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AGENT-BASED COMPUTATIONAL ECONOMICS AND EXCHANGE RATE MODELING: A TURKISH CASE

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TEZ DANIŞMANI
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ABSTRACT

AGENT-BASED COMPUTATIONAL ECONOMICS AND EXCHANGE RATE MODELING: A TURKISH CASE

Prepared by **Emrah Keleş**

July, 2012

Mainstream economics based on dynamic stochastic equilibrium models has suffered from rigorous assumptions of rationality and homogeneity, and framework of representative agent ruling out interactions between agents. Starting from late 1990s, agent-based computational approach has become increasingly popular in social sciences, especially in financial economics, industrial organization, macroeconomics, political economy, and economic network formation. Finally, 2008 global financial crisis has caused mainstream to be argued and welcome agent-based approach loudly. This new premising approach enable researchers to construct artificial worlds where agents ranging from passive world features to active decision makers who have states and rules of behavior. In this artificial world openness to the interactions which occur between two agents or between an agent and its physical environment lead agents be adaptive (learning) and create a complex adaptive system. Having bottom-up approach, agent-based models (ABMs) offer many advantages for agent-based computational economics (ACE) researchers while it has some insufficiencies. One of field that gets benefit from ABMs is the exchange rate market. In this market heterogeneity is provided by two different forecasting rules: fundamentalists and chartists. In my study, I try to explain the main dynamics of the model and explain the agent-based approach with the help of the simulations performed. I finally compare the simulation outcomes with Turkish exchange rate market and interpret behavior of agents in Turkey.

Keywords : Complex Adaptive Systems,Agent Based Computational Economics, Agent Based Modeling, Exchange Rate, Heterogeneous Interacting Agents

ÖZ

AJAN TABANLI HESAPLANABİLİR EKONOMİ VE DÖVİZ KURUNUN MODELLENMESİ: TÜRKİYE ÖRNEĞİ

Hazırlayan **Emrah Keleş**

Temmuz, 2012

Rasyonellik ve homojenlik varsayımları ile iktisadi ajanlar arasındaki etkileşimi göz ardı eden temsili ajan yaklaşımı dinamik stokastik genel denge modellerine dayanan yerleşik iktisada duyulan güvenin azalmasına yol açmıştır. 1990'ların sonlarından itibaren ajan tabalı hesaplanabilirlik yaklaşımı finansal ekonomi, endüstriyel organizasyon, makroiktisat, politik iktisat ve ekonomik şebeke formasyonu başta olmak üzere sosyal bilimlerde popüler olmaya başlamıştır.Son olarak 2008 küresel finansal kriz yerleşik iktisadın daha yüksek sesle tartışılmasına ve ajan-tabanlı yaklaşımının daha çok benimsenmesine neden olmuştur. Bu yeni yaklaşım araştırmacılara pasif haldeki fiziksel varlıklardan inanışları ve davranış kuralları olan aktif karar alıcılara kadarçeşitli ajanların bulunduğu suni bir dünya kurmalarına imkan vermektedir. Bu suni dünyada ajanların birbirleriyle yada çevreleriyle etkileşimi onların adaptif (öğrenen) olmasına ve kompleks adaptif bir sistem meydana getirmelerine izin vermektedir. Aşağıdan yukarıya yaklaşımı ile ajan tabanlı modeller görece daha az yetersiziliklerine rağmen birçok avantaja sahiptir. Ajan tabanlı modellerin kullanıldığı bir diğer alan olan döviz kuru piyasasında heterojenlik iki farklı tahmin kuralı ile sağlanmmaktadır: fundamentalist ve chartist. Bu çalışmada da döviz kuru modelinin temel dinamikleri açıklanmaya çalışılmış, ajan-tabanlı ekonominin temel unsurları yürütülen simülasyonlar yardımıyla gösterilmeye çalışılmıştır. Son olarak da simulasyon çıktıları Türkiye döviz kuru piyasası ile karşılaştırılarak Türkiye’deki ajanların davranışları yorumlanmıştır

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İstanbul, July 2012 **Emrah Keleş**

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ABBREVATIONS

ABM	: Agent-Based Model(ing)
ACE	: Agent-Based Economics
DM	: Decision-Making
DM	: Deutsche Mark
DSGE	: Dynamic Stochastic General Equilibrium
EU	: European Union
GDP	: Gross Domestic Product
NNS	: New Neoclassic Synthesis
RA	: Representative Agent
RBC	: Real Business Cycle
REEM	: Rational Expectations Efficient Market Theory
SOC	: Self-Organized Criticality
USA	: The United States of America
USD	: The United States Dollar

1.INTRODUCTION

For centuries economists have been seeking of the proper ways to analyze the economic systems. To provide right formula for economic problems variety of models which are inspired from physics have been used. Economists' interest to get benefit from physics led economics to be viewed as some kind of Newtonian machines. Since it was difficult to get analytical solutions from complicated mathematical analyses, economists discovered the "beauty" of making assumptions. Ceteris paribus which is one of oldest fundamentals that enable researchers to make predictions and assume a stable world. General equilibrium approach was prevailed among neo-classics. After Keynesians and Monetarists put more emphasize on macroeconomic phenomenon, i.e. inflation and money supply, respectively, dynamic stochastic general equilibrium (DSGE) models employed by neo-classics synthesis has given importance to microfoundation of macroeconomics. Representative approach was the tool for DSGE models to take individuals into account. However, the assumption of that individuals represent the whole economy and economy consists of n-replications make these model deviate from real world facts.

Models which neglect interactions has suffered from understand the real life dynamics. In fact, economic systems are complex adaptive systems where agents ranging from physical entities to individuals, firms, banks, governments and countries interact each other and with their environment and comprise a dynamic world.

Physicians have been attracted from complex economic models which carry variety of statistical data. Especially financial models such as exchange rate markets involve large numbers of interacting parts which cause particular regulatories to evolve. To distinguish, economic and physical systems are similar but have differences. In economic or financial systems agent-not unit as in physical ones- can learn and interact in more complicated ways.

Agent –based computational economics welcome complex systems and rule out rigorous mainstream economics assumptions. It enables researchers make predictions closer to real world facts unlike mainstream economics which is mainly performed by DSGE models. Agent-based models used in this premising approach create artificial worlds where agents has believes and interact, learn, adapt to environment in accordance with their believes which can change over time.

In this study, I first give general insight on complexity and complex systems. In the next part I try to offer macro side of agents based computational economics (ACE) and compare it to mainstream economics. Putting emphasize on building blocks of ACE and give samples of agent based models on financial markets. Then, I present exchange rate model, perform simulations and interpret the results. Then, I compare the results to Turkish actual exchange rate data. In the last part, conclusion appears with general comments.

2. LITERATURE SURVEY

2.1. Complexity and New Economics

2.1.1. Contribution of Physics to Economics

Heterogeneous agents, non-linearity, random, stochastic are some of the concepts in economics of last years. In real, these are the concepts that statistical physics improved especially. Nevertheless, econophysics, thermo economics, complexity economics (non-linearity, multi equilibrium, increasing return, inequality economics including the importance of minor events) have evolved. These improvements have impact on new economics starting from financial economics.[1] In recent years, physicists have started applying concepts and methods of statistical physics to study economic problems. The word, “econophysics" is sometimes used to refer to this work.[2] Econophysics is a new word, used to describe work being done by physicists in which financial and economic systems are treated as complex systems. Everyone is affected by economic fluctuations, and quantifying fluctuations is a topic that many physicists have contributed to in recent years. Moreover, everyone (rich and poor) would be powerfully affected by a breakdown of the world-wide financial system. Further, it is possible that methods and concepts developed in the study of strongly fluctuation systems might yield new results in economics. Finally, economic systems are complex interacting systems for which a tremendous amount of quantitative data exists, much of it never analyzed.[3] For many physicists, studying the economy means studying a wealth of data on a strongly fluctuating complex system.[4]

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[1] Ecan Eren, “ İktisat Eğitimi ve Yeni İktisat”, **Küresel Bunalım ve İktisat Eğitimi**, ed. Ercan Uygur (Ankara: İmaj Yayınları, 2011): 129-148:

[2] Plerou V. Et al., “Econophysics: Financial time series from a statistical physics point of view”, (Physica, Boston, 2000), 443.

[3] H.E Stanley, et al., “Econophysics: Can physicists contribute to the science of economics?”, (Physica A: Statistical Mechanics and its Applications, Volume 269, Issue 1, 1999): 156.

[4] Op. Cit., Pleou et al.: 444.

Statistical physics is a framework that allows systems consisting of many (possibly heterogeneous) particles to be rigorously analyzed. In econophysics these techniques are applied to ‘economic particles’, namely investors, traders, consumers, and so on. Markets are then viewed as (macroscopic) complex systems with an internal (microscopic) structure consisting of many of these ‘particles’ interacting so as to generate the systemic properties (the microstructural components being ‘reactive’ in this case, as mentioned already, thus resulting in an adaptive complex system). [5] Economic systems such as financial systems are similar to physical systems but comprised of “agents” rather than “units”. On the other hand, they are quite different and much more complex because economic agents are "thinking" units and they interact in complicated ways not yet quantified. Indeed, most physics approaches to finance view financial markets as a complex evolving system. [6]

In particular, economic time series, as e.g., stock market indices or currency exchange rates depend on the evolution of a large number of strongly interacting systems, and belong to the class of complex evolving systems.[7] Thus, the statistical properties of financial markets have attracted the interests of many physicists.[8] Recent studies attempt to uncover and explain the statistical properties of financial time series such as stock prices, stock market indices or currency exchange rates.[9]

De Gatti et al. agree with these saying “Sometimes complexity applied to economics overlaps with econophysics. The underlying methodological assumption of econophysics is that, even if economics is a social science and has to deal with incentives and human decisions the aggregate behavior can be described by models of statistical physics. Collective behavior is the outcome of the interaction of many heterogeneous individuals in ways which recall the interaction of particles in statistical mechanics. Recent works in econonophysics

[5] D. Rickles, “Econophysics and Financial Market Complexity”, **In Handbook of the Philosophy of Science**, ed. J. Collier and C. Hooker, (Nord Holland: Elsevier, Philosophy of Complex Systems, Vol. 10, 2004): 2.
[6] Op. Cit., Plerou, et al.: 444.
[7] Op. Cit., Stanley, et al.: 157.
[8] N. R. Mantegna, Stanley H. E., “Scaling Behaviour in the Dynamics of an Economic Index”, (Leters to Nature, Vol 376, 1995), 47.
[9] Op. Cit. Plerou, et al.: 446.

has focused mainly on three issues: the analysis of the time series of Stock prices, exchange rates and goods prices; the evolution over time of the distribution of firms' size, individual wealth and income; the exploration of economic phenomena by means of networks."[10]

2.1.2. Complexity

The so-called science of complexity, which has grown out of the joint efforts of hard and soft scientists in the '80s and '90s, in fact, claims that there are common properties of complex systems which are the object of study in many different fields such as the cell, the brain, language, the capitalist market economy. The focus therefore has moved from the macro to the micro level. Macroeconomic variables can be reconstructed by summing up individual magnitudes (bottom up procedure). Complex structures consisting of heterogeneous interacting agents generate complex dynamics also of the macro variables.[11] High-level (macroeconomic) systems may possess new and different properties than the low-level (microeconomic) systems on which they are based (much as water has different properties from the atoms of hydrogen and oxygen that constitute it.)[12]
The notion that financial economies are complex systems can be traced at least as far back as Adam Smith in the late 1700s. More recently John Maynard Keynes and his followers attempted to describe and quantify this complexity based on historical patterns. [13]

The foundation of Santa Fe Institute in 1984 also accelerated the development of the complexity economics.[14] In 1987 in Santa Fe Institute where researches on complexity and economics were done, an economic workshop lasting ten days conveyed. Contributing to the workshop consisting of 10 economists and 10 physicists had come to believe that a approach to economics is being created. The

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[10] Delli Gatti, et al.,**Emergent Macroeconomics. An Agent-Based Approach to Business Fluctuations,** (Milan, Springer, 2008), 18.
[11] Op. Cit., Gatti, et al.: 18.
[12] Joseph E. Stiglitz, and Mauro Gallegati, "Heterogeneous Interacting Agent Models for Understanding Monetary Economics", (Eastern Economic Journal, Volume 37, 2011), 10.
[13] D. Farmer and Foley D.,"The economy needs agent-based modelling"(Nature, vol. 460, 2009), 685–686.
[14] Ercan Eren et al., "Kompleksite İktisadı ve Ekonofizik", **Darwin ve Evrimsel İktisat Sempozyumu, 19-20 Kasım 2009**, (Ankara: Hacettepe Üniversitesi, 2009): 130.

views of Brian Arthur who become the director of the institute eventually was summarized by Walldrop:

> "Here was this elusive 'Santa Fe approach': Instead of emphasize the decreasing returns, static equilibrium and perfect rationality, as in the neoclassical view, The Santa Fe team would emphasize increasing returns, bounded rationality and the dynamics of evolution and learning. Instead of viewing the economy as some kind of Newtonian machine, they would see it as something organic, adaptive, surprising and alive…"[15]

Herbert Simon (1981) gives a rough characterization of a complex system as follows: By a complex system I mean one made up of a large number of parts that interact in a non-simple way. In such systems, the whole is more than the sum of its parts, not in an ultimate, metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole.[16]

There are almost as many definitions as there are discussions—indeed, the difficulty of the problem of definition points, Rickles thinks, to the fact that we should avoid 'unificatory' approaches to complexity. However, it is reasonably safe to assume a *kernel* that these diverse accounts share. This kernel involves a triplet of characteristics:

- A (unit) complex system must contain many subunits (the exact number being left vague).
- These subunits must be interdependent (at least some of the time).
- The interactions between the subunits must be nonlinear (at least some of the time).[17]

L. Tesfatsion (2006; 836) defines a system to be complex if it exhibits the following two properties:

- The system is composed of interacting units;
- The system exhibits emergent properties, that is, properties arising from the interactions of the units that are not properties of the individual units themselves.

[15] J.Wible,"What is Complexity", **Complexity and the history of economic thought: selected papers from the History of Economics Society Conference**, ed. Colander D., (2000): 25.
[16] Op. Cit., Rickles: 3.
[17] Op. Cit., Rickles: 4.

Complex economic structures are usually associated with adaptive agents so that they are often referred to in the literature as Complex Adaptive Systems.[18]

L. Tesfatsion (2006; page 836) defines a complex adaptive system with three characterizations: A complex adaptive system is a complex system that includes

- *reactive units*, i.e., units capable of exhibiting systematically different attributes in reaction to changed environmental conditions;
- *goal directed units*, i.e., units that are reactive and that direct at least some of their reactions towards the achievement of built-in (or evolved) goals and
- *planner units*, i.e., units that are goal-directed and that attempt to exert some degree of control over their environment to facilitate achievement of these goals.

Complex systems have no analytical solutions. As Arthur (2009:12) stated, with computer science agent based modeling has become applicable. Thus, there is close link between the development of computers and complexity economics.[19] With computer power doubling every 18 months, the need to rely on analytic solutions decreases and the ability to extract information from data increases. Both of these effects reduce the value of analytic deductive theory. One can get one's insights from the data and from simulations, reducing one's reliance on the deductive theory that characterized formalism.[20]

2.1.3. Complexity VersusNeo Classical Economics

Complexity theory is the most recent movement to rise up as an alternative to general-equilibrium-based, neoclassical mainstream economic theory.[21] Differences between these two approaches are listed below:

[18] Op. Cit., Gatti, et al.: 8.
[19] Op. Cit., Eren, et al.: 130.
[20] D. Colander, "The Complexity Revolution and the Future of Economics", (Middlebury College Economics Discussion Paper no. 03-19, 2003), 4.
[21] Michael R. Montgomery,"Complexity Theory: An Austrian Perspective", , **Complexity Theory and the History of Economic Thought,** ed. D. Colander, (Routledge Press, 1999): 4.

Table 1: Differences between Neo-Classical and Complexity Economics

	Neo Classical Economics	*Complexity Economics*
1.	Linear	Non-linear
2.	Representative agent	Heterogeneous agent
3.	Equilibrium	Disequilibrium (sometimes, inherently multiple-equilibrium)
4.	Rational Expectations	Adaptive, evolutionary, inductive, "groping" processes
5.	Diminishing returns	Increasing returns (positive feedback)
6.	No institution	Path dependence, adaptive evolution, and the vital importance of institutional structure
7.	Simplistic freemarkets presumptions	More complex policy implementations

Ercan Eren, “Yeni İktisatta Ortak Noktalar”, **İktisatta Yeni Yaklaşımlar**, ed. E. Eren, M.Sarfatı, (İletişim Yayınları, 2011): 21.

2.2. Agent-Based Computational Economics

2.2.1. Critiques to Mainstream Economics

The roots of mainstream models in economics can be found in the neoclassicalrevolution of the 1870s. Neoclassical economists, such as Jevons, Walras and Fisher, used methods drawn from mathematical physics (applied paradigms and analogies drawn from Newtonian mechanics) to analyze economic systems. In this world temporary shocks do not have permanent effects, and economic systems can retrace their steps when perturbed away from equilibria…

The neoclassical economic model was reformulated and axiomatised from the 1930s onwards, however many of the original analogies and paradigms were retained. In the 1950s a "neoclassical synthesis" model came to be the conventional wisdom in macroeconomics. Neoclassical equilibria were taken to describe the long-run states of macroeconomic systems, with Keynesian IS-LM type models describing short-run deviations from such equilibria. After a series of controversies sparked by the monetarist counter-revolution against Keynesian orthodoxy, a "new consensus" emerged. This was organized around a dynamic stochastic general equilibrium (DSGE) model apparently founded in microeconomic analysis. The short-run Keynesian features arise from various frictions such as fixed price contracts, but neoclassical output and employment levels are restored reasonably quickly once the shocks affecting the system abate. At the onset of the post-2007 world financial crisis many finance ministries and central banks were using this type of model to guide policy. [22]

In many economic models based on standard microeconomic theory, simplifying assumptions are made for analytical tractability. These assumptions include (1) economic agents are rational, which implies that agents have well-defined objectives and are able to optimize their behavior, (2) economic agents are homogeneous, that is, agents have identical characteristics and rules of behavior, (3) the system experiences primarily decreasing returns to scale from economic processes (decreasing marginal utility, decreasing marginal productivity, etc.), and (4) the long-run equilibrium state of the system is the primary information of interest. [23]

Robert Lucas and others argued in 1976 that Keynesian models had failed because they neglected the power of human learning and adaptation. Agent-based models potentially present a way to model the financial economy as a complex system, as Keynes attempted to do, while taking human adaptation and learning into account, as Lucas advocated. Such models allow for the creation of a kind of virtual universe, in which many players can act in complex — and realistic — ways. [24]

Despite widely use of mainstream approach, there are increasing critiques to the approach. The critiques arise from some main points. Among these, representative

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[22] R. Cross, H., et al, "Hysteresis and Post Walrasian Economics", **Oxford Center for Collobrative Applied Mathematics**, Report Number 11/18(2011) :3-4.

