the designers' control, the experimenters have* means to control various experimental factors and relate market behavior to observed phenomena. The enormous degrees of freedom that one faces when one designs an agent-based market make the process very complex." (LeBaron, 2006)

5.2 Agent-Based Model and Behavioral Finance

As underlined in the third section of this work BF has recognized the role played by investor's psychology on financial market identified with particular trading strategies such as: momentum trading, trend extrapolation, noise trading, overconfidence, overreaction, etc... To cite Chan, LeBaron and Poggio: "Agent-based models can easily work out both heterogeneous agents and ad hoc heuristics" (Chan et al., 1999). BF makes it possible to study the performance of capital markets as a result of human beings' actions governed much more by their cognitive biases than by their full rationality.

The traditional QF uses the mathematical approach that assures analytical tractability of the model. Although this approach is elegant and rigorous, it can also be considered a drawback since there are many limitations on what can be expressed, solved, or proven analytically. Moreover the computational models can be considered as a more general modeling approach due to their capability to implement both mathematical model and complex algorithms, allowing also the handling of complicate interactions among agents. By these characteristics they make it possible to build quasi-real models of financial markets with more realistic agent's behaviors and trading strategies as well as market mechanisms. Westerhoff clearly states the important role of the BF studies in economic theory:

> ***" Although people lack the cognitive capabilities to derive fully optimal actions, they*** **should not be regarded as irrational. In fact, people strive to do the right thing. It may be more accurate to describe their behavior as rule-governed behavior. This means that people rely on a limited number of simple heuristic principles which have proven to be useful in the past. These heuristics may evolve over time, i.e. bad heuristics are erased, and** ***new ones are created. An agent's choice of a particular rule from the set of available rules*** **in an actual decision situation may be influenced by several factors such as the rules past** ***performance, its appropriateness to the current situation, or simply by the agents' social*** **environment. Overall, these observations may be crucial to economic theory: if we are able to identify peopl*****es' main heuristics, it may*** **be possible to model their behavior. If we succeed in doing this, we may be able to study interactions between them and the effects of** ***such interactions on economic variables"*** **(Westerhoff, 2008).**

In the following section we will focus on a particular class of these models, recently denominated Heterogeneous Agent Model (henceforth, HAM) (Le Baron 2006), which are considered one of the most promising lines of research for understanding the complexity of the modern financial markets (Trichet, 2011). Finally we will briefly review Westerhoff's model (Westerhoff, 2008) as one of the empirical applications in this field of study. In fact, the author used it for studying regulatory policies.

5.3 Heterogeneous Agent Model (HAM)

Heterogeneous agent models are agent-based models very similar to ASF. Like ASF they try to explain facts observed in financial time series going beyond the limits of Autonomous representative agent model (Hommes, 2006). The main difference between the two approaches is that in agent-based computational finance the market simulation is the result of the interactions of a very large numbers of agents, more than hundreds, while in HAM the main focus is on few different types of traders (Westerhoff, 2008). In fact, most of these models focus on behavioral assumptions while neglecting the market structural assumptions". In the introduction to the 2006 survey Hommes states that:

> ***"Economics and finance are witnessing an important paradigm shift, from a* representative, rational agent approach towards a behavioral, agent-based approach in which markets are populated with boundedly rational, heterogeneous agents using rule of *thumb strategies."*** **(Hommes, 2006)**

To overcome the traditional market selection hypothesis that non-rational traders cannot survive on the market, these models resort to Evolutionary Computation as "one of the plausible ways to discipline the wilderness of bounded rationality" [24] due to the excessive number of ways individual agents can deviate from full rationality. The seminal work of the ASF scholars showed that the market does not generally select according to the rational, fundamental strategy, and that simple technical trading strategies may survive in artificial markets (Hommes & Wagener, 2008). Nevertheless, these models are very often too complex to be understandable

[24] Many contributions have showed that the traditional hypothesis does not always hold Even if we are not able yet to clear understand the conditions under which irrational traders can survive. (Hommes & Wagener, 2008) pagg.6-7.

and manageable. In the last decade, scholars introduced quite a number of "simple complexity models" where markets are always viewed as evolutionary adaptive systems with bounded rational interacting agents, but the models are simple enough to be "at least partly analytically tractable." (Hommes, 2006)

We refer the reader to the survey of Hommes (Hommes, 2006) for a review of the models and a technical detailed illustration of these models' structure and how they match important stylized facts such as fat tails in the returns distribution and long memory, which are beyond the scope of this work.

HAM are generally small type models with only a few different types of traders[25]. Among the many advantages of these models a very important one "…is that we are able to pin down some of the causalities acting inside these models" (Westerhoff, 2008).

In the heterogeneous agent model, two assumptions have been set up; different groups of traders could coexist and individual traders have different beliefs on expectations about the next period prices of risky assets based on the same information. While Hommes underlines the need for much work on HAMs to provide a comprehensive review of the subject, in his survey he focuses on stylized dynamic HAMs using some simple examples and tries to give a general overview of this class of models. In particular his review is organized as follows: 1) early HAMs with chartists and fundamentalists and work on survey data analysis of expectations of financial experts;2) a presentation of relation of the work on HAMs to behavioral finance; 3) examples of disequilibrium HAMs, where the interaction of agents leads to complex market dynamics such as cycles or chaotic fluctuations 4) stochastic interacting agent systems and work on social interactions; 5)

[25] LeBaron makes a distinction between ASF with "few type" and "much type" models (LeBaron, 2006).

simple financial market HAMs with herding behavior, able to generate important stylized facts such as clustered volatility; 6) models where sophisticated agents using advanced but costly strategies compete against simple agents using cheap rule of thumb strategies; 7) asset pricing model with heterogeneous beliefs with endogenous evolutionary switching of strategies. Many open issues remain. Examples are: a) the analysis of conditions where irrational traders survive rational ones. b) How the framing judgmental biases affects the evolutionary adaptive system. c) The major part of model works with just two asset classes, the usual risky and risk-free ones, this due to the fact that the study of multiclass market has proved very complex.

