IS MORE INFORMATION BETTER? THE EFFECT OF TRADERS' IRRATIONAL BEHAVIOR ON AN ARTIFICIAL STOCK MARKET

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Abstract

This paper presents a computer simulated artificial stock market to examine market rationality issues. We construct economic agents with different degrees of irrationality to participate in the stock market. The agents replicate the irrational behaviors described in the psychology and finance literatures and determine the outcome of the market. The main focus of this study is to examine the two contradicting (efficient market versus noise trading) finance hypotheses in the presence of rational and irrational traders.

1. INTRODUCTION

The Internet has brought about an explosion of information in every aspect of human life. Never has information been so readily available and easily shared among people. Nor are financial markets above this information deluge. This gives rise to an important question of how information can alter human behaviors and what effects such behavioral transformations have on financial markets. The ubiquity of online trading services allows individuals to trade without the need to consult a human broker. Also, financial intermediaries and portals have emerged offering market information and trading tips. This information rich environment enhances the cumulative and the individual knowledge of traders, thereby making the market more informed and rational. However, the availability of online trading avenues also introduces a high number of uninformed traders into the systems, thus introducing irrationality into the market.

Finance theorists have argued that financial markets are intrinsically efficient (Fama 1965; Friedman 1953). This argument stems from the fact that rational traders possess perfect information and play the role of arbitrageurs when stock prices deviate from their fundamental values. Thus, in the long run, security prices stay in line with their fundamental values. This belief, however, contradicts the general market sentiments of irrational markets where many investors continuously behave irrationally. The noise trading approach (Shleifer and Summers 1990) explains the phenomenon by suggesting that rational traders may adopt practical yet irrational strategies to survive in a competitive environment faced with budget constraints and influences from the irrational traders.

The discrepancy between the efficient market hypothesis and the empirical evidence has encouraged researchers in finance and economics to study the patterns of investor behaviors. Many of them have applied Kahneman and Tversky's (1979) human decision-making model to analyze market behavior. Daniel et al. (1998) analyze the effect of overconfident[1] traders in market underreaction and overreaction. Odean (1998) looked at the overall market outcome when traders are overconfident. Others, like Bloomfield and O'Hara (1999) and Flood et al. (1999), used a laboratory experiment approach to study human behaviors in financial markets.

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[1]Overconfident investors are the people who overestimate the precision of their private information signals, but not the public signals (Daniel et al. 1998).

This paper attempts to analyze the behavioral phenomenon from a bottom-up approach by building individual agent traders that constitute the overall dynamic market behaviors. This approach allows us to look at the market from the individual and aggregate perspectives. We have created an artificial stock market to observe the market behavior. The market is comprised of heterogeneous economic agents that behave based on a theoretical model from psychology.

2. MOTIVATIONS AND OBJECTIVES

The financial market is created by an aggregation of traders. As a result, viewpoints from both the macro and micro sides are important in understanding the overall market dynamics. This research aims to model low-level individual building blocks to capture the aggregate market behavior.

The primary objective of this research is to build a stock market system that is comprised of heterogeneous agents to provide insights into how different agent characteristics may affect the overall market outcome and dynamics.[2] Agents are constructed to emulate the irrational psychological tendencies of human behaviors such as overconfidence, trend chasing, noise trading, etc.

This research seeks to answer the "dual" influences of the agent behaviors and the market outcome. The phenomena to be studied are how agents' decisions may influence the market and how the presence of agent induced irrationality in the market may influence the decision and performance of the individual agents.

3. RESEARCH METHODOLOGY AND PLAN

The agent-based computational simulation approach we use is similar the genetic algorithms used to model the "adaptive" agent behaviors (Alemdar and Ozyildirim 1998; Arthur et al. 1997; Bulard and Duffy 1998; LeBaron et al. 1998; Lettau 1997). This research will implement more specific agent behaviors such as noise trading, momentum chasing, overconfidence, etc. Our computational model entails artificial agents performing the role of individual traders in a synthetic market environment.

The first stage of this research is to build a market mechanism that describes the stock market structure. More intelligent and adaptive agents will be built in the later stage.[3] The future plan includes conducting laboratory experiments involving human subjects with artificial agents.