[23] CM Macal and MJ North, "Tutorial on agent-based modelling and simulation", **Journal of Simulation,**(2010): 151-162

[24] Op. Cit. Farmer and Foley: 685

agent frameworks, assumptions of rational expectations and perfect competition are the prominent ones. Joseph E. Stiglitz and Mauro Gallegati claim that built upon the representative agent framework, DSGE models rule out the key macro-economic interactions by assumption. The models also trivially make a conclusion of that there can be no unemployment or liquidity crisis and has nothing to say about the network aspects of lending and inter-bank linkages thathave become apparent during the current crisis.[25]

2.2.1.1.Representative Agent

Since economies are complex systems and non-linarites are pervasive, mainstream economics generally adopts the trick of linearizing functional relationships. Moreover agents are supposed to be all alike and not to interact. Therefore, any economic system can be conceptualized as consisting of several identical and isolated components, each one being a copy of a Representative Agent (RA). The aggregate solution can thus be obtained by means of a simple "N-replication" of the choices made by each optimizing agent. The RA device, of course, is a way of avoiding the problem of aggregation by eliminating heterogeneity. The key point of the aggregation problem: starting from the micro-equations describing/representing the (optimal) choices of the economic units, there is doubt on saying that the macro-equations are same functional form of the micro-equations (the analogy principle) and deriving the macro-theory is problematic.[26]
Modern macroeconomic theory is largely founded on assumptions of perfect competition, driven to this modeling strategy not so much by empirical evidence as by considerations of analytical tractability. Coordination issues are commonly sidestepped by one of two means. One is high level aggregate constructs for which incredibly stringent conditions required, e.g., aggregates Y, K, and L satisfying an aggregate production relation Y=AF(K,L). Another is singlerepresentative agents for the household and firm sectors behaving as competitive price takers.[27]

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[25] Op. Cit. Stiglitz and Gallegatti: 10
[26] Op. Cit., Gatti, et al.: 4.
[27] BlakeLeBaron and Leigh Tesfatsion, “Modeling Macroeconomies as Open-Ended Dynamic Systems of Interaction Agents”, **American Economic Review**, vol.98, no. 2, (2008): 250.

Kirman rejects the defenses that representative agents are designed to examine some central macroeconomics problems rather than studying problems involving coordination matters for four reasons: First, there is no plausible formal justification for the assumption that the aggregate of individuals, even maximizers, acts itself like an individual maximizer. There is simply no direct relation between individual and collective behavior. Secondly, the reaction of the representative to some change in a parameter of the original model may not be the same as the aggregate reaction of the individuals he "represents." Thirdly, the "representative individual" whose choices coincide with the aggregate choices of the individuals in the economy is a utility maximizer. Lastly, the sum of the behavior of simple economically plausible individuals may generate complicated dynamics, whereas constructing one individual whose behavior has these dynamics may lead to that individual having very unnatural characteristics.[28]

There are at least three fundamental features of the real-world mechanisms based on the effects of shocks on the network of credit relationships that are ignored by the RA approach:

First and foremost, by construction, the shock which gives rise to the macroeconomic fluctuation is uniform across agents. The presumption is that idiosyncratic shocks, affecting different individuals differently, would ‘‘cancel out. In a financial network idiosyncratic shocks usually do not cancel out in the aggregate, especially if the shocks hit crucial nodes (hubs) of the network. Second, the aggregate (RA) view does not (cannot) capture the fact that the spreading of a financial disease may proceed at different speeds in different parts ofthe macroeconomics. For some agents, financial robustness may be procyclical, whereas for other agents it is financial fragility that may be pro-cyclical. Last but not least, in a credit network a shock (bankruptcy) in one firm (bank) can lead to an avalanche of bankruptcies.[29]

[28] A. Kirman, "Whom or What Does the Representative Individual Represent", **Journal of Economic Perspectives,** vol. 6 (1992): 118.

[29] Op. Cit., Stiglitz and Gallegati: 8.

The ubiquitous RA is often at odds with the empirical evidence which is a major problem in the foundation of general equilibrium theory and is not perfectly coherent with many econometric investigations and tools.[30]

A flaw in the mainstream model is the assumption that economic agents behave homogenously, and that their collective behavior can be captured by looking at a “representative” agent. The reality is somewhat different — for example, financial capital flows may be intended for start-up of production, or it may be intended as a deposit for a fixed term. Furthermore, different agents use different methods to predict the future behavior of the markets, and so two agents today could have quite different expectations of future returns.[31] As the complexity of economic models increases-with the addition of uncertainty, infinite horizons, infinite commodity spaces, and so on-the plausibility of the single representative agent, acting optimally in all markets and at all times, diminishes.[32]

The RA framework of the DSGE models adopts the most extreme form of conceptual reductionism in which macroeconomics and the financial network are reduced to the behavior of an individual agent. The RA in economics tantamount to saying that ‘‘macroeconomics equals microeconomics.”[33]

All modeling requires simplifications; and in making simplifications there are tradeoffs. The RA approach allows a richer analysis of inter-temporal maximization, but it rules out the possibility of the analysis of complex interactions.[34]

2.2.1.2. Aggregation Problem

On the contrary to Representative Agent concept that evolves in Walrasian Auction aggregate phenomena emerge spontaneously from the interactions of individuals struggling to coordinate their actions on markets: macroscopic regularities emerge from microscopic behavior. In other words, aggregate "laws" are due to emergence rather than to microscopic rules. In turn, emergent

[30] Op. Cit. Gatti, et al., (2008): 661-62.
[31] Op. Cit. Cross, et al.:8-9
[32] Op. Cit., Kirman: 131.
[33] Op. Cit., Stiglitz and Gallegati: 7.
[34] Op. Cit., Stiglitz and Gallegati: 10.

macroeconomic dynamics feeds back on microeconomic behavior through a downward causation process, in which economic and social structures affect the evolution of opportunities and preferences characterizing microeconomic units.

If interactions and aggregations are ruled out from the beginning of the analysis, there will be no substantial difference between microeconomics and macroeconomics. What macroeconomists typically fail to realize is that the correct procedure of aggregation is not a sum whenever there exists interaction of heterogeneous individuals.

There is a further problem with this assumption from a mathematical point of view — the behavior of the aggregate of a large number of individual agents may not be similar to the behavior of the "average" agent.

Moreover, if the aggregate is the sum of its constitutive elements, its dynamics cannot but be identical to that of each single unit. The reductionist methodology implies that to understand the working of a system, one has to focus on the working of each single element. Assuming that elements are similar and do not interact - i.e. the economy is completely described by a representative agent - the dynamics of the aggregate replicate the dynamics of the sub-unit. [35]

2.2.1.3. Dynamic Stochastic General Equilibrium

The clash between the two competing business cycle theories, the Real Business Cycle perspective and the New Keynesian paradigm ended in the last decade with the development of a New Neoclassical Synthesis. In a nutshell, the canonical model employed by the NNS paradigm is basically a RBC dynamic stochastic general equilibrium (DSGE) model with monopolistic competition, nominal imperfections and a monetary policy rule.[36] Formulated as a DSGE model, it is based upon the process of inter-temporal maximization of utility in the market clearing context of a standard competitive equilibrium theory.

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[35] Op. Cit. Gatti, et al.: 69.

[36] G. Fagiolo and Roventini, A., "On the scientific status of economic policy: a tale of alternative paradigms", **The Knowledge Engineering Review,** vol. 27, (2012): 163–185.

The macroeconomics of the last quarter century, from Lucas through Prescott to Woodford, has been very strongly wedded to stochastic inter-temporal general equilibrium theory.[37]

Macroeconomic analysis needs to be founded in microeconomic theory, but in the practice of the DSGE model this has meant inventing a "representative agent" who maximizes a utility function subject to a national income identity budget constraint, and simultaneously maximizes profits subject to an aggregate production function. This fiction not only violates the obvious fact that economic agents are different in important respects, but also leaves the model without sound micro foundations.

Almost all studies on macroeconomics use the same common methodology, that of DSGE theory, according to which the economy should be represented by a model with explicit micro foundations – endowments, technology (of production and of transaction), preferences and demography – as well as explicit stochastic processes governing shocks to these constituent components, and the economy should be assumed always to be in a state of rational-expectations equilibrium. Even modern Keynesians, the intellectual descendants of those who fought so hard to resist the rational expectations revolution, have adopted this common methodology, largely because the definition of DSGE is broad enough to include transaction technologies that give rise to the wage/price stickiness that has always been the hallmark of Keynesian economics.[38]

However, the equilibrium that actually obtains in these agent-based models are always idiosyncratic with respect to the agents, in the sense that from realization to realization any particular agent's allocation may vary substantially. But the macro statistics of these models are quite robust across realizations. Thus we have a weak form of path dependence in which the history of agent interactions is important for the individuals, although not for the economy overall.[39]

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[37] Axel Leijonhufvud, "Agent-Based Macro", **Handbook of Computational Economics**, ed. Leigh Tesfatsion and Kenneth L. Judd, (Vol. 2, Amsterdam: North-Holland, 2006): 1625-1637.
[38] P. Howitt, "What have central bankers learned from modern macroeconomic theory?", **Journal of Macroeconomics**, (2011): 1-11.
[39] R. Axtell, "Why Agents? On the Varied Motivations for Agent Computing in the Social Aciences", **Workshop on Agent Simulation: Applications Models and Tools,** ed. C. M. Macal and D. Sallach, (University of Chicago, 1999): 1-22.

Log linear approximation of New Keynesian DSGE Models can be reduced to three forward looking equations,

namely the IS curve: $$y_t = E_t y_{t+1} - \frac{1}{\sigma} \quad i_t - E_t \pi_{t+1} \quad + \varepsilon_t^y$$

the Philips curve: $$\mathrm{K} y_t + \beta E_t \pi_{t-1} + \varepsilon_t^{\pi}$$

and the Taylor rule: $$i_t = \varphi_y y_t + \varphi_\pi \pi_t + \varepsilon_t^i$$

and $\beta < 1$.

where the unknowns (y_t, π_t, i_t) are the output gap, inflation and the nominal interest rate, the expectation operator E_t denotes the rational expectation conditional on time t information, the ε's are random shocks, the coefficients $(\sigma, \beta, \varphi_y, \varphi_\pi, \kappa)$are all positive.[40]

New Keynesian DSGE models do of course model one aspect of the coordination mechanism, which is the setting of wages and prices.

The case for low inflation did not come from the original Kydland–Prescott analysis, which merely assumed that low inflation was one of the goals of monetary policy. Instead, the modern case comes from various DSGE studies that have confirmed the optimality of Friedman's rule, which is to reduce inflation to the point where the nominal rate of interest equals zero.[41]

The methodology of ACE is in some sense the polar opposite to that of DSGE. Instead of assuming that people have an incredibly sophisticated ability to solve a computationally challenging inter-temporal planning problem in an incredibly simple environment (the simplicity being needed in order to make the equilibrium computable), the ACE approach is to assume that people have very simple rules of

[40] Op. Cit.: Howitt, 3.
[41] Op. Cit.: Howitt, 5.

behavior for coping with an environment that is too complex for anyone fully to understand. In short, it portrays an economic system as a human anthill, in which orderly social behavior can possibly emerge as a property of the interaction between diverse agents, none of whom has any understanding of how the overall system functions.[42]

2.2.1.4. Rational Expectations

Claims on Keynesian models' failure due to lack of human learning and adaption there have been alternative approaches and tools to overcome the problem. One is "rational expectations" that emerged as the dominant paradigm in economics during the last quarter of the twentieth century. This approach assumes that humans have perfect access to information and adapt instantly and rationally to new situations, maximizing their long-run personal advantage. Another one is related to ambition for the tractability of results: Even if rational expectations are a reasonable model of human behavior, the mathematical machinery is cumbersome and requires drastic simplifications to get tractable results.

Micro-based new classical models that represented mainstream economics of 80s were based on homogenous agents having rational expectations or at least representative agents. These models kept having general equilibrium assumption. But fluctuations in stock markets in 80s which was much higher than the projection of efficient market models led to a questioning of the consistency of these models. In the later of 20th century rationality of agents were started to be restricted.

2.2.1.5. Non-linearity

Agent-based simulations can handle a far wider range of nonlinear behavior than conventional equilibrium models. Policy-makers can thus simulate an artificial economy under different policy scenarios and quantitatively explore their consequences.

[42] Op. Cit.: Howit, 10.

The equilibrium models that were developed, such as those used by the US Federal Reserve, by necessity stripped away most of the structure of a real economy. There are no banks or derivatives, much less sub-prime mortgages or credit default swaps — these introduce too much nonlinearity and complexity for equilibrium methods to handle.

2.2.2.Rising of Agent-Based Computational Economics after Crisis

After 2008 global financial crisis doubts on mainstream economics increased. During the crisis ACE researchers have claimed that mainstream economics is not enough to prevent economic system from crises. Furthermore, researchers relying on agent based approach think that mainstream economics has been on a ground that ignores crises. J. Doyne Farmer and Duncan Foley[43] underline the weakness of the instruments US economic team and its international counterparts use as follow:

> “The best models they have are of two types, both with fatal flaws. Type one is econometric: empirical statistical models that are fitted to past data. These successfullyforecast a few quarters ahead as long as things stay more or less the same, but fail in the face of great change. Type two goes by the name of ‘dynamic stochastic general equilibrium’. These models assume a perfect world, and by their very nature rule out crises of the type we are experiencing now.”

Mathematical models are used for but for a completely different purpose: modeling the potential profit and risk of individual trades. There is no attempt to assemble the pieces and understand the behavior of the whole economic system. There is a better way: agent-based models. Such models do not rely on the assumption that the economy will move towards a predetermined equilibrium state, as other models do. Instead, at any given time, each agent acts according to its current situation, the state of the world around it and the rules governing its behavior.

Economic theory based on the RA model has, in short, nothing to say about financial crises, bankruptcies, domino’s effects, systemic risk and any pathology in general. Policy makers, comforted by the notion that they were following ‘‘best practices’’ of the most advanced monetary theories in taming inflation, assuring

[43] Op. Cit., Farmer, Foley: 685–686.

the stability of the economy, paid no attention to the far more important issues of financial structure.[44]

Highly leveraged (i.e., financially fragile) firms, in turns, are exposedto a high risk of default, that is of going bankrupt. When bankruptcies occur, loans not refunded negatively affect banks' net worth, with banks responding to their worsened financial position by reducing credit supply. The reduction in credit supply impacts on the lending interest rate all other firms have to pay to serve their financial commitments. This approach also has (by construction) nothing to say about the network aspects of lending and inter-bank linkages that have become apparent during the current crisis.

S Joseph E. Stiglitz and Mauro Gallegati emphasize risk sharing on their researches. Standard models argue that the more widely shared risks, the better the performance of the economic system. Before crises, they focus on the benefits of risk diversification; only in the midst of a crisis does the emphasis switch to the risk of contagion. On the contrary, researches show that interdependencies in real and financial assets are beneficial from a social point of view when the economic environment is favorable and detrimental when the economic environment deteriorates. The authors have a conclusion that there is a trade-off between decreasing - because of risk sharing - increasing systematic risk - because of the propagation of financial distress.[45]

There is a crucial need to change the mindset of those working in economics and financial engineering. They need to move away from a science that follows all the apparent precepts and forms of scientific investigation, while still missing something essential. An overly formal and dogmatic education in the economic sciences and financial mathematics are part of the problem. Economic curriculums need to include more natural science. The prerequisites for more stability in the long run are the development of a more pragmatic and realistic representation of what is going on in financial markets, and to focus on data, which should always supersede perfect equations and aesthetic axioms.

[44] Op. Cit., Stiglitz and Gallegati: 6.
[45] Op. Cit., Stiglitz and Gallegati: 10.

It is now clear that model cannot provide an understanding of what happened in this and other crises. But we would argue that it cannot provide an adequate framework for understanding the economy even in more normal times. The heterogeneous agent approach provides an alternative, one which has already proven its metal in helping us understand the interlink ages which helped give rise to the crisis.[46]

L.Tesfatsion quotes speech by Jean-Claude Trichet, President of the European Central Bank, on November 18, 2010:

> "When the crisis came, the serious limitation of existing economic and financial models immediately became apparent. Arbitrage broke down ... markets froze ... market participants were gripped by panic. Macro models failed to predict the crisis and ... [to explain] what was happening ..."
>
> "[In] the face of crisis, we felt abandoned by conventional tools. ... The key lesson ... is the danger of relying on a single tool, methodology or paradigm. The atomistic, optimizing agents underlying exiting models do not capture behavior during a crisis period. Agent-based modeling ... allows for more complex interactions between agents. ... We need to better integrate the crucial role played by the financial system into our macroscopic models."

"I would very much welcome inspiration from other disciplines: physics, engineering, psychology, biology. Bringing experts from these fields together with economists and central bankers is potentially very ... valuable."

> "A large number of aspects of the observed behavior of financial markets is hard to reconcile with the efficient market hypothesis... But a determinedly empirical approach -- which places a premium on inductive reasoning based on the data, rather than deductive reasoning grounded in abstract premises or assumptions -- lies at the heart of these methods ... simulations will play a helpful role."[47]

"It's remarkable," says Helbing, "that while any new technical device or medical drug has extensive testing for efficiency, reliability and safety before it ever hits the market, we still implement new economic measures without any prior testing."[48]

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[46] Op. Cit., Stiglitz and Gallegati: 11.

[47] Leigh Tesfation, ACE Reserach Area: Agent-Based Financial Economics, www.econ.iastate.edu/tesfatsi/aapplic.htm, [10.04.2012].

