**1 Background**

*1.1 Agent-based modeling for economic science*

Scientists can analyze human behavior, social interaction, and society in general with quantitative or qualitative methods. Quantitative methods often take the form of equation-based models, such as those which describe the behavior of gases, fluids, or solid bodies. While being easily applicable to the “hard” sciences, equations tend to be quite deterministic in nature, and as such are not easily adaptable to the social sciences in non-idealized scenarios (Helbing, 2014). A method better suited to socio-economic simulations is agent-based modeling (ABM). Depending on the subject of interest, agents may represent individuals, groups, companies, or countries; the main purpose is to simulate the interactions between these agents. Agent behavior can be formalized through equations, however they may be more generally specified by decision rules, implementing if-then logic and heuristics (Helbing, 2014). Agents can have any number of properties, which can be qualitative or quantitative in nature. For example, emotion, perception, sociability, risk-tolerance, etc, can all affect agent behavior (though each agent may be uniquely affected by changes in these parameters). For the purposes of this research, these qualitative properties will be reduced into a numerical value (along a spectrum of possible values, ranging from 0 to 1).

Previous work in the realm of applying ABM to financial markets provides fertile ground for potential research. In particular, the Santa Fe Artificial Stock Market is an exemplary starting point (Ehrentreich, 2002). In this research, agents are given a choice between investing their money in a stock or leaving it in the bank, where it pays a fixed interest. Agents forecasted the future value of the stock individually, based on a unique strategy optimized by genetic algorithms. This forecast then determined whether they acted, and if so, whether they bought or sold. The rate at which the agents “explored” new hypotheses about the market was the exploration rate. The researchers found that the market can enter one of two regimes, one being a rational expectations equilibrium (more stable), and the other a complex, albeit realistic, regime featuring high trading volume, high volatility, with bubbles and crashes (less stable). Interestingly, the occurrence of the second regime is correlated to a higher exploration rate. At the boundary between the two regimes, the behavior of the market is determined by agent beliefs: if the agents believe in rational expectations, the market follows that belief, otherwise it develops into the second regime. This study employed the Swarm platform for agent-based modeling and have published their code online, providing a good general framework for future research in this field.

One important aspect of note in such research is that the behavior of the agents being modelled is assumed to be rational. For example, the agents in the Santa Fe Artificial Stock Market were entirely technical traders, basing their decisions on the output of their models. In reality, while many traders operate in this fashion, many do not. Individuals who trade on their emotions, “intuition”, the status quo, etc, can be described as “irrational”. Because real markets are affected by the actions of irrational traders, there is room for improvement in this field by accounting for the behavior of such individuals.

*1.2 Irrational agent-based financial models*

A good illustration of such improvement can be found in a recent study which focused on the effects of financial news on an agent-based simulation (Dhesi, 2016). In this study, irrationally acting agents receive financial news, which was either positive or negative, and the effect of their resultant behavior was analyzed. The researchers concluded that the behavior of the simulated market resembled that of a soliton, a self reinforcing solitary wave packet, which suggests how analysts’ forecast errors could cause prices to adjust accordingly, demonstrating an irrational force.

While this is a step in the right direction, the opportunity remains to more fully model irrational agent behavior. Specifically, this simulation would account for individual propensities towards risk, crowding/herding, sentiment such as hope or fear, degree of greediness, etc. Of course, the main barrier towards such simulation is the daunting task of quantifying such unique and diverse emotions and experiences. Fortunately, the emerging field of neuroeconomics, which lies at the crossroads between neuroscience, behavioral economics, and psychology, can provide us with methods to answer such questions.

*1.3 Neuroeconomics*

Neuroeconomics combines methods and theories from neuroscience, psychology, sociology, and economics to study the human decision-making process. One such method is Functional Magnetic Resonance Imaging (fMRI), which has become the dominant technology for neuroscientific study. This method provides insight into the mechanisms within the brain which are present when different decisions are being made. For example, analytical and emotional thinking take place in different parts of the brain, and their activation during the decision-making process can affect the outcome (reflective vs. reflexive brain). This emotional/sentimental side of the brain, while the origin of irrational behavior, can be logically understood in terms of evolutionary adaptation.

The human brain has only changed by about 1% in the past 100,000 years, and is in many ways a living fossil (Sapra, 2008). It is designed to interface with a Stone Age world, where dangers and opportunities were immediate, and social interaction limited to the tribe or group to which an individual belonged. As a result, the human brain has retained, especially in the subconscious, a wide set of behaviors which, while seemingly irrational in the modern era, were entirely rational during the period in which they evolved. Examples are abundant, and include the flight or flight response, herding behavior, stereotyping, and impulsive judgements, just to name a few. These cognitive patterns are essential to understand, as 90% of decision-making processes take place subconsciously (Sapra, 2008).

Much of the research in neuroeconomics attempts to understand these paleolithic holdovers, and their effects on human behavior. For example, one study sought to understand the relationship between investment decisions and the different regions of the brain (Rocha, 2013). To accomplish this, they took fMRI scans of traders as financial transactions took place. By analyzing these images, the researchers arrived at a several important conclusions. For example, their results showed that the trading strategy of a particular individual is heavily influenced by their previous experiences, and are by no means consistent across even professional traders. Additionally, they found that trading strategy varied between genders, suggesting the employment of different neuronal circuits. Ultimately, they concluded that financial decisions, and the strategies used to make those decisions, are highly subjective, and originate from various factors such as socioeconomic status, goals, personality, and learning ability.

Since different individuals can act in different ways in the same situation, it seems that neuroeconomics research points towards underlying inefficiencies in financial markets. These inefficiencies could potentially be identified through an agent-based model, where a combination of analytical/emotional thinking is accounted for. Specifically, a more “analytical” agent would base its decisions on a technical analysis of the market (applying financial models), whereas a more “emotional” agent would base its decisions on more personal factors (Has the agent lost a lot of money recently? What is their risk tolerance?). Once identified, such inefficiencies would provide financial opportunities for investors implementing such a model.

**2 References**

Helbing, D. (2014). Social Self-Organization Agent-Based Simulations and Experiments to Study Emergent Social Behavior. Berlin: Springer Berlin.

Ehrentreich, N. (2002). The Santa Fe Artificial Stock Market Re-Examined - Suggested Corrections. SSRN Electronic Journal. doi:10.2139/ssrn.329780

Dhesi, Gurjeet, and Marcel Ausloos. (2016) “Modelling and measuring the irrational behaviour of agents in financial markets: Discovering the psychological soliton.” Chaos, Solitons & Fractals, vol. 88, 2016, pp. 119–125., doi:10.1016/j.chaos.2015.12.015.

Sapra, S. G., & Zak, P. J. (2008). Neurofinance: Bridging Psychology, Neurology, and Investor Behavior. SSRN Electronic Journal. doi:10.2139/ssrn.1323051

Rocha, A. F., Vieito, J. P., & Rocha, F. T. (2013). Neurofinance: How Do We Make Financial Decisions. SSRN Electronic Journal. doi:10.2139/ssrn.2352820