4. EXPECTED CONTRIBUTION

This research takes an alternate approach to investigate competing viewpoints between the rational expectation hypothesis and the noise trading approach. The study of a complex, agent-based stock market system can further extend contributions to the current empirical and theoretical research.

The findings help us to answer some of the fundamental questions surrounding the role of information and irrationality in the market. Given that people receive may different signals nowadays, it is important to study heterogeneity in information and investor sentiments. The implementation of an adaptive artificial intelligent agent may also be able to contribute to building an e-commerce intelligent agent.

The hypotheses can also be examined in different market scenarios. For example, we can study a market that is dominated by combinations of agents not only having diverse preferences and information, but also wealth, propensity to risk, and other individual characteristics. The richness of simulations is that it can illustrate and display complex economics processes that cannot be easily or possibly an answered in a theoretical model.

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[2]Issues include price movement, percentage of particular type agent, characteristics of the successful agents, deviation amount between market price and actual price, etc.

[3]For more information about the design of irrational agents, please refer to the conclusion and future direction section.

5. MODEL DESCRIPTION

The model consists of two entities: the agents and the market.

5.1 The Agents

Agents in the market can be either informed or uninformed traders. Each period, agents allocate their wealth into risk free and risky assets contingent upon the information they received from the stock market. Informed agents apply all of the information available to them when they make financial decisions. On the other hand, uninformed agents consider and process partial information. Each agent does not interact with other agents and they do not have information (such as type and strategies) of the other agents. In a sense, agents are assumed to be "bounded rational" in optimizing their utilities with imperfect information about the other agents and the market (uninformed agents). In addition, an irrational agent will be modeled to capture the elements of irrational behaviors in the market.

5.2 The Market

Agents generate their own demand functions based on the information they receive from the market. The aggregation of all individual demand functions equates with the total outstanding stock shares to generate the market equilibrium price for the risky asset. The actual value of the stock is externally generated and it is linked to the information agents receive from the market. Agents may earn capital gains or losses based on the differences of the actual and the market prices. Agents with negative wealth will be eliminated from the market. In addition, the new entering agent that replaces the eliminated agent will imitate the wealthiest agent; as a result, they will be the same type.

Fluctuations of the total market value introduce inflation and deflation issues. For simplicity, we keep the total market value fixed and assume a zero sum game for the participating agents. When the market value is above the initial market value, all agents will be taxed a lump sum amount of which the total equals the exceeding amount. New agents will be introduced into the market to inject new capital when the market value is below its initial level. The new agent type will be identical to the wealthiest agent to bestow the idea the new agents imitate the strategies of the best agent.

In this paper, we define the overall "market irrationality" as the number of agents engaged in irrational strategies and the total market value they command.

6. SYSTEM DESIGN

In terms of the system logic, it can be separated into four parts. They are expectation formulation, market equilibrium, agent evaluation, and market value evaluation. The market equilibrium segment uses Grossman's (1976) competitive stock market model to generate market equilibrium price.

6.1 Expectation Formulation

Agents receive private information from the market and form their price expectation. The actual value of the stock is determined by equation (1)

$$p(t + 1) = \alpha_i(t) + \alpha_2(t) + \varepsilon(t) + p(t) \tag{1}$$

where α_1, α_2, and ε are randomly generated with normal distribution $N(\mu_{\alpha 1}, \sigma_{\alpha 1})$, $N(\mu_{\alpha 2}, \sigma_{\alpha 2})$, and $N(\mu_{\varepsilon}, \sigma_{\varepsilon})$. The actual value of the stock price is determined by two factors, α_1 and α_2, and the noise term, ε. All agents observe the distributions of the two factors. In each period, each agent randomly generates α_1 and α_2. Informed agents make decision based on both factors and their noise term and uninformed agents make decision only based on factor 1 and their own noise. The estimated price for the informed and the uninformed agents for the current period can be represented by equation (2) and (3) respectively.

$$\tilde{p}_i(t) = \alpha_{1i} + \alpha_{2i} + \varepsilon_i(t) + p_i(t - 1) \tag{2}$$

$$\tilde{p}_j(t) = \alpha_{1j} + \varepsilon_j(t) + p_j(t-1) \tag{3}$$

Note that equations (2) and (3) are only true for "bounded" rational agents. For irrational agents, specific algorithms will be executed to form expected price.