[48] M. Buchahan, "Meltdown Modelling", **Nature**, Volume 460, no. 6, (2009): 680-683

2.2.3. Building Blocks of Agent Based Economics

2.2.3.1. Heterogeneous Interacting Agents

Social systems consist of heterogeneous communicating entities in an evolving network of relationships.[49] Social scientists, by definition, must address the problem of human interaction impinging on world events. These interactions leave traces on the human interactors themselves, changing their memories, their knowledge, their future interaction patterns, and their expressed behaviors in these future interactions. In consequence, social systems are intrinsically heterogeneous and path dependent. This has led some physical scientists to question the scientific status of the social "sciences."[50]

The idea that systems which consist of a large number of interacting agents generates universal, or scaling, laws that do not depend on microscopic details is now popular in statistical physics and is gaining momentum in economics as well. The quantum revolution of last century radically changed the perspective in contemporary physics, leading to a widespread rejection of reductionism. According to the holistic approach, the aggregate is different from the sum of its components because of the interaction of particles. The equilibrium of a system does not require any more that every element is in equilibrium, but rather that the aggregate is quasi-stable. Moreover agents' choice should not necessarily be an equilibrium one, derived from their optimizing behavior, because agents' interaction generates self-organizing solutions. It follows from this that one should not analyze the individual problem in isolation from the others (a game against nature) but rather the interconnections among heterogeneous interacting agents.[51]

The practice of combining heterogeneity and interactions is at odds with mainstream macroeconomics which is unable, by construction, to explain non-

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[49] Paul L. Borill and Leigh Tesfatsion, "Agent-Based Modeling: The Right Mathematics for the Social Sciences?", ed. J. B. Davis and D. W. Hands, **Elgar Recent Economic Modeling Methodology Companion**,(Edward Elgar Publishers, 2011): 1-29.
[50] Op. Cit.,Borill and Tesfatsion: 17.
[51] Op. Cit., Gatti, et al.: 62-63.

normal distributions, scaling behavior or the occurrence of large aggregate fluctuations as a consequence of small idiosyncratic shocks.[52]

In order to take heterogeneity seriously in macroeconomic modeling, one should start with heterogeneous behavioral rules at the micro level and determine the aggregate (macroeconomic) quantity.[53]

If one allows for heterogeneity in individual choices, it is impossible to use the analogy principle even if we are interested in an aggregate model that holds only on average.[54] There is a general point that explicit consideration of agents' heterogeneity might indeed lead to qualitatively different policy recommendations compared to a model in which only dynamics of "average" agent characteristics are captured.[55]

In General Equilibrium theory one can put all the heterogeneity s/he likes, but no direct interaction among agents. In this case one cannot have any sort of informational perfection. If information is not perfect markets cannot be efficient. Market failure leads to agents' interaction and to coordination failures, emerging properties of aggregate behavior, and to a pathological nature of business fluctuations.[56]

2.2.3.2. Self-organizing/Self-organizations

If the system is far from equilibrium, self-organizing phenomena and a state of self-organized criticality (SOC) may occur. In the SOC literature the concept of equilibrium is borrowed from statistical mechanics and is very different from that of mainstream economics. In fact, equilibrium results from the balance of actions of a large number of many interacting particles.[57]

By modeling systems from the 'ground up' - agent-by-agent and interaction-by-interaction - self-organization can often be observed in such models. Patterns,

[52] Op. Cit., Gatti, et al.: 96.
[53] Op. Cit., Gatti, et al.: 95.
[54] Op. Cit., Gatti, et al.: 86.
[55] H. Dawid and Neugart, M., "Agent-Based Models for Economic Policy Design", **Eastern Economic Journal**, Vol.37, no. 1(2011): 47.
[56] Op. Cit., Gatti, et al.: 62.
[57] Op. Cit., Gatti, et al.: 63.

structures, and behaviors emerge that were not explicitly programmed into the models, but arise through the agent interactions.[58]

2.2.3.3. Bounded Rationality

A very common motivation for such models is, broadly speaking, a basic dissatisfaction with rational agents. Thus, essentially all agent-based models that have appeared to date involve some form of boundedly rational agent.[59]
A huge body of experimental evidence supports the notion that human agents are boundedly rational.

The environment in which real-world economic agents live is too complex for hyper-rationality to be a viable simplifying assumption. It is suggested that one can, at most, impute to agents some local and partial (both in time and space) principles of rationality (e.g., myopic optimization rules). More generally, agents are assumed to behave as boundedly rational entities with adaptive expectations.[60]

2.2.3.4. Evolution

Evolution can occur in several forms. First, agents may evolve their behavior over time, adapting new strategies that enable them to gain or lose. For example, a trader in a financial market may discover a new trading algorithm that yields him a higher profit. Second, the simulation may spawn new agents over time. These agents may have better strategies that enable them to compete with and possibly defeat the older agents in the simulation. Third, the microstructure of the simulation itself may change over time. A financial market may develop new trading rules that speed up order execution.

2.2.3.5. Emerging Properties

As an important type of simulation in the social sciences, agent-based modeling is characterized by the existence of many agents who interact with each other with

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[58] Op. Cit., Macal and North:151- 162.
[59] Op. Cit., Axtell: 2.
[60] Op. Cit., Fagiolo and Roventini: 178.

little or no central direction. The emergent properties of an agent-based model are then the result of "bottom-up" processes, rather than "top-down" direction.[61]

Statistical regularities at the aggregate level are characterized by emerging properties which do not show up at the microscopic level.[62]

High-level (macroeconomic) systems may possess new and different properties than the low-level (microeconomic) systems on which they are based. [63]

2.2.3.6. Microfoundation

In a sense, agent-based computational techniques provide a route to develop microfoundations for macroeconomics completely at odds with the RA approach. The relevance and reliability of these new microfoundations are grounded in the empirical evidence they can account for. From this viewpoint, microfoundations can be defined as sound if they are based on a reasonable model of individual behavior and market and non-market interactions,whoin the aggregate can produce regularities consistent with the empirical evidence, instead of being grounded on optimizing principles and equilibrium solutions.

The evolving macroeconomic features of the economy, in turn, feedback on microscopic behavior in many ways, for instance by means of externalities or mean field effects.

Macroeconomics, in fact, should have microfoundations: we do not agree with a purely holistic approach to macro-modeling. The appropriate microfoundations must take into account heterogeneity and interaction. Moreover microeconomic behavior should be not be modeled in isolation because it is deeply affected by the macroeconomic scenario. In other words, a good research strategy is based on an explicit consideration of a two-way causation link between micro-behavior and macro-variables. [64] In order to develop sound micro founded models, requires a methodology which allows for the interactions of economic agents and their links in a networked economy there has to be some degree of heterogeneity of agents.

[61] R. Axelroad, "Advancing the Art of Simulation in the Social Sciences", **Japanese Journal for Management Information Systems**, (2003): 1-19.
[62] Op. Cit., Gatti, et al.: 95.
[63] Op. Cit., Stiglitz and Gallegati: 6.
[64] Op. Cit.,Gatti, et al.: 100.

They may be affected, for instance, by different shocks. Even more important are differences in information.[65]

2.2.3.7. Bottom-up Approach

Two-way feedback between microstructure and macrostructure has been recognized within economics for a very long time. Nevertheless, for much of this time economists have lacked the means to model this feedback quantitatively in its full dynamic complexity. The most salient characteristic of traditional quantitative economic models supported by microfoundations has been their top–down construction. Heavy reliance is placed on extraneous coordination devices such as fixed decision rules, common knowledge assumptions, representative agents, and imposed market equilibrium constraints. Face-to-face personal interactions typically play no role or appear in the form of tightly constrained and stylized game interactions. In short, agents in these models have had little room to breathe.[66]

Starting from initial conditions, specified by the modeler, the computational economy evolves over time as its constituent agents repeatedly interact with each other and learn from these interactions. ACE is therefore a bottom-up culture-dish approach to the study of economic systems.[67]

2.2.4. Agent-Based Computational Economics

2.2.4.1. General Overview

Slowly but surely advances in modeling tools have been enlarging the possibility set for economists. Researchers can now quantitatively model a wide variety of complex phenomena associated with decentralized market economies, such as inductive learning, imperfect competition, trade network formation, and the open-ended co-evolution of individual behaviors and economic institutions. One branch

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[65] Op. Cit., Stiglitz and Gallegati: 7.

[66] L. Tesfatsion,"Agent-based computational economics: Modeling economies as complex adaptive systems",**Information Sciences**, Vol. 149, no. 4, (2003): 263-264.

[67] L. Tesfatsion, "Agent-Based Computational Economics", **ISU Economics Working,** Paper No. 1, Revised August 24, 2003: 1.

of this work has come to be known as agent-based computational economics (ACE), the computational study of economies modeled as evolving systems of autonomous interacting agents. ACE researchers generally rely on computational laboratories to study the evolution of decentralized market economies under controlled experimental conditions.[68] Some benefits of such an approach are immediately clear. One may generate as much data as needed, control for exogenous shocks, simulate special events such as a financial market crisis, measure all variables precisely and vary the policy maker's control parameter smoothly.[69]

D. Delli Gatti et al. claim that the agent-based approach represents a fruitful methodology to do realistic macroeconomics that is one based on bounded rational, heterogeneous interacting agents adapting to a complex world.[70]

Colander et al discuss the technical difficulty of analytic macro models and offer another approach that uses agent based computational economics (ACE) models to analyze the macro economy because of increase in computing power over the past decade.[71] Traditional economics relies on modeling agents with objective functions and systems of differential equations. These mathematical formulas can become cumbersome, especially when trying to model complex behaviors, such as collusion among agents. In a computational framework, however, it is relatively painless to develop algorithms that simulate those behaviors.[72]

A crucial point is that modelers do not need to constrain agent interactions a priori by the imposition of equilibrium conditions, homogeneity assumptions, or other external coordination devices that have no real-world referents. Ideally, the agents in ACE models should be as free to act within their computational worlds as theirempirical counterparts are within the real world.[73]

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[68] Op. Cit.,Tesfatsion,Agent-based computational economics: Modeling... : 263-64.

[69] F. Westerhoff, "The Use of Agent-Based Financial Market Models to Test the Effectiveness of Regulatory Policies", **Jahrbücher für Nationalökonomie und Statistik-Journal of Economics and Statistics,** (2008): 3-4.

[70] Op. Cit.,Gatti, et al.: 65

[71] David Colander, et al, "Beyond DSGE Models: Toward an Empirically Based Macroeconomics", **American Economic Review: Papers and Proceedings**, Vol. 98, No. 2, (2008): 237.

[72] A. Mistry, "Agent-Based Computational Economics", **Visible Hands,** Vol. 10, Issue 2, (2003): 9-10.

[73] Op. Cit., LeBaron and Tesfatsion: 247.

One of the initial goals of agent-based computational economics was to simulate entire markets by modeling the details of each agent in the market. Although the widespread availability of computational power seems to render this plausible, most markets are so complicated that pegging every last detail into a simulation is intractable. Smaller and more imprecise models, however, can be developed. One goal of computational economics is to develop such models and calibrate them to approximate real world economic data.[74]

As in a culture-dish laboratory experiment, the ACE modeler starts by constructing an economy comprising an initial population of agents. These agents can include both economic agents (e.g., consumers, producers, intermediaries,. . .) and agents representing various other social and environmental phenomena (e.g., government agencies, land areas, weather,. . .). The ACE modeler specifies the initial state of the economy by specifying the initial attributes of the agents. The initial attributes of any one agent might include type characteristics, internalized behavioral norms, internal modes of behavior (including modes of communication and learning), and internally stored information about itself and other agents. The economy then evolves over time without further intervention from the modeler. All events that subsequently occur must arise from the historical time-line of agent-agent interactions. No extraneous coordination devices are permitted. For example, no resort can be made to the off-line determination and imposition of market-clearing prices through fixed point calculations. [75]

In order for an ACE model to facilitate the understanding of a real-world macroeconomics, however, three criteria must be met. First, the model must include an appropriate empirically-based taxonomy of agents. Second, the scale of the model must be suitable for the particular purpose at hand. Third, model specifications must be subject to empirical validation in an attempt to provide genuine insight into proximate and ultimate causal mechanisms. The following sections address each of these criteria in turn.[76]

[74] Op. Cit.,Mistry: 9-10.

[75] Op. Cit.,Tesfatsion, **Handbook of Computational Economics,** Agent-Based Computational Economics, Handbook in Economics Series,Vol. 2, (Amsterdam, Elsevier, 2006), .

[76] Op. Cit. LeBaron and Tesfatsion, p: 248.

A principal concern of ACE researchers is to understand the apparently spontaneous formation of global regularities in economic processes, such as the unplanned coordination of trading activities in decentralized market economies that economists associate with Adam Smith's invisible hand. The challenge is to explain how these global regularities arise from the bottom up, through the repeated local interactions of autonomous agents channeled through socioeconomic institutions, rather than from the top-down imposition of fictitious coordination mechanisms such as market clearing constraints or an assumption of single representative agents. [77]

2.2.4.2. Agents

An "agent" is basically someone who acts on someone else's behalf. Usually, the agent refers to a human. For example, the American Heritage Dictionary defines an agent as "one that acts or has the power or authority to act… or represent another." In the computer world, an agent most often refers to a software program that acts on a user's behalf. For example, the agent collects and analyzes information, draws conclusions, makes recommendations, and performs transactions.[78]

Agent-based computational economics (ACE) is the computational study of dynamic economic systems modeled as virtual worlds of interacting agents. Here "agent" refers broadly to a bundle of data and behavioral methods representing an entity residing within the world. Examples of possible agents include: individuals (e.g., consumers and producers); social groupings (e.g., families, firms, communities, and government agencies); institutions (e.g., markets and regulatory systems); biological entities (e.g., crops, livestock, and forests) and physical entities (e.g., infrastructure, weather, and geographical regions). Thus, agents can range from passive world features to active data-gathering decision makers capable of sophisticated social behaviors. Moreover, agents can be composed of other agents, permitting hierarchical constructions. For example, a firm might be

[77] L. Tesfastion, "Agent-Based Computational Economics: A brief Guide to the Literature", Discussion Paper, **Reader's Guide to the Social Sciences**, (London, 2000): 1.

[78] Serenko and Detlor, "Agent Toolkits: A General Overiew Of The Market And An Assessment Of Instructor Satisfaction With Utilizing Toolkits In The Classroom", **Michael G. DeGroote School of Business, McMaster University, Working Paper**, no. 455, (2002): 3.

composed of workers and managers.[79] Agent-based models of many real-world systems tend to consist of a mix of physical components (modeled as agents) and social agents, termed 'socio-technic' systems.[80] Agents can also be composed of more elementary agents in various forms of hierarchical organization. For example, an ACE macroeconomic model might include the following hierarchy of nested agent refinements: national economy → {financial sector, business sector, household sector, government sector, foreign sector}; financial sector → {commercial banks, insurance companies, stock brokers, bond dealers}; commercial banks → {employees, shareholders}; employees → {salaried workers, wage workers}; and so forth. ACE modeling thus provides macroeconomists with tremendous flexibility to tailor the breadth and depth of the "representative agents" in their models to particular applications at hand.[81]

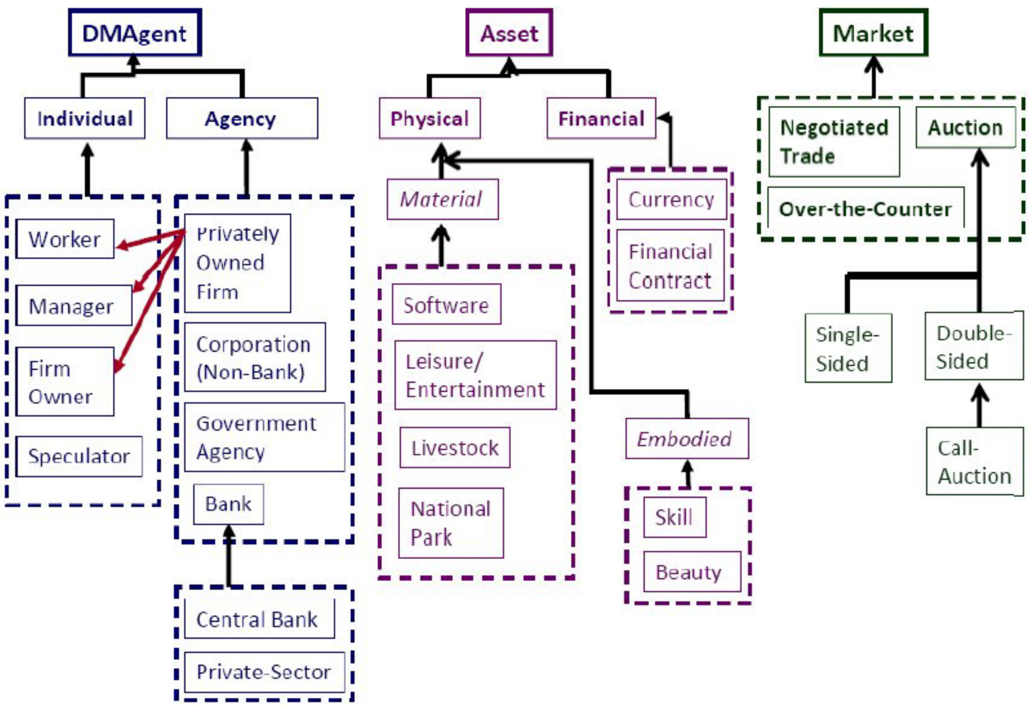

Figure 1: Illustrative Partial Agent Hierarchy for an Economic ABM

Source: Op. Cit., Borill and Tesfatsion: 5.

[79] Leigh Tesfatsion, Agent-Based Computational Economics (ACE) Homepage, www.econ.iastate.edu/tesfatsi/ace.htm [22.04.2012].
[80] Op. Cit, Macal and North: 157.
[81] Op. Cit.,LeBaron and Tesfatsion: 249.