5.4 The fundamentalist and chartist approach.

The chartist-fundamental model makes it possible to mimic virtually the effect of the interaction of the two types of strategies that may lead to complex endogenous dynamics. “When technical analysis governs the market, we may observe the start of a bubble. When the market is dominated by fundamental traders, the price adjusts towards its fundamental value. Due to the fact that agents may switch between trading rules, e.g. due to profit differences or herding effects, use nonlinear trading rules or exit markets, there are in fact recurrent episodes where either technical or fundamental trading drives the market” (Westerhoff, 2008). The fundamental strategy is the approach of traders who base their investment decisions upon a certain rational evaluation of the asset price like, for example, the company’s discounted cash flows of future earnings for a stock. Based on this evaluation the fundamentalists buy (sell) assets that are undervalued (overvalued). Technical trading, also known as charting is the approach of traders who try to find simple patterns in asset prices, for example trends; they decide their investment strategy upon the extrapolation of these patterns. A well-known example of chartists' decision-making is the "moving average" trading rule. Investors should buy assets when a short term moving average (i.e. 1 week) is above a long term moving average (i.e. 12 weeks or longer) from below and vice versa (Hommes, 2006). Now there is a huge body of evidence[26] for the use of this 'irrational' trading. Some authors[27] have underlined the possibility of a destabilizing effect on the market by these strategies because of their ability to amplify the trend (Hommes, 2006).

5.5 An example of HAM studying regulatory policies

Westerhoff (Westerhoff, 2008) implemented such a type of model to test the effectiveness of regulatory policies. In his model, agents may be of two types (chartists and fundamentalists) and may switch trading rules. Hence they have three alternatives: relying on technical, or fundamental trading rules or, remaining inactive. The model defines the attractiveness of each strategy and the ways by which agents can decide which trading rule to adopt.

Westeroff's model main findings are:

[26] "Frankel and Froot (1986) were among the first to emphasize the role of fundamentalists and chartists in real financial markets. Evidence from survey data on exchange rate expectations (e.g. Frankel and Froot, 1987, and Allen and Taylor, 1990) shows that at short time horizons (say up to 3 months) financial forecasters tend to use destabilizing, trend following forecasting rules, whereas at longer horizons (say 3-12 months or longer) they tend to use stabilizing, mean reverting, fundamental forecasts." (Hommes 2006 interactions)

[27] Frankel and Froot (1986) argue that the interaction of chartists and fundamentalists amplified the strong rise and subsequent fall of the dollar exchange rate in the mid eighties." (Hommes 2006 interactions)

- It makes it possible to mimic virtually the effect of the interaction of the two types of strategies that may lead to complex endogenous dynamics.
- It is able to match stylized facts quite well.
- It shows that, when technical strategies govern the market, a bubble starts, when fundamentalist strategies, the price adjusts toward the fundamental.
- It shows recurrent episodes of alternation due to agent changing strategy.

In the remainder of the paper Westerhoff uses the model to test the effectiveness of regulatory policies. His purpose is to show how this class of models “may be regarded as a reasonable alternative to traditional economic theorizing, human subject experiments, and empirical studies” (Westerhoff, 2008).

Here we report neither the regulatory policies he studies nor the results obtained, but the main limits and open issues which he found in this approach:

- These models have been used mainly for theoretical studies rather than for real political economic implications.
- Model validation, calibration, and estimation “could be paramount issues in this type of work” (Westerhoff, 2008).
- Among the best known theoretical issues are the large degree of freedom of designing and the consequent difficulty in a clear understanding of the main causes of the stylized facts.

6. Conclusions

This paper has given an overview of theoretical and historical reasons that led to the birth of the new discipline of the Quantitative Behavioral Finance. We started with an introduction to the traditional neoclassic model of asset pricing. After that, we gave an outline of the behavioral finance field of study that has emerged in the last fifty years as an attempt to establish a cognitive bounded rational agents' behavior for the explanation of the overwhelming evidence of anomalies in financial markets. We have seen that psychologists and behavioral scientists have reported systematic violations of the principles of the rationality assumption due to the cognitive characteristics of choice processes proving they are very important for explaining investment decisions. This theory has gained consensus among professionals and a section of the academe because of its capability of explaining financial phenomena such as the recurring financial crises. Nevertheless, BF researchers were unable to quantify the effect of cognitive biases at the market level. QBF is a new multidisciplinary approach which emerging to address this theoretical challenge by using quantitative methods to measure the impact of human cognitive biases over asset prices at market level. Then we reviewed one of the most promising lines of research in quantitative modeling: The agent-based model approach. Scholars and regulators are looking with great interest at a particular class of these models, namely the Heterogeneous agent models. They allow modeling the action on the market of agents with both rational and bounded rationality. The existing literature has been able to reproduce almost all the recognized market anomalies and enable a virtual lab analysis. One aspect which researchers are agreed on is the need for a clearer definition of QBF and, at a theoretical level, of Heterogeneous Agent models.

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