Upward-pointing (black) arrows denote “is a” relationships and downward-pointing (red) arrows denote “has a” relationships.[82]

An agent-based model consists of individual agents, commonly implemented in software as objects. Agent objects have states and rules of behavior. Running such a model simply amounts to instantiating agent population, letting the agents interact, and monitoring what happens.[83]

The data and methods of each ABM agent are encapsulated in the sense that their form and content can be hidden from other agents. These encapsulations give ABMs a striking resemblance to real-world systems. Information hiding (state containment) results in uncertainty in agent interactions, in the sense that agents can never be entirely certain how other agents will behave. Even if an agent is acting in accordance with a fixed private behavioral method, it can appear as a “different entity” in different interactions at different times due to the differences in its expressed behaviors induced in these interactions.[84]

In any ABM that is closed – that is, without external runtime interactions–agent encapsulation enforces the real-world constraint that all calculations must be carried out by the agents that actually reside within the ABM world. Free-floating procedures and restrictions influencing ABM world outcomes, such as global continuity or equilibrium conditions externally imposed across agents, are not permitted. Conversely, the procedures and restrictions encapsulated in the methods of a particular ABM agent can only be implemented using the particular resources available to that agent. An ABM agent that exhausts its resources is constrained in its future ability to act effectively within its world. Thus, relative to traditional equation-based modeling, agent encapsulation in ABM permits a more realistic representation of real-world systems composed of interacting distributed entities with limited information, limited possible responses, limited material resources,and limited computational capabilities.[85]

A key aspect of decision-making agents (DMAgents) in ABM is their increased autonomy relative to the decision makers appearing in analytical social science

[82] Op. Cit., Borill and Tesfatsion: 5.
[83] Op. Cit., Axtell: 2.
[84] Op. Cit.,Borill and Tesfatsion:6-8.
[85] Op. Cit.,Borill and Tesfatsion: 7.

models. This increased autonomy arises from agent encapsulation. DMAgents can self-activate and self-determine their actions on the basis of hidden internal data and methods. The data and methods of DMAgents can change or agents can evolve over time as they interact within their world and learn from these interactions. The form and strength of these interaction networks can evolve over time through necessity (e.g., the death of agents) as well as through choice and chance.[86]

Just as the simple fixed rules of a chess game can produce an enormously large space of different games through player interactions, the simple fixed methods of individual agents within ABMs can produce unexpectedly rich global system behaviors through agent interactions. Alternatively, individual ABM agents can have methods permitting more complex behaviors characteristic of people in real life. These behaviors can include: state-conditioned adaptive response (if this happens, what should I do?); anticipatory learning (if I do this, what will happen?); inter-temporal planning; social communication; goal-directed learning leading to changes in state-conditioned responses; and reproduction (birth and death) leading to changes in the composition of agent populations.[87]

Autonomous Agents

Tesfatsion L. describes autonomy as self-activation and self-determination based on private internal data and methods as well as on external data streams (including from real world)[88]

The single most important defining characteristic of an agent is its capability to act *autonomously*, that is, to act on its own without external direction in response to situations it encounters. Agents are endowed with behaviors that allow them to make independent decisions.[89]

Franklin S. and Graesser have attempted to capture the essence of agency in a formal definition, which allows a clear distinction between a software agent and

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[86] Op. Cit.,Borill and Tesfatsion: 8.
[87] Op. Cit., Borill and Tesfatsion: 6.
[88] L. Tesfatsion, "Agent-Based Macroeconomics: Constructive Modeling of Decentralized Market Economies", (2011):.11.
[89] Op. Cit., Macal and North: 153.

an arbitrary program. Before doing that, they examine and compare some agentdefinitions in their study. They summarize some definitions as follows:

- A KidSim Agent of the authors from Apple Computer, Inc. is dedicated to a specific purpose, i.e., is a task-specific agent.
- A Hayes-Roth, Barbara Hayes-Roth of Stanford's Knowledge Systems Laboratory, Agent reasons to interpret perceptions, solve problems, draw inferences, and determine actions, i.e., is a reasoning agent.
- An IBM Agent from IBM's Intelligent Agent Strategy white paper carries out some set of operations on behalf of a user or another program, i.e., is a task-specific agent.
- A Wooldridge-Jennings Agent interacts with other agents (and possibly humans) via some kind of agent-communication language, i.e., is a communicative agent.
- A SodaBot, a development environment for software agent being constructed at the MIT AI Lab by Michael Coen., Agent engages in dialog, and negotiates and coordinates transfer of information, i.e., is a negotiating, information agent. [90]

They classify the agents and showthe autonomous agents in sub-groups by following table and figure:

Table 2: Types of Agents

Property	**Other Names**	**Meaning**
Reactive	Sensing and acting	responds in a timely fashion to changes in the environment
Autonomous		exercises control over its own actions
Goal-oriented	Pro-active purposeful	does not simply act in response to the environment
Temporally continuous		is a continuously running process

[90] Franklin Stan and Art Graesser, "Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents",**Proceedings of the Third International Workshop on Agent Theories, Architectures, and Languages**, (Springer Verlag, New York, 1996):29.

Table 2- continues

Communicative	Socially able	communicates with other agents, perhaps including people
Learning	Adaptive	changes its behavior based on its previous experience
Mobile		able to transport itself from one machine to another
Flexible		actions are not scripted
Character		believable "personality" and emotional state

Source: Franklin Stan and Art Graesser, "Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents",**Proceedings of the Third International Workshop on Agent Theories, Architectures, and Languages**, (Springer Verlag, New York, 1996): 29.

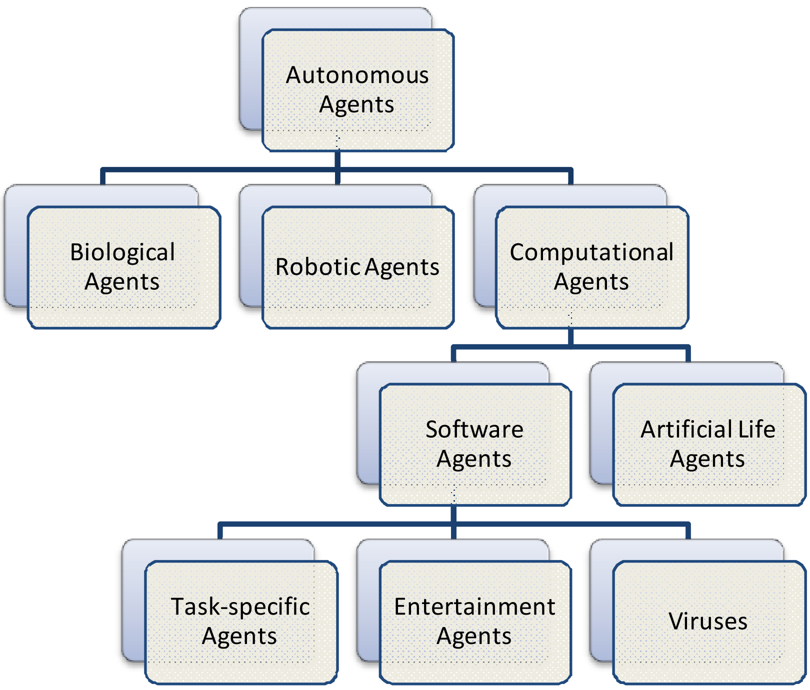

Figure 2: Natural Kind Classification of Autonomous Agents

Op. Cit., Franklin and Graesser: 31.

"An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future." [91]

Intelligent Agent

Intelligence is the degree of learning by an agent. The agent should be able to perceive, understand and analyze the environment. Given that the environment constantly changes, the agent should be capable of learning and adapting to these changes. Further, the agent should draw conclusions from the information collected and perform actions on the user's behalf.[92]

All agents are not created equal. Some are more advanced than others. Basic software agents exhibit the common characteristics of autonomy (independence), persistence (long-livedness), monitoring of the environment, and communication and collaboration with other agents and/or the user. More "intelligent" agents possess higher-level abilities, such as mobility, decision-making, and the ability to learn. [93]

Adaptive Agent

An agent may be adaptive, for example, by having rules or more abstract mechanisms that modify its behaviors. An agent may have the ability to learn and adapt its behaviors based on its accumulated experiences. Learning requires some form of memory. In addition to adaptation at the individual level, populations of agents may be adaptive through the process of selection, as individuals better suited to the environment proportionately increase in numbers.[94]

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[91] Op. Cit., Franklin and Graesser: 31.
[92] Op. Cit., Serenko and Detlor: 3-4.
[93] Op. Cit., Serenko and Detlor: 3-4.
[94] Op. Cit., Macal and North: 153.

Artificial Agents

Brandouy and Meathieu define artificial agent as a virtual entity endowed with artificial intelligence, mimicking a real investor, and able to deal with information, learning, and adaptation procedures.[95]

2.2.4.3. ACE Research Areas

The range of ABM research is now extensive.[96] Within economics, ABM research areas that have been particularly active in recent years include agricultural and environmental economics, automated markets, business and management, electricity markets, financial economics, industrial organization, labor markets, macroeconomics, political economy, and economic network formation. Within the social sciences more generally, highly active ABM research areas include emergence of collective behavior, evolution of cooperation and trust, innovation, institutional design, learning, norms, social influence, and social network formation.[97]

L. Tesfatsion summarizes the topics in diverse sampling of current ACE researches by roughly dividing into eight research areas: (i) learning and the embodied mind; (ii) evolution of behavioral norms; (iii) bottom-up modeling of market processes; (iv) formation of economic networks; (v) modeling of organizations; (vi) design of computational agents for automated markets; (vii) parallel experiments with real and computational agents; and (viii) building ACE computational laboratories.[98]

2.2.4.4. Attitudes toward the Contributions to Economics in ACE

Works bringing social and physical scientists together to develop economy policies that provide answers to economic matters is somewhat problematic. Some

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[95] O. Brandouy and Mathieu, P. (2007). "A conceptual framework for the evaluation of agent-based trading and technical analysis.", **Artificial Markets Modeling**, **Lecture Notes in Economics and Mathematical Systems**, vol. 599 part 2, (Springer, 2007): 64.

[96] Leigh Tesfation, Agent-Based Computational Economics: Key Application Areas, www.econ.iastate.edu/tesfatsi/aapplic.htm [14.04.2012].

[97] Op. Cit., Borill and Tesfatsion: 12.

[98] L. Tesfatsion, "Agent-based computational economics: Modeling economies as complex adaptive systems", **Information Sciences**, Vol. 149, no. 4, (2003): 263-264

welcome the newcomers from other fields. Buchanan sees Eric Weinstein and Helbing as the prominent ones leading to organizeinterdisciplinary works. To state briefly,Dirk Helbing of the Swiss Federal Institute of Technology Zurich, physicist-turned-sociologist, has spent the past two decades modeling largescale human systems such as urban traffic or pedestrian flows and Eric Weinstein is a physicist working in mathematical finance for the Natron Group, a hedge fund in New York.Weinstein urges to find right people to deal with the failure of the dominant economic model by saying "I think ideas from physics and other parts of science really have a chance to catalyze something remarkable." Helbing points out that computational simulations are used elsewhere in science to explore complex nonlinear processes and adds as

> "Complimentary knowledge of experts from different fields could collide, creating new ideas. Ultimately, such an effort would bring together social scientists, economists, physicists, ecologists, computer scientists and engineers in a network of large centers for socioeconomic data mining and crisis forecasting, as well as in supercomputer centers for social simulation and wind-tunnel like testing of policy."

Blake LeBaron from Brandeis University in Waltham, Massachusetts worked with physicists to develop an ABM of the stock market. [99]

Ecology and evolutionary biology have a great deal to offer for the study of decentralized adaptive systems. Likewise, computer science has recently started to pay a great deal of attention to how large systems of more or less independent artificial agents can work with each other in vast networks. In addition, mathematics has developed some very powerful tools for the mathematical analysis of dynamic systems. Even the playful field of artificial life offers many insights into the vast potential of complex adaptive systems. Conversely, social scientists have a great deal to offer evolutionary biologists, computer scientists and others because of our experience in the analysis of social systems with large numbers of interacting agents.[100]

On the contrary some researchers are not so pleased to get contribute from other fields. M. Buchanan quotes Paul Romer of Stanford University as

> "You hear recommendations to recruit scientists from other fields who can purge economics and finance of ideology and failed assumptions. But we should ask if there is any evidence that more theory, developed by people who don't have domain experience, is the key to scientific progress in this area."[101]

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[99] Op. Cit. Buchanan: 680-683
[100] Op. Cit.,Axelroad:15.
[101] Op. Cit., Buchanan:681

2.2.4.5. Advantages of ACE

ACE can be applied to a broad spectrum of economic systems ranging from micro to macro in scope. This application has both advantages and disadvantages relative to more standard modeling approaches.[102]

One of the virtues of the ACE approach to economics, as outlined by Tesfatsion is that it forces one to make explicit the mechanisms through which individual actions are coordinated, for better or worse. That is, in order to make a model "dynamically complete," in Tesfatsion's terminology, one has to specify what will happen from any given set of initial conditions, including those in which different people are acting on the basis of inconsistent beliefs and hence in which aggregate outcomes will necessarily diverge from individual intentions. Another virtue of the ACE approach is that it provides a method for discovering a system's "emergent properties," i.e. those properties that are not inherent in the individual components.[103]

The advantage of the ACE approach for macroeconomics in particular is that it removes the tractability limitations that so limit analytic macroeconomics. ACE modeling allows researchers to choose a form of microeconomics appropriate for the issues at hand, including breadth of agent types, number of agents of each type, and nested hierarchical arrangements of agents. It also allows researchers to consider the interactions among agents simultaneously with agent decisions, and to study the dynamic macro interplay among agents. Researchers can relatively easily develop ACE models with large numbers of heterogeneous agents, and no equilibrium conditions have to be imposed. Multiple equilibria can be considered, since equilibrium is a potential outcome rather than an imposed requirement. Stability and robustness analysis can be done simultaneously with analysis of solutions.[104] The failure to achieve equilibrium is a characteristic result of such models. However, while it is often quite difficult to characterize non-equilibrium

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[102]L. Tesfatsion, "Agent-Based Computational Economics: A Constructive Approach to Economic Theory", **Handbook of Computational Economics**, Vol. 2, ed. Leigh Tesfatsion and Kenneth L. Judd, (Elsevier, North-Holland, 2006): 842.

[103] Peter Howitt, "Coordination Issues in Long-Run Growth", **In Handbook of ComputationalEconomics,** Vol 2, ed. Leigh Tesfatsion and Kenneth Judd, (Amsterdam: North Holland, 2006): 1608.

[104] Op. Cit., D. Colander, et al., "Beyond DSGE models: toward….", (2008): 239.

phenomena analytically, the ability to systematically study dynamics is one of the powerful features of agent-based computational models.[105]

One of the greatest potential contributions that ACE could make to macroeconomic theory is permitting the constructive exploration of scale effects without the external imposition of artificial coordination devices.[106]

2.2.4.6. ACE Evolutionary Economics Relation

The study of evolutionary economics is by no means new, of course. Even before Darwin, attempts were made to apply evolutionary ideas to socioeconomic behavior. Although this early work is now largely ignored by economists, later many researchers have contributed to the application of evolution, evolutionary theories and approaches to economics. [107] As Tesfatsion states, leading ACE researchers have been able to extend the earlier works on evolutionary economics in four key ways:

First, agents in ACE frameworks are typically modeled as heterogeneous entities that determine their interactions with other agents and with their environment on the basis of internalized data and behavioral rules. These agents thus tend to have a great deal more internal cognitive structure and autonomy than conventionally modeled economic agents. Second, a broader range of agent interactions is typically permitted in ACE frameworks. Third, the evolutionary process is generally represented as natural selection pressures acting directly on agent characteristics rather than as population-level laws of motion. These natural selection pressures result in the continual creation of new modes of agent behavior and an ever-changing network of agent interactions. Fourth, ACE frameworks are computer implemented as virtual economic worlds that grow themselves along a real time-line, much like a culture grows in a petri dish. In principle, once initial conditions are set, all subsequent events in these virtual economic worlds are initiated and driven by agent-agent and agent-environment interactions; no further

[105] Op. Cit., Axtell: 10.
[106] Op. Cit., LeBaron and Tesfatsion: 6.
[107] Op. Cit., Tesfastion, (2000): 1-2.

outside interventions by the modeler (e.g., off-line fixed point calculations) are permitted.[108]

The pre-analytic vision of a complex market economy, in fact, is centered upon agents endowed with limited information and computational capability (bounded rationality) so that they adopt rules of thumb (instead of optimization procedures) and are naturally led to interact with other agents to access information, learn and imitate. In this sense, complexity goes hand in hand with evolutionary dynamics and direct interaction among agents.[109]

ABM is particularly well suited for the modeling of shifting landscapes involving changes in the behavioral methods of individual agents as well as evolutionary changes in the composition of agent populations.[110]

ACE is a blend of concepts and tools from evolutionary economics, cognitive science, and computer science. It represents a methodological approach that may ultimately permit two important developments: (a) the rigorous testing, refinement, and extension of theories developed in the earlier literature on evolutionary economics that were found to be analytically intractable; and (b) the rigorous formulation and testing of conceptually integrated socioeconomic theories compatible with theory and data from many different relevant fields currently separated by artificial disciplinary boundaries. [111]

2.2.4.6. Agent Based Models

Agent-based modeling (ABM) is the computational modeling of systems as collections of autonomous interacting entities(“agents”) with encapsulated functionality that operate within a computational world.[112]

Various social phenomena have been investigated using agent-based models that are not easily modeled using other approaches. Agent-based models (ABMs) began largely as the set of ideas, techniques, and tools for implementing computational models of complex adaptive systems… ABMs can explicitly model

[108] Op. Cit., Tesfastion, (2000): 2.
[109] Op. Cit., Gatti, et al.: 8.
[110] Op. Cit.,Borill and Tesfatsion (2011): 9.
[111] Op. Cit., Tesfastion, (2000): 2-3.
[112] Op. Cit., Borill and Tesfatsion, (2011): 2-4.

the complexity arising from individual actions and interactions that exist in the real world. These models explicitly consider the role of people's behavior and interactions through social networks as they affect the spread of infectious diseases.[113]

ABM is well suited for this social science objective. It is a method for studying systems exhibiting the following two properties: (1) the system is composed of interacting agents; and (2) the system exhibits emergent properties, that is, properties arising from the interactions of the agents that cannot be deduced simply by aggregating the properties of the agents. When the interaction of the agents is contingent on past experience, and especially when the agents continually adapt to that experience, mathematical analysis is typically very limited in its ability to derive the dynamic consequences. In this case, ABM might be the only practical method of analysis. [114]

According to Macal and North a typical agent-based model has three elements:

1. A set of agents, their attributes and behaviors.

2. A set of agent relationships and methods of interaction: An underlying topology of connectedness defines how and with whom agents interact.

3. The agents' environment: Agents interact with their environment in addition to other agents.[115]

ABM researchers use controlled computer experiments to investigate how large-scale effects arise from the micro-level interactions of dispersed autonomous agents. In principle, as in wetware culture-dish experimentation, the only intervention permitted by ABM researchers is the setting of initial experimental conditions.[116]

Economists can get reasonably good insights by assuming that human behavior leads to stable, self- regulating markets, with the prices of stocks, houses and other things never departing too far from equilibrium. But 'stability' is a word few

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[113] Op. Cit., Macal and North:152- 156.

[114] R. Axelroad, Tesfatsion L., "A guide for newcomers to agent-based modelling in the social sciences", **Handbook of Computational Economics**, Vol.2, ed. Leigh Tesfatsion and Kenneth L. Judd, (2006): 1648-1658.

[115] Op. Cit., Macal and North: 152.

[116] Op. Cit.,Borill andTesfatsion, (2011): 11.

would use to describe the chaotic markets of the past few years, when complex, nonlinear feedbacks fuelled the boom and bust of the dot-com and housing bubbles, and when banks took extreme risks in pursuit of ever higher profits. In an effort to deal with such messy realities, a few economists — often working with physicists and others outside the economic mainstream — have spent the past decade or so exploring 'agent-based' models that make only minimal assumptions about human behavior or inherent market stability. The idea is to build a virtual market in a computer and populate it with artificially intelligent bits of software — 'agents' — that interact with one another much as people do in a real market. The computer then lets the overall behavior of the market emerge from the actions of the individual agents, without pre-supposing the result.

There exist three distinct uses of agent-based computational models. First, when numerical realizations are relevant agents can perform a variant of classical simulation. Second, when a model is only incompletely solved mathematically — its equilibrium unknown, stability of equilibrium undetermined, or the dependence on parameters opaque — then an agent-based model can be a useful tool of analysis, a complement to mathematics. Third, there are cases in which mathematical models are either apparently intractable or provably insoluble. In such circumstances it would seem that agent computing is perhaps the only technique available for systematic analysis, a substitute for formal mathematical analysis.[117]

Axtell listed several advantages of agent-based computational modeling over conventional mathematical theorizing: First, it is easy to limit agent rationality in agent-based computational models. Second, there is no need to appeal to representative agents. Third, since the model is "solved" merely by executing it, there results an entire dynamical history of the process under study. That is, one need not focus exclusively on the equilibrium, should they exist, for the dynamics are an inescapable part of running the agent model. Finally, in most social processes, either physical space or social networks matter. These are difficult to account for mathematically except in highly stylized ways. However, in agent-based models it is usually quite easy to have the agent interactions mediated by

[117] Op. Cit., Axtell: 17-18.

space or networks or both. What is more, When mathematical models are only incompletely soluble it may prove difficult to determine how the known results depend on particular assumptions or exogenous parameters. In such cases agent-based computational models may prove insightful.[118]

ABM is a great leap forward in the effort to equip the profession with the appropriate tools to deal with heterogeneity and interaction in macroeconomics.[119]

Agent-based models have roots dating back to the 1940s and the first 'cellular automata', which were essentially, just simulated grids of on–off switches that interacted with their nearest neighbors. But they didn't spark much interest beyond the physical-science community until the 1990s, when advances in computer power began to make realistic social simulations more feasible. Since then they have found increasing use in problems such as traffic flow and the spread of infectious diseases.[120] Historically, the birth of the agent-based model as a model for social systems can be primarily attributed to a computer scientist, Craig Reynolds. He tried to model the reality of lively biological agents, known as artificial life, a term coined by Christopher Langton. In 1996 Joshua M. Epstein and Robert Axtell developed the first large scale agent model, the Sugarscape, to simulate and explore the role of social phenomenon such as seasonal migrations, pollution, sexual reproduction, combat, transmission of disease and even culture.[121]

There are many studies based on agent-based models targeting the different part of the economies. Some were summarized by J. F. Farmer and D. Foley as Le Baron's works on explanations for bubbles and crash, Axtell's power law distributions studies where he has devised firm dynamics models that simulate how companies grow and decline as workers move between them, Creditsector Model of Mauro Gallegati's group from Polytechnic University in Ancona, Italy and The Monetary Model of Robert Clower and Peter Howitt. [122]

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[118] Op. Cit., Axtell: 2-12.
[119] Op. Cit., et al.: 101.
[120] Op. Cit., Buchanan: 680
[121] F. Castiglione, Robert A. Meyers (Ed.), Agent Based Modeling and Simulation, Introduction to in Encyclopedia of Complexity and Systems Science.
[122] Op. Cit., Farmer, Foley: 686.

Buchanan's work offers a well-arranged source of implications of ABM which is used widely through public and private sectors. Starting to use ABM in the late 1990s, NASDAQ Stock Exchange which tried ABM to stop listing its stock prices as fractions such as 12¼ and instead list them as decimal. The goal was to improve the accuracy of stock prices. Proctor &Gamble, has used ABMs to optimize the flow of goods through its network of suppliers, warehouses and stores. Southwest Airlines of Dallas, Texas, has used ABMs for routing cargo. Other models have successfully simulated financial markets. At Yale University, for example, economist John Geanakoplos, working with physicists Doyne Farmer of the Santa Fe Institute and Stefan Thurner of the Medical University of Vienna, has constructed an ABM exploring the systemic consequences of massive borrowing by hedge funds to finance their investments.[123]

ABM applied to social processes uses concepts and tools from social science and computer science. It represents a methodological approach that could ultimately permit two important developments: (1) the rigorous testing, refinement, and extension of existing theories that have proved to be difficult to formulate and evaluate using standard statistical and mathematical tools; and (2) a deeper understanding of fundamental causal mechanisms in multi-agent systems whose study is currently separated by artificial disciplinary boundaries.[124]

Even Financial regulators do not have the tools they need to predict and prevent meltdowns, still, agent-based techniques are beginning to enter the regulatory process. For example, decision-makers in Illinois and several other US states use computational models of complex electricity markets. At the University of Genoa in Italy, meanwhile, Silvano Cincotti and his colleagues are creating an agent-based model of the entire European Union economy. Their model includes markets for consumer goods and financial assets, firms that interact with banks to obtain loans, and banks that compete with one another by offering different interest rates. Based on real economic data, the model currently represents some 10 million households, 100,000 firms and about 100 banks, all of which can learn and change their strategies if they find more profitable ways of doing business.[125]

[123] Op. Cit., Buchanan: 681.
[124] Op. Cit., Axelroad, Tesfatsion: 1648-1658.
[125] Op. Cit., Buchanan: 681.

A combination of several synergistic factors is moving ABMs forward rapidly. These factors include the continuing development of specialized agent-based modeling methods and toolkits, the widespread application of agent-based modeling, the mounting collective experience of the agent-based modeling community, the recognition that behavior is an important missing element in existing models, the increasing availability of micro-data to support agent-based models, and advances in computer performance.[126]

Dawid and Neugart argue that policy makers can benefit from Agent-based models. According to them ABMs can do well in replicating stylized facts but are currently not well suited for forecasting the business cycle. They have the ability to give meaningful insights into the effect of policy measures for the medium and longer run:

> "In many circumstances agent-based models have a menu to offer that allows to incorporate into our models economic, institutional, and behavioral structure. This provides a sound starting point for economic policy advice and allows us to address issues and phenomena that can hardly be captured by alternative approaches."[127]

2.2.4.7. Agent Based Simulation

Works using simulation are getting widely placed in social science. There are three types of simulation: discrete event simulation, system dynamics and finally agent-based simulation. Macal and North distinguish the ABM from other two technics with its two features: modeling heterogeneity of agents and the emergence of self-organization.[128]

Mistry tries to explain the agent-based computational simulation with an simple example as;

> "Consider an English auction. This simulation has a number of agents, each of which represents one bidder in the auction. We can represent each agent by his bidding algorithm. The agent places bids until either he wins the auction or the price rises above a predefined maximum amount the agent is willing to bid. The simulation program can provide the mechanism by which the items are sold, also known as the market clearing mechanism."[129]

Whenever stochastic governing equations of a social process can be written out and their solution space characterized, so that all that remains to be done is

[126] Op. Cit., Macal and North: 160.
[127] Op. Cit., Dawid and Neugart: 47-49.
[128] Op. Cit., Macal and North: 151.
[129] Op. Cit., A. Mistry, 9-10

generate numerical realizations, then the use of the term simulation to describe agent-based computational models corresponds to its traditional usage in operations research.[130]

Oeffner M claims that agent based simulations are a tool and IT-based technique of simulating a certain model unlike Walrasian' general equilibrium approach which is the methodological framework of modern neoclassical macroeconomics. However, an agent–based framework in principle can allow the analysis of a GE model. In fact, this would lead to the degeneration of the virtues of an agent–based technique.The main problem of such an approach would be the calculation of rational expectations in a forward–looking framework. However, when the model is completely developed within the boundaries of GE models (e.g. by the application of one 'representative agent'), one could handle this problem in the same way as 'orthodox' economics does, so that the 'representative agent' knows all structural equations of the mechanical system. As a result, he could calculate the rational expectations outcomes of the economy far into the future.[131]

The most commonly questioned foundations, such as rational behavior, perfect competition, liquid capital markets, and so on, do not need to hold in an agent-based simulation. Many theories may be strengthened by eliminating some of their most controversial assumptions.[132]

2.2.4.8. Insufficiency of ACE and ABMs

Mistry (2003) divide insufficiency of ABMs into three groups: m*odeling, evolution,need for general software and relation to equilibrium models.*

The biggest problem facing researchers in ACE is in modeling individual agents. It is not clear how to model agents within all but the most trivial of simulations. The list of modeling decisions for each agent is seemingly infinite. Furthermore, it

[130] Op. Cit., Axtell: 7.

[131] M. Oeffner, "Agent–Based Keynesian Macroeconomics - An Evolutionary Model Embedded in an Agent–Based Computer Simulation", (Dissertation, Julius-Maximilians-Universität Würzburg, Germany, September 2008), 16-17.

[132] Op. Cit.,Mistry: 9-10.

is not clear that any particular decision is valid. Researchers need to pinpoint techniques for modeling agents.[133]

Farmer and support Mistry as many does. According to them agent-based models are not a panacea. The major challenge lies in specifying how the agents behave and, in particular, in choosing the rules they use to make decisions. In many cases this is still done by common sense and guesswork, which is only sometimes sufficient to mimic real behavior. To make agent-based modeling useful one must proceed systematically, avoiding arbitrary assumptions, carefully grounding and testing each piece of the model against reality and introducing additional complexity only when it is needed. Done right, the agent-based method can provide an unprecedented understanding of the emergent properties of interacting parts in complex circumstances where intuition fails. [134]

As another problem,it is still not clear how to introduce evolution in these models. Need for strong programming skills (general software) is matter too. Finally, agent-based simulations tend to create and emphasize markets that are continually in disequilibrium. This is in stark contrast to traditional analytic models, which tend to seek a market equilibrium for a given set of assumptions.[135]

The attempts by ACE researchers to conduct parallel experiments with real and computational agents have raised a number of challenging issues. One major hurdle is the need to ensure that the salient aspects of an experimental design as perceived by the human participants are captured in the initial conditions specified for the computational agents. Another major hurdle is that experiments run with human participants generally have to be kept short, both to prevent boredom among the participants and to prevent the bankruptcy of the investigators who provide the participants with monetary payments. Thus, the ‘‘shadow of the past’’ might be strongly affecting experimental outcomes for individual human participants in ways not understood and controlled for by investigators. In contrast, experiments with computational agents can be run for many generations to diminish dependence on initial conditions.[136]

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[133] Op. Cit.,Mistry:.9-10.
[134] Op. Cit., Farmer, Foley: 685–686.
[135] Op. Cit.,Mistry: 9-10.
[136] Op. Cit., Tesfatsion, “Agent-based computational economics: modeling…”, (2003): 267.

ACE models generate a complete distributional dynamics for a modeled economy. This micro-level distributional approach to empirical validation requires information that might not always be available. However one can gather more data with the help of electronic transactions. Limited but representative samples of real-world micro data provide an important check on the empirical plausibility of simulated micro-level distributions.[137]

Due to risk of the new agent-based models remain at the fringe of mainstream economics, and most economists continue to prefer conventional mathematical models. Many of them argue that agent-based models haven't had the same level of testing. Another problem is that an agent-based model of a market with many diverse players and a rich structure may contain many variable parameters. So even if its output matches reality, it's not always clear if this is because of careful tuning of those parameters, or because the model succeeds in capturing realistic system dynamics. That leads many economists and social scientists to wonder whether any such model can be trusted. But agent-based enthusiasts counter that conventional economic models also contain many tunable parameters and are therefore subject to the same criticism.[138]

While some economists, mainly in the unorthodox camp, eagerly embrace the new research strategy, some others, mainly in the mainstream, are skeptical or even dismissal. There are at least three reasons for this skepticism: (i) a basic distrust for the output of computer simulations, which is generally very sensitive to the choice of initial conditions and parameter values; (ii) a critique of the prevailing research strategy in ABM, whose pillars are adaptive micro-behavioral rules and out-of-equilibrium processes, often considered ad hoc; (iii) the difficulty and sometimes the impossibility of thinking in macroeconomic terms, i.e. of using macro-variables in the theoretical framework.[139]

Empirical validation is obviously important for more traditional economic models as well as for ACE models. Nevertheless, ACE researchers and critical observers both acknowledge that certain validation problems facing ACE researchers are

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[137] Op. Cit., LeBaron and Tesfatsion: 8.
[138] Op. Cit., Buchanan: 681.
[139] T. Assenza, et al., "Heterogeneity and Aggregation in a FinancialAccelerator Framework", **CENDEF Working Papers**, (2007): 2-3.

special to the ACE methodology. One problem involves degrees of freedom. ACE models often contain many parameters, and the claim is that the clever researcher can match any desired empirical feature using these degrees of freedom. Another problem is that the properties of many ACE models are currently not well understood and not well motivated by observed human behavior… ACE models can be modeled commonly by connecting agent-level behavior to experiments with real people, i.e. laboratory experiments. In addition to laboratory data comparisons, another direct and obvious empirical validation test for an ACE model is to replicate empirical features at many levels and at multiple time scales.[140]

The agent-based modeling methodology has a significant disadvantage vis-a-vis mathematical modeling. Despite the fact that each run of such a model yields is a sufficiency theorem, a single run does not provide any information on the robustness of such theorems. That is, given that agent model A yields result R, how much change in A is necessary in order for R to no longer obtain? In mathematical economics such questions are often formally resolvable via inspection, simple differentiation, the implicit function theorem, comparative statics, and so on. The only way to treat this problem in agent computing is through multiple runs, systematically varying initial conditions or parameters in order to assess the robustness of results.[141]

In fact, differently from mainstream economics, the ABM approach is particularly suitable to address issues of heterogeneity, interaction and complexity. Multi-agent models allow the comparison of the impact of different behavioral rules of thumb, which are often traced back to bounded rationality and adaptive behavior.[142]

2.2.4.9. Financial Studies with ACE in general and Exchange Rate Market

Financial markets are particularly appealing applications for agent-based methods for several reasons. First, the key debates in finance about market efficiency and rationality are still unresolved. Second, financial time series contain many curious

[140] Op. Cit., LeBaron and Tesfatsion, (2008): 7.
[141] Op. Cit., Axtell: 2-12.
[142] Op. Cit., Gatti, et al.: 96.

puzzles that are not well understood. Third, financial markets provide a wealth of pricing and volume data that can be analyzed. Fourth, when considering evolution, financial markets provide a good approximation to a crude fitness measure through wealth or return performance. Finally, there are strong connections to relevant experimental results that in some cases operate at the same time scales as actual financial markets.[143]

The dynamics of international financial markets display certain stylized facts. These features include a random walk-like behavior of prices, the sporadic appearance of bubbles and crashes, excess volatility, fat tails of the distribution of returns, and volatility clustering.[144] Agent-based financial market model may help us to comprehend the dynamics of financial markets. For instance, it reveals that nonlinear interactions between heterogeneous market participants may account for emergent phenomena such as bubbles and crashes, excess volatility and volatility clustering. [145]

The use of agent-based models in finance is increasing. Asset pricing behaviors including exchange rate determination, explanation of bubbles, crash and stylized facts have been focus of interest. LeBaron[146], LeBaron[147] and Hommes[148] give details about agent based models used in finance.

> LeBaron who dedicated his time to develop an agent based model of the stock market claims that traditional models do not go very far in explaining the statistical features of real markets while detailed analyses of agent-based model show. He explains why the prices do not come to equilibrium in his model as:
>
> "Because the agents can learn from and respond to emerging market behavior, they often shift their strategies, leading other agents to change their behavior in turn. As a result, prices don't settle down into a stable equilibrium, as standard economic theory predicts. Much as in the real stock market, the prices keep bouncing up and down erratically, driven by an ever-shifting ecology of strategies and behaviors."[149]

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[143] B. LeBaron, "Agent-Based Computational Finance", **Handbook of Computational Economics**, Vol. 2, Chapter 24, ed. L. Tesfatsion and K.L. Judd, (North-Holland, Amsterdam, 2006): 1190.

[144] F. Westerhoff, "A simple Agent-Based Financial Market Model: Direct Interactions and Comparisons of Trading Profits", **BERG Working Paper Series on Government and Growth**, Working Paper No. 61, (2009): 9-10.

[145] Op. Cit., Westerhoff: 3.

[146] B. LeBaron, "Agent-Based Computational Finance: Suggested Readings and Early Research", **Journal of Economic Dynamics and Control,** vol. 24, (2000), 679-702.

[147] Op. Cit., LeBaron: 1188-1227

[148] C.H. Hommes, "Heterogeneous Agent-Based Models", **Handbook of Computational Economics - Agent-Based Computational Economics**, vol. 2, chapter 24, ed. L. Tesfatsion and K.L. Judd, (Elsevier, North-Holland-Amsterdam, 2006): 1110-1146.

[149] Op. Cit., Buchanan: 681.

Buchanan summarized the Eurace Project which is an agent-based model of the entire European Union economy and funded in the scope of European Union Sixth Frame Programme. The model created by University of Genoa in Italy, meanwhile, Silvano Cincotti and his colleagues includes markets for consumer goods and financial assets, firms that interact with banks to obtain loans, and banks that compete with one another by offering different interest rates. Based on real economic data, the model currently represents some 10 million households, 100,000 firms and about 100 banks, all of which can learn and change their strategies if they find more profitable ways of doing business. This work also appreciates the researches of Helbing focusing on simulations of human behaviors in relatively small groups — how traffic ebbs and flows through a road network, for example, or how crowds crush towards a door in a panic situation. 'Eurace' agree with that "complex collective phenomena can emerge from even the simples individual interactions." If pedestrians can organize themselves into smoothly flowing streams just by trying to walk through a crowded shopping center — as he as shown they do — just imagine how much richer the emergent phenomena must be in a group the size of a national economy.[150]

Among the agent-based modeling studies related financial markets, those mainly focusing in exchange rate are widespread. P.D. Grauwe [151], Westerhoff[152], Winker and Gili[153], Winker et.al[154]and Manzan[155] have contributed the realm.

C.Altavilla and P.D. Grauwe summarizes the researches on the relationship of exchange rate and its fundamentals. According to them the results of these works suggest that the speed at which exchange rate converges to the long-run fundamental equilibrium mostly depends on the nominal exchange rate regime in operation. Thus, there is increasing evidence that the relation between the exchange rate and its fundamentals has important non-linear features. In their

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[150] Op. Cit., Buchanan: 681.

[151]De Grauwe, P., and H. Dewachter, "A Chaotic Model of the Exchange Rate: The Role of Fundamentalists and Chartists," **Open Economies Review**, no. 4,(1993), 351-379.

[152] Op. Cit., Westerhoff, "The Use of Agent-Based…", (2008): 1-57

[153] Winker, P., Gilli, M., "Indirect estimation of the parameters of agent based models of financial markets", **FAME Research Paper** No. 38, (University of Geneva, 2001): 1-24.

[154]P. Winker, M. Gilli, and V. Jeleskovic," An objective function for simulation based inference on exchange rate data",**Journal of Economic Interaction and Coordination**, no. 2 (2007): 125-145.

[155] S. Manzan, "Agent Based Modeling in Finance", **Encyclopedia of Complexity and Systems Science,** (Springer,2009): 3374–3388.

work they also investigate whether the dynamic interaction between the exchange rate and its fundamentals is time-varying. For doing that, they first developed a simple theoretical model of the exchange rate in which chartists and fundamentalists interact and then analyzed the nature of these non-linarites using evidence of the dollar/ DM (euro) exchange rate. This model predicts that exchange rate movements will be characterized by different regimes, which are called fundamental and non-fundamental regimes. When in a fundamental regime the exchange rate stays close to the fundamental. There are also non-fundamental regimes in which the exchange rate is disconnected from the fundamentals.They assume that the equilibrium value of the euro-dollar exchange rate is determined by a set of economic fundamentals. The study concentrates on three of such fundamentals: *the relative GDP* (measured as the difference between the EU and USA real GDP), *the relative inflation rate* (the inflation rate differential) and *the interest rate differential.*(short term).[156]

The empirical evidence suggests that the relationship between the exchange rate and the fundamentals is a non-linear one, characterized by frequent changes in the regimes linking the exchange rate to the fundamentals. Traditional linear rational expectations models cannot account for this except by introducing exogenous changes in regimes, i.e. by leaving these switches unexplained. [157]

Exchange rate economics has been dominated by the rational expectations efficient market theory (REEM). This theory however has not been empirically validated. First, survey evidence indicates that traders' expectations strongly deviate from rational expectations. Second, technical trading rules appear to make risk-adjusted excess returns, violating the efficient markets hypothesis. As this empirical evidence against REEM theory has tended to accumulate, researchers have increasingly looked for alternative modeling approaches. One of these approaches challenges the assumptions about the way the agents form their expectations. First, in line with strong survey evidence, a number of researchers have modeled the agents in the foreign exchange market as chartists and

[156] C. Altavilla and GrauweP. D., "Non-Linearities in the Relation Between the Exchange Rate and its Fundamentals", **CESifo Working Paper,**no. 1561, (2005): 2-20.
[157] Op. Cit., Altavilla: 2.

fundamentalists. Second, several researchers, instead of assuming full rationality introduced some sort of adapting mechanisms into agents' behavior. [158]

In their model, D. Delli Gatti et al. shows that the individual choice variable depends on the individual financial conditions and on the average or aggregate financial condition. This is the cornerstone of modeling financial-real interrelations in an heterogeneous setting.[159]

In the literature there are two forecasting rules or strategies: "chartism" and "fundamentalism". The traders using these strategies are called chartists and fundamentalists, respectively. Frankel J. and Froot K. mentioned these traders first time by making classification of these actors as fundamentalists, chartists and portfolio managers who actually buy and sell foreign assets, from their expectations as a weighted average of the predictions of the fundamentalists and chartists[160]. Then, Grawue and Dewatcher used these two rules.[161] In some studies authors call fundamentalists as mean reverting and chartists as technical[162], extrapolative, moving average indicators Brandouy[163] or noise traders[164]. The decision in favor of one of these three strategies is repeated every trading period and is based on the strategies' past performance.[165] Frankel describe the participants in the foreign exchange market as investors (long-term) and speculators (short-term).[166]

The interplay between the traders may lead to complex endogenous dynamics. When technical analysis governs the market, it is possible to observe the start of a bubble. When the market is dominated by fundamental traders, the price adjusts towards its fundamental value.[167]

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[158] Paul De Grauwe and Agnieszka Markiewicz, "Learning to Forecast the Exchange Rate: Two Competing Approaches", **CESifo Working Paper Series**,no. 1717, (2009): 2.
[159] Op. Cit., Gatti, et al.: 99.
[160] Frankel, J. A., and K. A. Froot, Understanding the us dollar in the eighties: The expectations of chartists and fundamentalists, **Economic Record, Supp**. No. 62 (1987): 24-38
[161] Op. Cit. Grauwe and Dewachter: 351-379
[162] Op. Cit., Westerhoff, "The Use of Agent-Based…", (2008): 1-57
[163] Op. Cit., Brandouy and Mathieu: 63-79
[164] Op. Cit. Grauwe and Dewachter: 351-379
[165] Op. Cit., Westerhoff, "The Use of Agent-Based…", (2008): 3.
[166] J. Frankel, "How well foreign exchange market function: might a tobin tax help?", **Nber Working paper series**, no. 5422, (1996): 1-59.
[167] Op. Cit., Westerhoff, "The use of agent-based…", (2008), 6.

When the exchange rate is close to its fundamental value, non-monetary factors largely affect exchange rates. During these periods exchange rate movements do not depend on economic fundamentals but instead on self-fulfilling beliefs and expectations.[168]

M. Lengnick and H-W. Wohltman combine the financial markets using ABC chartist-fundamentalist model and the real sector of the economy described by new keynesian macroeconomic framework.[169]

P. D. Grauwe and A. Markiewicz specify two types of alternative selection procedures (learning mechanism):

- *Fitness learning* is the dynamic predictor selection which assumes that agents evaluate forecasts by computing their past profitability. Accordingly, they increase (reduce) the weight of one rule if it is more (less) profitable than the alternative rule.
- *Statistical learning* is the mechanism in whichagents learn to improve their forecasting rules using statistical methods as in the literature of adaptive learning in macroeconomics.[170]

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[168] Op. Cit., Altavilla and Grauwe: 14.
[169] M. Lengnick, Wohltmann, H. W., "Agent-Based Financial Markets and New Keynesian Macroeconomics – A Synthesis", **Economics Working Paper,** no. 9, (Department of Economics, Christian-Albrechts-Universitat zu Kiel, 2011): 1-30.
[170] Op. Cit.,Grauwe and Markiewicz:2

3. METHODOLOGY

3.1. Purpose of This Study

In this study I aimed to see the connection of exchange rate and its fundamentals. I intended to analyze the building blocks of agent based model, i.e heterogeneity, learning, micro foundation. Showing many advantages and disadvantages of agent-based modeling, I tried to measure whether agent-based simulation can represent Turkish actual exchange rate market.

3.2. A Simple Exchange Rate Model

I used the model proposed by De Grauwe and Grimaldi I also got benefit from MATLAB software of their study. [171]

To start up, fundamental rate can be explained. This is the exchange rate that is consistent with equilibrium in the real part of the economy.[172]

In the basic non-linear exchange rate it is assumed that the agents have heterogeneous beliefs about the future exchange rate. Two types of exchange rate traders are introduced for simplicity: chartists and fundamentalists.

Fundamentalists compare the past market exchange rates with the fundamental rate and they forecast the future market rate to move towards the fundamental rate. They are said to follow a negative feedback rule.

$$E_{f,t}(\Delta s_{t+1}) = -\psi(s_{t-1} - s^*_{t-1})$$

where;

[171]Paul De Grauwe, Roberto Dieci and Marianna Grimaldi, “Fundamental and Non-Fundemantal Equilibria in the Foreign Exchange Market. A Behavioral Finance Framework”, CESifo Working Paper, no. 1431, (2005): 1-46.

[172]Op. Cit. Grauwe: 1-46

s_t^*;fundamental exchange rate at time t

$s_t^*$is assumed to follow a random walk and 0 < ψ < 1.

In the model,firstly, fundamental rate is assumed as exogenous.

Chartists use their past experiences to forecast future exchange rate. Thus they can compute moving average of the past exchange rate changes and they extrapolate this into the future exchange rate change. More clearly they use past information to make forecast about future exchange rate. Chartists' forecasts can be written as follow:

$$\mathrm{E}_{c,t}(\Delta s_{t+1}) = \beta \sum_{i=0}^{T} \rho_h \Delta s_{i-t}$$

here;

$E_{c,t}$;forecast made by the chartists using information up to time t-1

Δs_t; change in the exchange rate

β;coefficient expressing the degree with which chartists extrapolate the past change in the exchange rate

0 <β< 1 is assumed to ensure dynamic stability.

Number of agents shapes fundamental and chartist (non-fundamental) regimes. Non-fundamental regimes are characterized by situations in which the chartists' weights are very close to 1.[173] In these regimes market exchange rate is deviated strongly from its fundamental value while in fundamental exchange rate regimesbehave parallel to its fundamental value.

Weights of chartists and fundamentalists can be show as the function of profits and intensity of choice parameter, γ. This parameter measures whether agents react to different profitable strategies. With an increasing γ agents react strongly to the relative profitability of the rules.

Weights of the forecasting rules are determined by afunction of the relative profitability of these rules:

$$\omega_{c,t} = \frac{exp\ [\gamma\pi'_{c,t}]}{exp[\gamma\pi'_{c,t}] + exp[\gamma\pi'_{f,t}]}$$

[173] Op. Cit., Altavilla C. and GrauweP. D.: 5.

$$\omega_{f,t} = \frac{exp\,[\gamma\pi'_{f,t}]}{exp[\gamma\pi'_{c,t}] + exp[\gamma\pi'_{f,t}]} = 1 - \omega_{c,t}$$

where;

$\pi'_{c,t}$; risk adjusted net profits computed by chartistswho forecast the exchange rate in period t using information up to$t - 1$.

$\pi'_{f,t}$;risk adjusted net profits computed by fundamentalists who forecast the exchange rate in period t using information up to $t - 1$.

Last equations above can be interpreted as switching rules. When the risk adjusted profits of the technical traders' rule increases relative to the risk adjusted net profits of the fundamentalists rule, then the share of agents who switches and use technical trader rules in period t increases, and vice versa. [174]

Intensity of choice parameter, γ captures how sensitive the traders (agents) are to selecting the most attractive strategy.The higher, the more agents will select the strategy with the highest fitness.[175]Thus, γis a measure of inertia in the decision to switch to the more profitable rule. This parameter is of great importance in generating bubbles.[176]

Note that,

$$\pi'_{c,t} = \pi_{c,t} - \mu\sigma^2_{c,t}$$

$$\pi'_{f,t} = \pi_{f,t} - \mu\sigma^2_{f,t}$$

where;

$\pi'_{c,t}$and $\pi'_{f,t}$; gross profits

$\pi_{c,t}$and $\pi_{f,t}$;net profits

Risk is measured above by the variance terms defined as the weighted average of the squared (one period ahead) forecasting errors made by technical traders and fundamentalists, respectively. Formally, risk can be shown below:

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174 Op. Cit.,Paul De Grauwe, Roberto Dieci and Marianna Grimaldi: 7.
175 Op. Cit., Westerhoff, "The use of agent-based…", (2008), 9.
176 Op. Cit.,Paul De Grauwe, Roberto Dieci and Marianna Grimaldi: 7-8.

$$\sigma_{i,t}^2 = (1 + r^*)^2 V_t^i(s_{t+1})$$

$$V_t^i(s_{t+1}) = \sum_{k=1}^{K} \theta [E_{t-k-1}^i(s_{t-k}) - s_{t-k}]^2$$

where;

θ;geometrically declining weight ($0 < \theta < 1$) and

V_t^i; conditional variance of wealth of agent *i*.

Profits are defined here as the one-period earnings of investing \$1in the foreign asset. More formally,

$$\pi_{i,t} = [s_{t-1}(1 + r^*) - s_{t-2}(1 + r)] sgn[(1 + r^*)E_{t-2}^i(s_{t-1}) - (1 + r)s_{t-2}]$$

where;

$$sgn(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}$$

In the model agents do not have rational expectations. The implication of rational expectations in models with heterogeneous agents is that it creates "infinite regress," i.e. the exchange rate depends on the expectations of other agents' expectations, which depends on the expectations of the expectations of other agents' expectations, and so on, ad infinitum. This leads to intractable mathematical problems except under very restrictive simplifying assumptions.[177]

3.3. Dynamics and Stylized Facts

I start the simulation with following initial conditions and parameters. Firstly, I run simulation for different initial conditions. Secondly, the outcomes of the simulation are evaluated by changing some key parameters (sensitivity

[177] P.D. Grauwe and Grimaldi M., "The Exchange Rate and its Fundamentals in a Complex World", **Review of International Economics**, Vol. 13, no.3, (2005):553.

analysis).List of initial conditions and model parameter of which will be fix during the all simulations are below:

Table 3: Initial Conditions

Number of observations (T)	10000
Cost of fundamentalists	0
Cost of chartists	0
Number of fundamentalists	400
Number of chartists	600
Transaction costs (C)	0
Initial random shock (permanent)	0.1
Initial random fundamental shock	0

Table 4: Model Parameters

Parameters	**Symbol**	**Value**
Speed of adjustment	Ψ	-0.2
Weight of chartists moving average, geometrically declining weight variance	ρ	0.5
Extrapolation parameter	β	0.9
Variance of fundamental exchange rate	σ_*	0.1
Variance of noise	σ_ε	0.05
Domestic interest rate (Turkey)	r^*	1.1
Foreign interest rate (USA)	r	0.25
Intensity of choice	γ	5

The simulations run are stochastic. Stochastic shocks occur in the model because the fundamental exchange rate is assumed to be driven by a random walk, i.e.

$$s_t^* = s_{t-1}^* + \varepsilon_t$$

It is assumed that ε_t is normally distributed with mean equal to 0, and standard deviation equal to 0.1.

I first run two stochastic consecutive simulations to see the connections of exchange rate with fundamental exchange rate which is so-called fundamentals. In figure 3 this connection is shown by running the simulations with the same parameters.

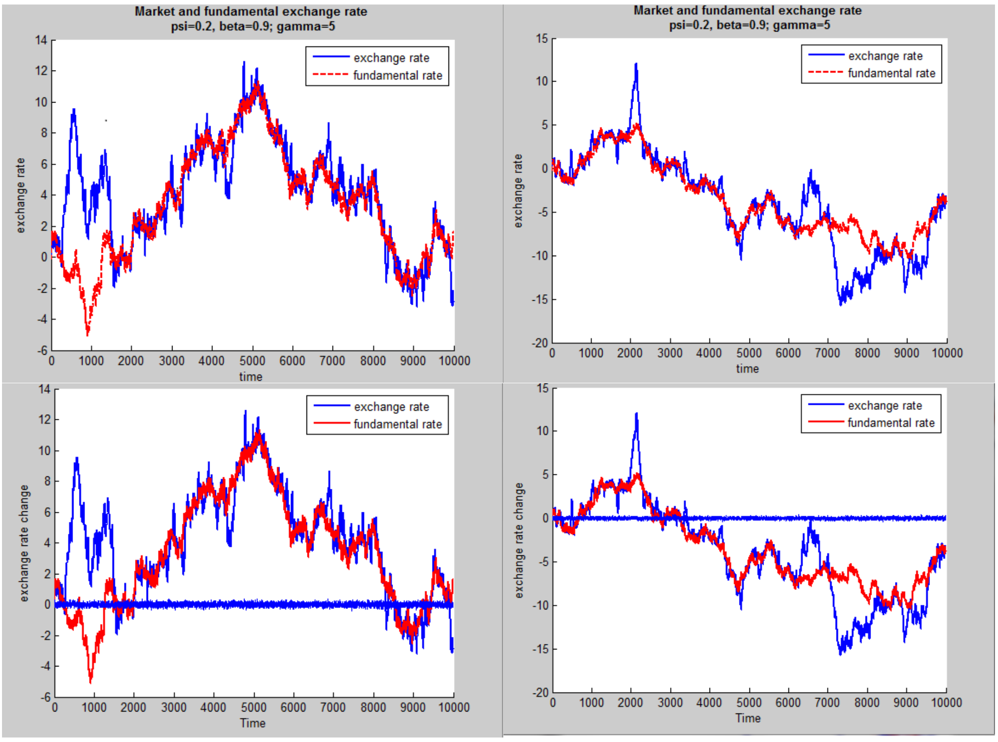

Figure 3: Market and Fundamental Exchange Rate

As a result, the difference in exchange rates and exchange rate changes are clear. The left side of the figures shows that exchange rate is disconnected from its fundamentals. It can be interpreted as that chartist regimes are leading and thus, exchange rate deviates from its fundamental rate frequently. However, the difference declines in the second simulations. This give insight about to fact that in this run fundamental regimes take more place than the chartist regimes do. One can easily guess that in such regimes exchange rate is close to fundamental rate. Changes in exchange rates are more appear in bottom side of figure 3.

Transaction cost is another source of non-linearity in the determination of exchange rate. When the exchange rate deviations from the fundamental value are smaller than the transaction costs in the goods markets, there is no mechanism that drives the exchange rate towards its equilibrium value. As a result, fundamentalists expect the changes in the exchange rate to follow a white noise processε_t. The best they can do is to forecast no change. More formally,

when$|s_t - s_t^* |$<C, then $E_{f,t}(\Delta s_{t+1}) = 0$

when the exchange rate deviation from its fundamental value is larger than the transaction costs C (assumed to be of the 'iceberg' type), then the fundamentalists follow the same forecasting rule. More formally,

when$|s_t - s_t^* |$>C holds, then the equation for fundamental forecasting rule applies.[178]

As another experiment I run simulation with different value of transaction costs. In figure 4, 5 and 6 transaction cost has value of 0, 5 and 10 respectively.

[178] Paul De Grauwe,Marianna Grimaldi, Heterogeneity of agents, transactions costs and the exchange rate, **Journal of Economic Dynamics & Control,** (Elsevier, 2004): 691-71.

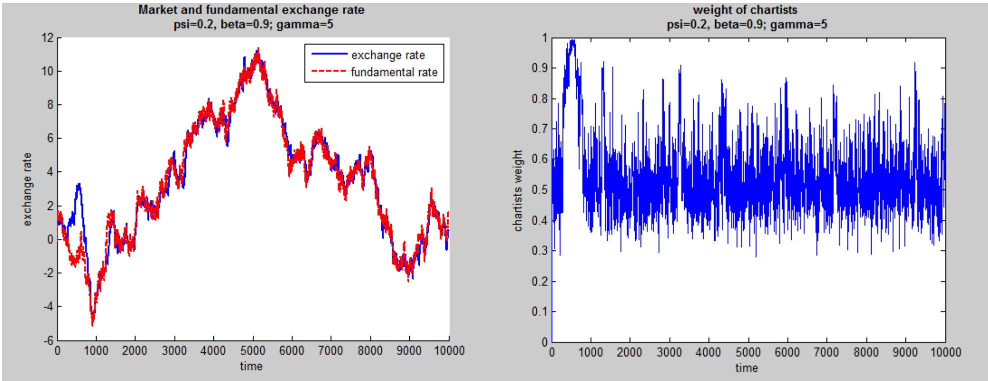

Figure 4: Effect of Transaction Cost, C=0 (initial)

In figure 5 where transaction cost rises up, exchange rate starts to deviate from its fundamental value.

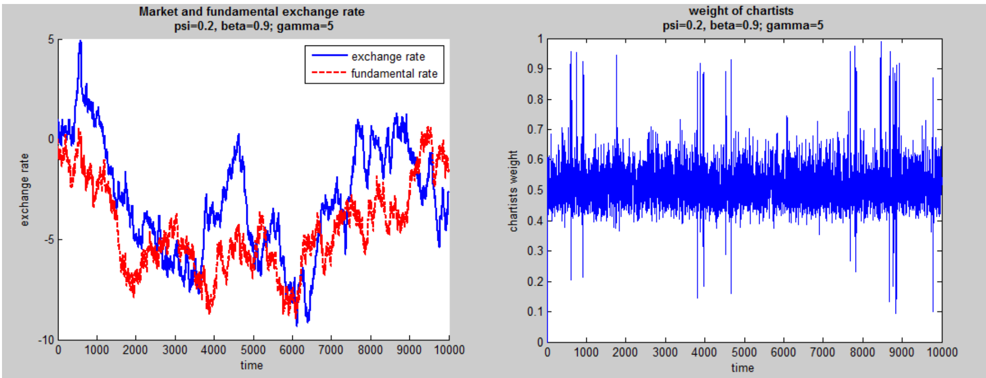

Figure 5: Effect of Transaction Cost, C=5

The gap between exchange rates increasesas the transaction cost is equal to 10.

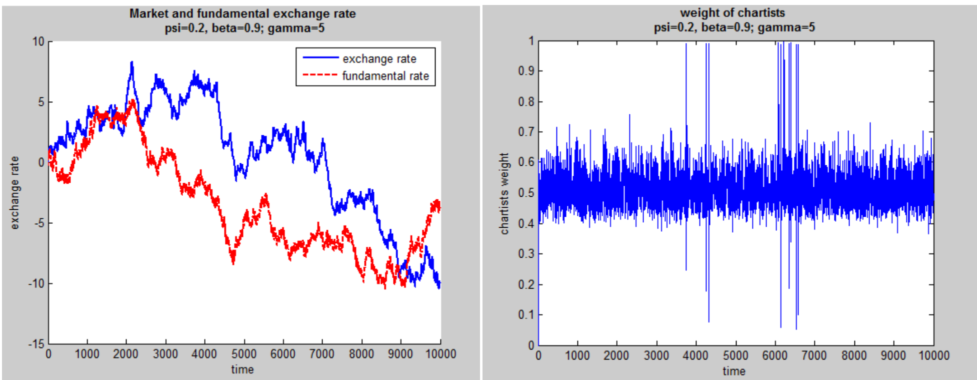

Figure 6: Effect of Transaction Cost, C=10

Weight of chartist is more volatile when there is no cost. With the increase in transaction cost, C, chartist weight get more stabilized and fluctuations decrease.

The price dynamics of a wide range of financial markets exhibits certain universal properties.[179] These stylized facts include the following phenomena:

Bubbles and crashes: In the model, exchange rates often disconnect from their fundamental values and show features of bubbles and crashes.

Excess volatility: asset prices vary far more than their fundamental values. Even

extreme price changes may be unrelated to fundamental shocks

Fat tails: It can be measured by excess kurtosis. But in the model I did not trace for the evidences.

Random walk: fundamental rate behave as random walk in the stochastic version of the model.

Volatility clustering: The differences between exchange rate and its fundamental appear as high (small) in some periods followed by small (high) gaps.

The model I use shows nearly all of the stylized facts.

[179] Op. Cit.,Westerhoff, (2008): 11-12.

3.4. Sensitivity Analysis

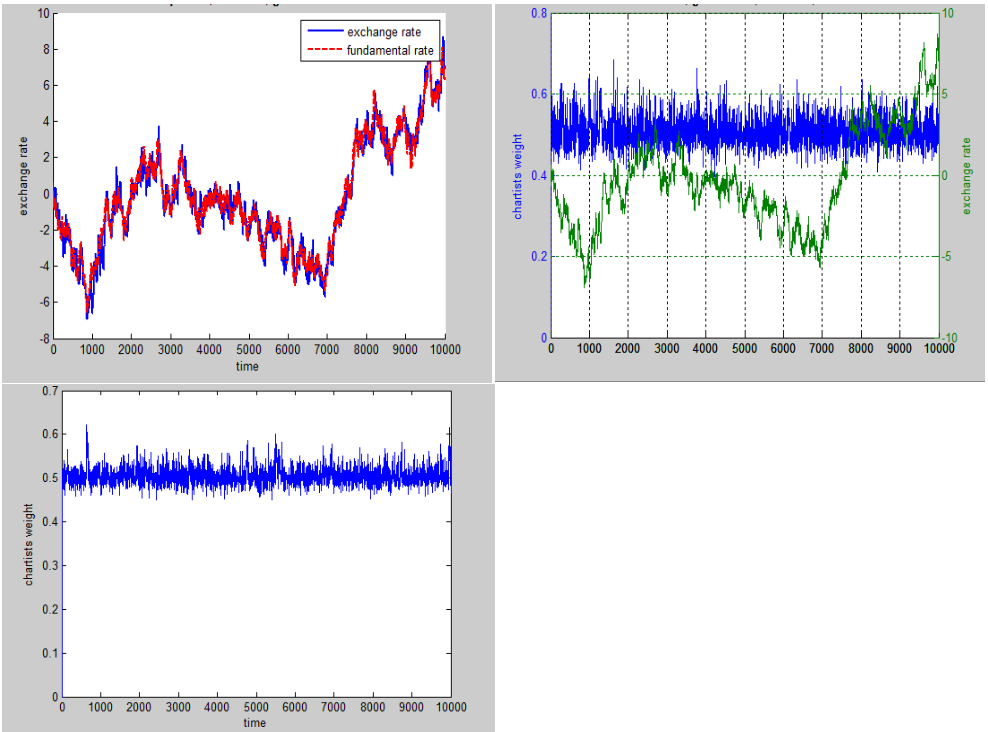

Figure 7: Intensity of Choice, γ=1

In sensitivity analysis, firstly, market and fundamental exchange rate are observed under different value of intensity of choice parameter, γ. For two different simulations were run with γ=5 and γ=1, respectively. According to this, higher γ is the more agents take the relative profitability of forecasting rules into considerations. When γ goes to ∞ agents choose the rules instantonously. On the contrary, weights of chartists and fundamentalists become constant and 0.5 when γ equals to zero. As one can see from the figure, for higher γ – sensitive to profabilities of the rules – cause exchange rate to deviate strongly from its fundamental value. But for lower γ value exchange rate move parallel to fundamental value.

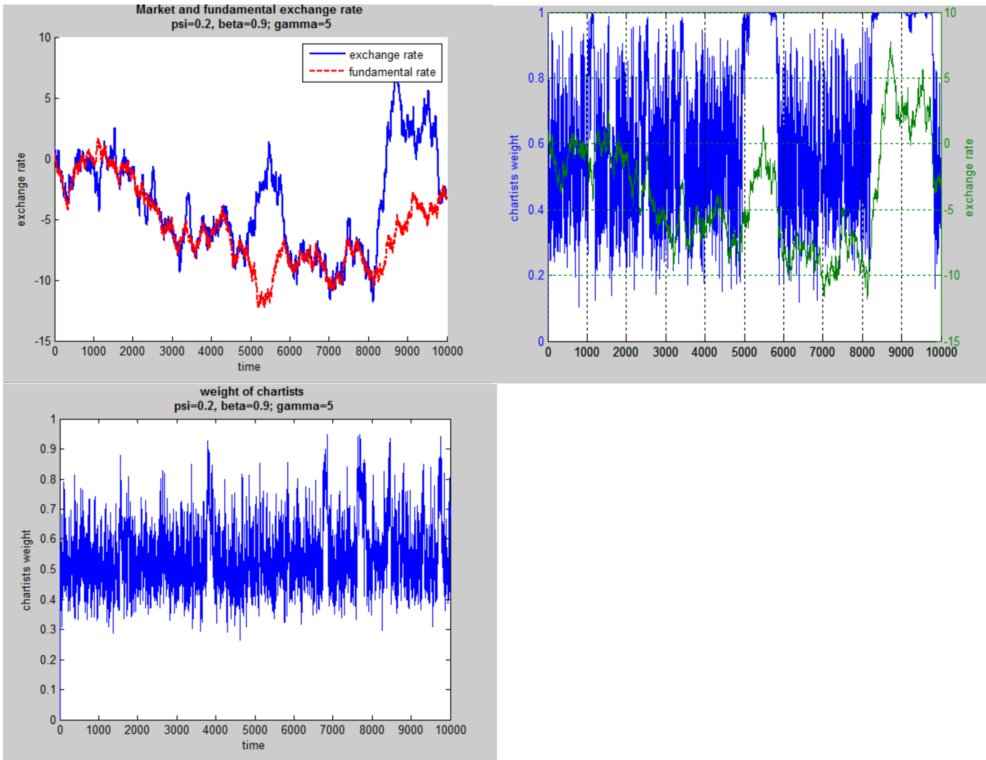

Figure 8: Intensity of Choice, γ=5 (initial)

In figure 9, I increased the value of intensity of choice parameter to 10.

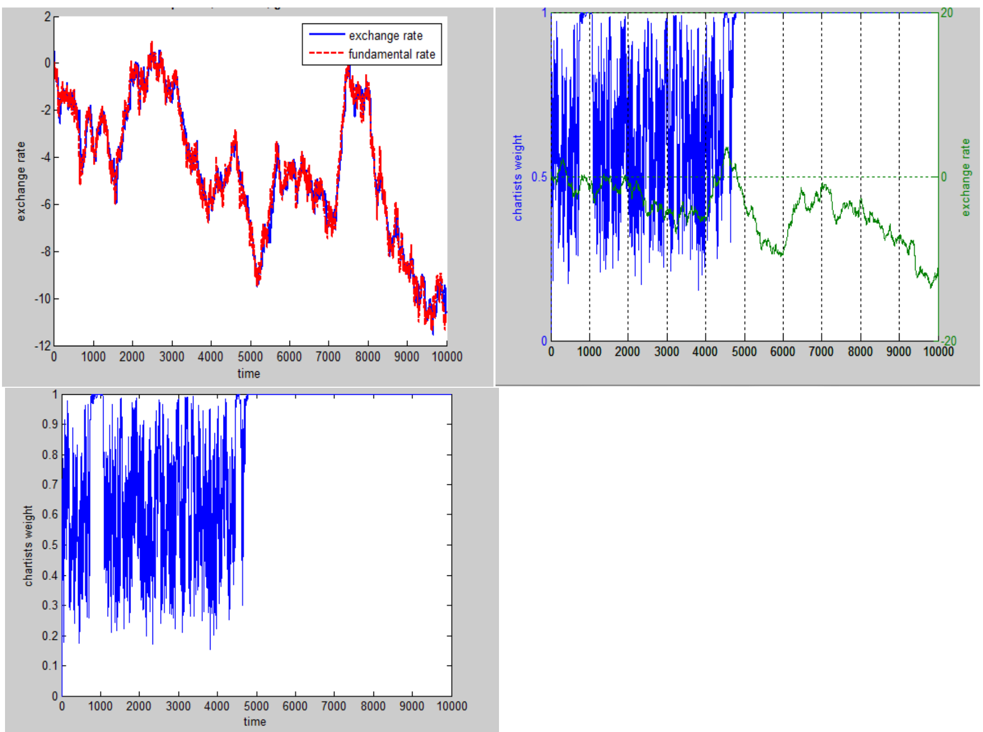

Figure 9: Intensity of Choice, γ =10

To see the move of chartist weight and exchange rate together, right side of the figure make a clear visualization. Becoming more sensitive to profitability of the rules, chartistweight behaves more volatile. On the other hand, chartists become less voluntary to switch between forecasting rules in the presence of exchange rate changes due to lowγ, respectively.

Being sufficiently low extrapolation parameter, β let us get exchange rate which is nearly equal to fundamental rate. Figure shows the results of the experiments done with three different β values: 0.85, 0.90 and 0.95 respectively. Not surprisingly, for higher β value exchange rate gets closer from its fundamental value. Figure 10, 11 and 12 show the related changes.

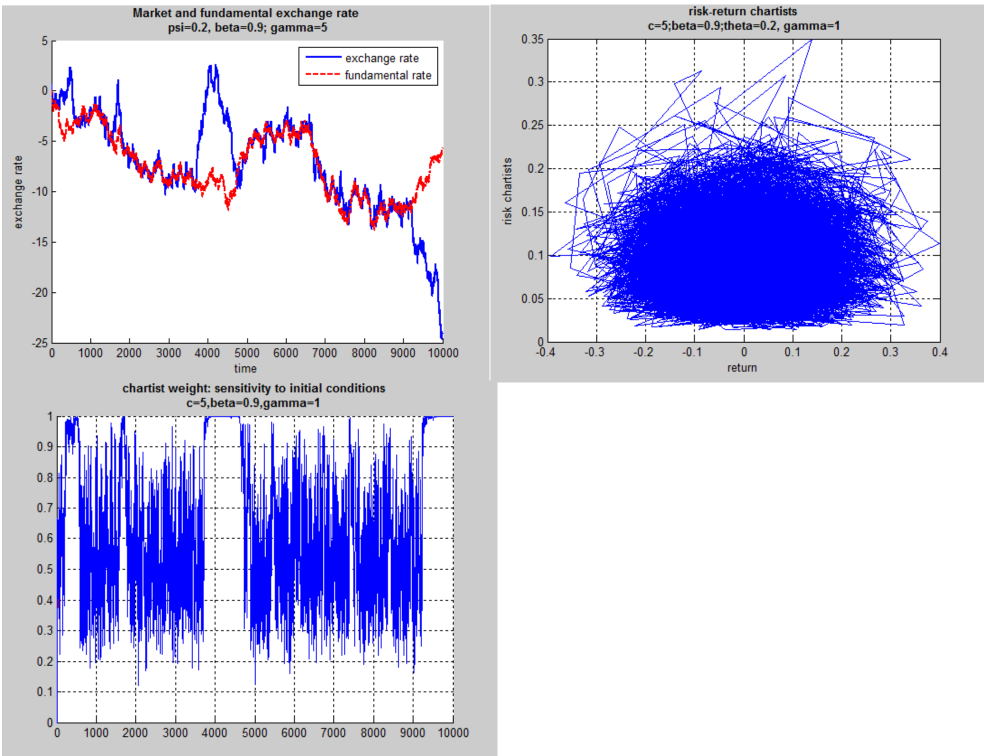

Figure 10: Extrapolation Parameter of Chartists,β=0.85

As β increases as in figure 11 weight of chartists start to dominate the market. Beside this right side of the figure can give insight about that the risk of chartists increases.

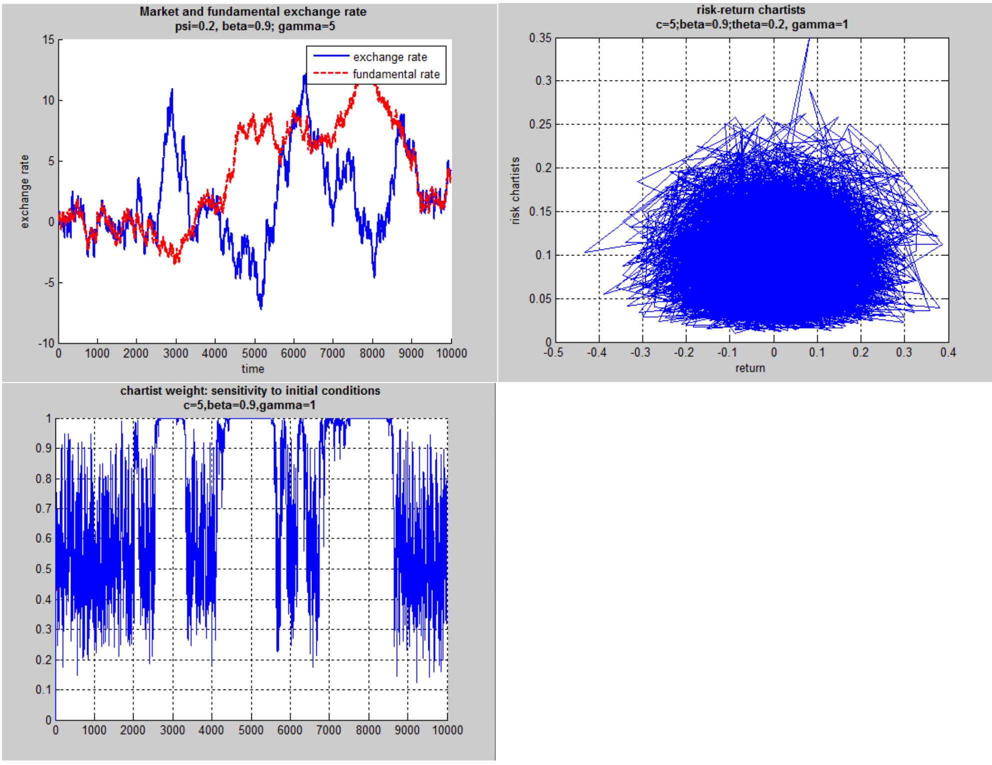

Figure 11: Extrapolation Parameter of Chartists, β=0.9 (initial)

Figure 12 gives more clear results. According to figure, after 4000 observations all agents turn out to be chartist. This results show that exchange rate model is sufficiently sensitive to changes in extrapolation parameter.

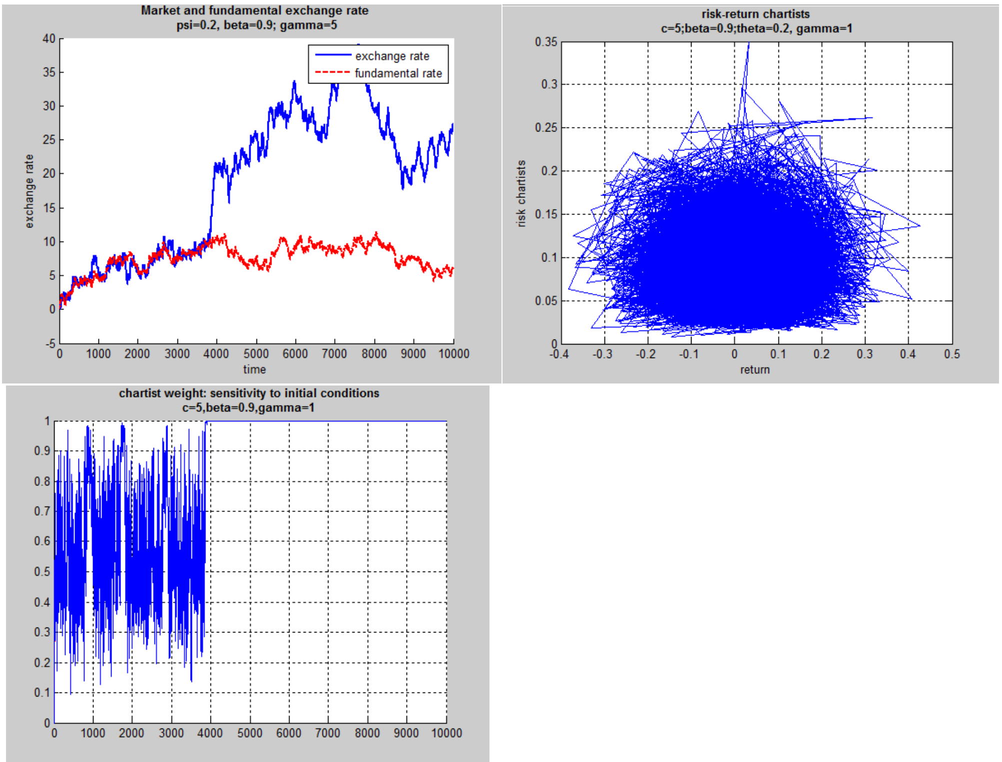

Figure 12: Extrapolation Parameter of Chartists, β=0.95

3.5. Validation

The behavior data of the simulation model and the system are graphed for various sets of experimental conditions to determine if the model's output behavior has sufficient accuracy for the model's intended purpose. Three types of graphs are used: histograms, box (and whisker) plots, and behavior graphs using scatter plots.[180]

Whatever the exact nature of their objectives, ABM researchers must also address challenging model verification and empirical validation issues. Verification concerns consistency with objectives: Does an ABM do what a researcher intends, or is there some form of logical or conceptual programming error?

[180] R. G. Sargent, "Verification And Validation of Simulation Models", **Proceedings of the 2010 Winter Simulation Conference**, ed. B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan: 175.

Empirical validation concerns consistency with empirical reality: Does an ABM appropriately capture the salient characteristics of a real-world system of interest, and does it provide outcomes that cohere with empirical observations?[181]

Unfortunately, there is no set of specific tests that can easily be applied to determine the "correctness" of a model. Furthermore, no algorithm exists to determine what techniques or procedures to use. Every simulation project presents a new and unique challenge to the model development team.[182]

In this step I use the data provided by Central Bank of Turkish Republic. U.S. Dollar rate (USD) between 01.03.2001 and 26.06.2012 were hold. The period is consists of 2853 day and the model simulation was fixed to the same number of observations. Since exchange rate was dominantly active in the determination of exchange rate, I took the period after fixed exchange rate system was replaced by flexible rate systems. The exchange rates until 01.01.2005 show the TL values before the YTL conversion done on 01.01.2005. For the period before this date I multiplied the prices with 10^{-6} to extract six zeros from lira.

Figure 13 and 14 show the movement of actual exchange rate of Turkey and comparison of theserates with the market rate of basic agent-based model, respectively. One can easily say that in 2853 observations actual exchange rate is less volatile than ABM's. Data belong to Turkish market fits with the basic exchange rate model.

First of all, in the Turkish market, agents are sensitive to relative probability of the rules. Sensitivity of choice parameter $\gamma$is far away from zero. Remember that, in case of zero (0) value, parameter agents are insensitive to profitability of the rules. As a feature of the model when deviations from fundamental exchange rate occur, weight of chartists increase. More chartists extrapolate the past increase in exchange rate to future and decline in actual rate leads to decrease in returns. This fact happens in Turkish case, too. With the beginning of 2009 rapid increase in the exchange rate between the period of 16.10.2008-30.10.2008 which rise from 1, 3964 to 1, 6942. On 31^{th} of October 2008 rate dropped to 1, 5036 which

[181] Op. Cit.,Borill and Tesfatsion, (2011): 10.
[182] Op. Cit., Sargent: 179.

causedto sharp decrease in returns which probably mainly from chartists behaving optimistically.

Another important point is that the model is more volatile and has more bubbles and crashes than the actual market. But low number of observation, which is explained above, likely to be reason for that.

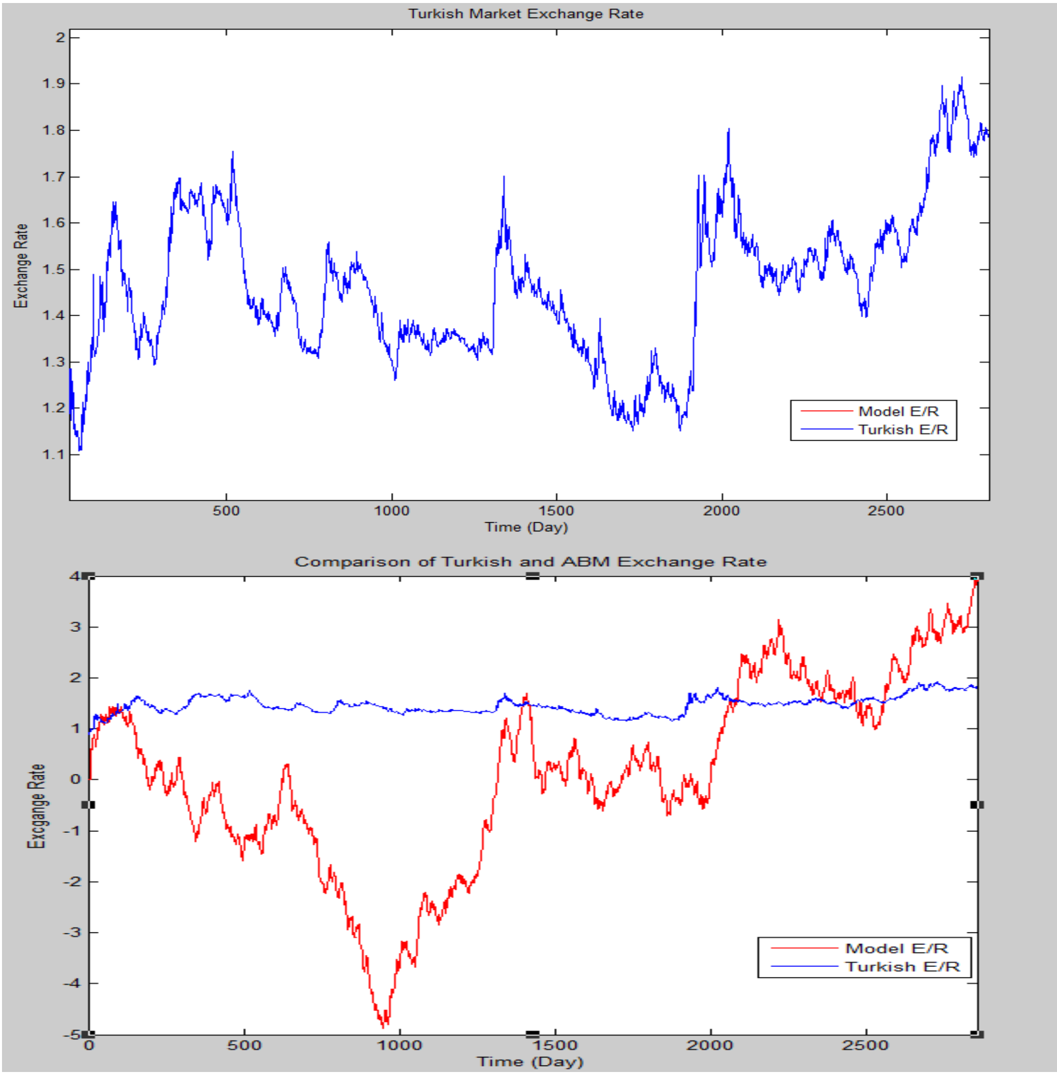

Figure 13: Exchange Rate in Turkey Between 2001 –2012

The up side of figure 13 show the exchange rate movement in Turkey between the related dates whereas bottom side enable us to see both exchange rates which are rate of the virtual world and real worlds (evidence from Turkey).

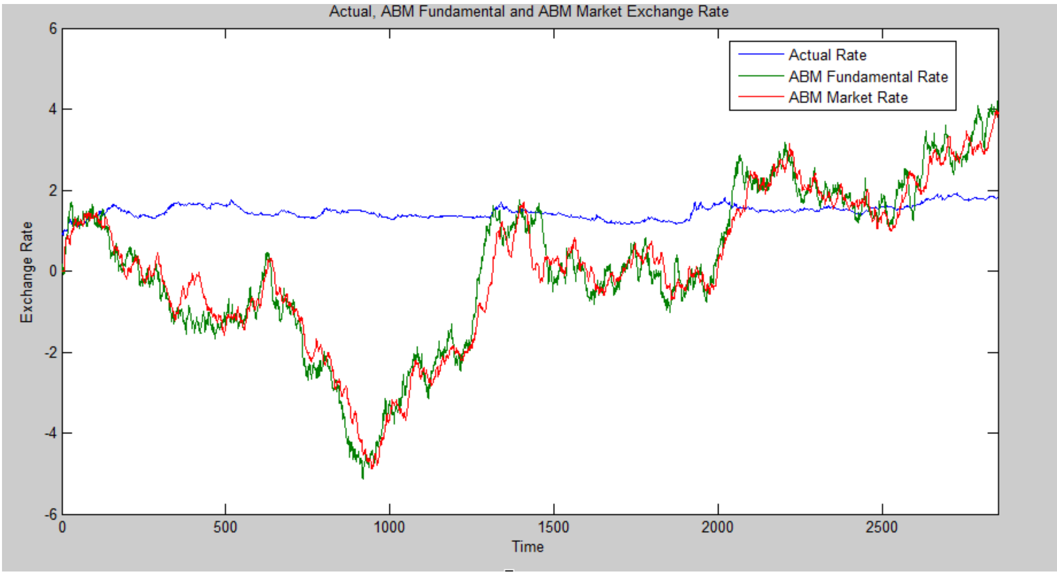

Figure 14: Actual, Fundamental and Market Exchange Rate Comparison

Figure 14 presents movements of fundamental rate of the model as well in addition to virtual and real exchange rates.

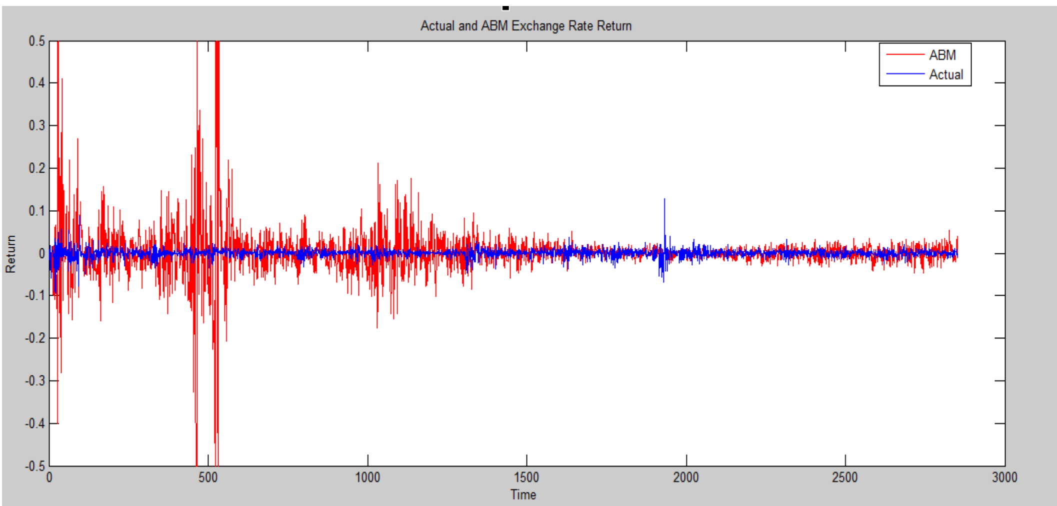

Figure 15:Actual and ABM Market Exchange Rate Returns

As it can be seen in figure 15, return of the model follows less volatile path after some period.

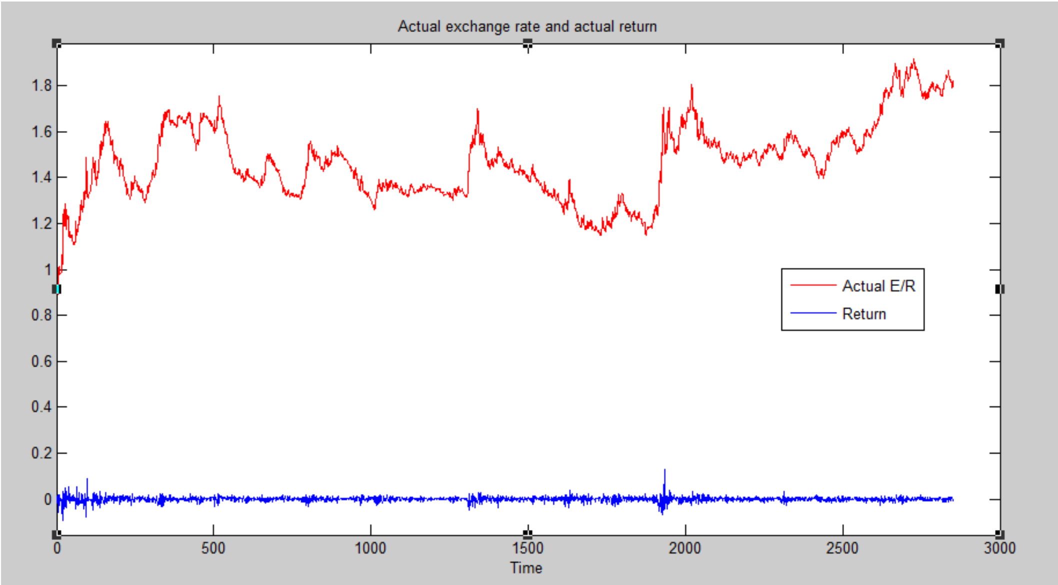

Figure 16: Actual Exchange Rate and Actual Return

Figure 16 and 17 give ease to evaluate the exchange rate and return together by showing them in the same surface.

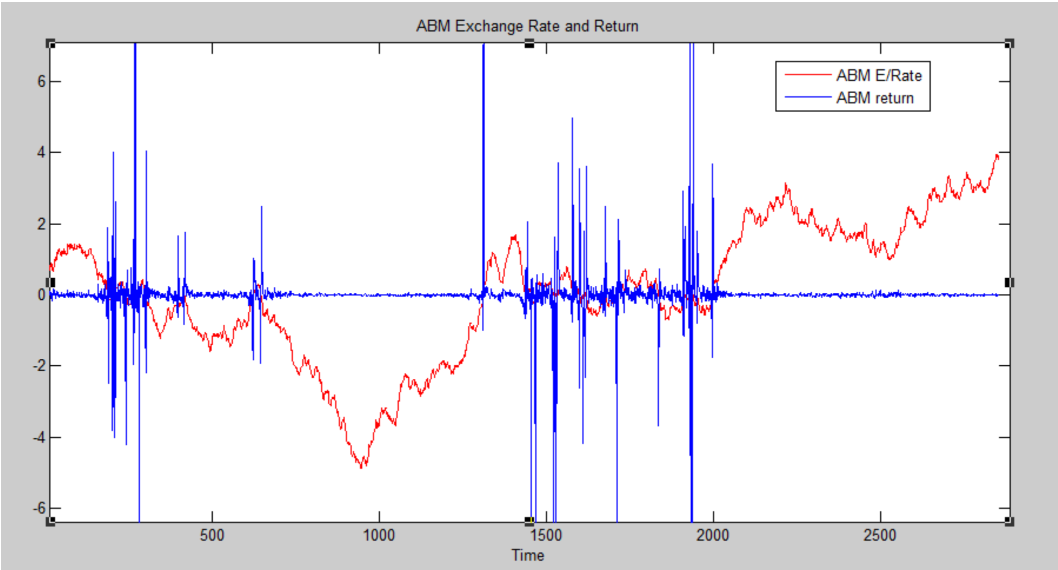

Figure 17: ABM Exchange Rate and Return

4. CONCLUSION

In this study I aimed to draw a general picture about agent-based computational economics and its building blocks. I also intended to show the dynamics of agent-based models in exchange rate markets by using a simple exchange rate model.

Unlike mainstream economics and its favorite DSGE models, agent-based approachenables researchers to conduct the heterogeneity in their models. Having many critiques due to its assumptions, representative agents framework is ignored in such models. In exchange rate markets two type of forecasting rule agents use to guess exchange rate which are fundamentalist and chartist rule, respectively in order to ensure the heterogeneity. Interactions between agents are permitted and these tell us agents are influenced one another. Switching the forecasting rules are the key to create complex adaptive systems here. Agents use one forecasting rules according to their profitability and more importantly they can shift between these two strategies as determined pattern in their behaviors. One can say easily that agents are adaptive, which means agents are learning and adapting in accordance with their environments. This gives the model to be dynamic and adaptive feature.

Rationality is another assumption that makes models of mainstream economics unrealistic. Assuming that people are rational - they have perfect information about future as well as past, and their forecast are based on this “super-natural” foresight – is not question in agent-based models. In the exchange rate model, chartists use past information to make forecast about the future rate, but information they have is limited since they have no idea about what will going to in the future. From that point, one can identify the exchange rate agents as boundedly rational.

Despite its valuable contributions to economics, robustness to initial conditions is still problematic in agent-based model. Validation is another point. Comparing results to real-world is somehow different. Because agent-based models can be evaluated as in its “childhood”, in exchange rate models these comparisons suffer.

Considering the behaviors of the agents lead researchers to use difficultly tested parameters, i.e. memory parameter in their models. This problem causes validationto be done painfully.

In the model that I borrowed from De Grauwe, identified two agents as fundamentalists who use fundamental rate as a base for forecasting the future exchange rate and chartists who make forecast by past information. No agent has full information which makes them to be boundedly rational. According to profitability of their forecasting rules they can switch to another rule and their weights change in accordance with these switch. These features lead the model to be dynamic and adaptive.

I analyzed how sensitive the initial conditions are robust. Different number of observations, weights of agents and transaction costs were simulated. According to my simulation results in small number of simulation runs the model is highly dependent on initial conditions. Because the system is adaptive andhas changing feature, simulation offered different results to different runs, i.e., I could not determine the effect of change in number of chartists and fundamentalist,unfortunately.

Making sensitivity analysis I checked the effects of the basic parameters.

Finally I compared the simulation results with Turkish exchange rate market. Using USD rate data obtained from Turkish Central Bank, I tried to validate the simulation outcomes. I reached the results that the basic agent-based model fit what Turkish exchange rate market offers.

As further study, simple exchange rate models can be combined with real sector which is modeled in agent-based approach, too.

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