6.2 Market Equilibrium

In the market equilibrium segment, the program determines the market equilibrium price. It is assumed that each agent has CARA utility function in (4)

$$U_i(W_i) = -e^{-a_i w_{ij}}, \qquad a_i > 0 \tag{4}$$

Each agent is given a fixed amount of cash c(t) and stock q(t) at the initial period. The initial budget equation can be written as (5).

$$W_i(t_0) = c_i(t_0) + p(t_0)q_i(t) \tag{5}$$

The expected next period budget can be represented by (6).

$$\tilde{W}_i(t) = (1 + r)c_i(t_0) + \tilde{p}(t)q_i(t) \tag{6}$$

The wealth of an agent includes the risk free asset (cash) and the risky asset (stock). The anticipated wealth is conditioned on the α's of the agents. The cash asset has a fixed rate of return (r) and the rate of return of the risky asset is determined by the actual price. Substituting (5) into (6) we get equation (7).

$$\tilde{W}_i(t) = (1 + r)W_i(t_0) + [\tilde{p}_i(t) - (1 + r)p(t_0)]q_i(t) \tag{7}$$

To maximize the utility function, equation (4) can be represented by (8).

$$Max E[U_i(\tilde{W}_i)] = Max[a(E(\tilde{W}_i) - \frac{a}{2}\text{var}(\tilde{W}_i))] \tag{8}$$

From (7), we can derive (9) and (10).

$$E(\tilde{W}_i) = E((1 + r)W(t_0) + [\tilde{p}_i(t) - (1 + r)p(t_0)]q_i(t)) \tag{9}$$

$$Var(\tilde{W}_i(t)) + [q_i(t)]^2 Var(\tilde{p}_i(t)) \tag{10}$$

Substitute (9) and (10) into (8), we get

$$\underset{q}{Max} \left\{ a[E((1 + r)W_i(t_0) + (\tilde{p}_i(t) - (1 + r)p(t_0))q_i(t))] - \frac{a}{2}[q_i(t)]^2 Var(\tilde{p}_i(t)) \right\} \tag{11}$$

From equation (11), we get (12).

$$[\tilde{p}_i(t) - (1 + r)p(t_0)] - a[q_i(t)]Var(\tilde{p}_i(t)) = 0 \tag{12}$$

The individual demand can be represented by (13).

$$[q_i(t)] = \frac{[\tilde{p}_i(t) - (1 + r)p(t_0)]}{a Var(\tilde{p}_i(t))} \tag{13}$$

The individual cash demand can be represented by (14).

$$c_i(t) = W_i(t) - \tilde{p}_i(t) \frac{[\tilde{p}_i(t) - (1 + r)p(t_0)]}{a \, Var(\tilde{p}_i(t))} \tag{14}$$

Given a constant X number of outstanding shares, m number informed and n number uninformed agents in the market, the market price is determined in equation (15).

$$p_{market} = \frac{\sum_{i=1}^{m+n} (W_i(t) - c_i(t))}{X} \tag{15}$$

Using the market price, the actual individual demand can be represented by (16).

$$q_i(t) = \frac{W_i(t) - c_i(t)}{p_{market}(t)} \tag{16}$$

In the end of the period, given that all agents realize the actual value of the stock, individual wealth can be represented by (17).

$$W_i(t + 1) = [p(t) - p_{market}]q_i(t) + (1 + r)c_i(t) \tag{17}$$

6.3 Agent Evaluation

The main task in this segment is to update the agent status. Individual agent wealth is evaluated once the actual wealth is realized. Agents with negative wealth are considered bankrupt and will be eliminated from the market. In future experiments, agent's belief, agent learning, agent strategies effectiveness, etc will be evaluated and updated in this stage.

6.4 Market Value Evaluation

This segment makes sure the market value stays constant. The gain or loss of the stock market value is determined by (18).

$$S(t) = r \sum_{i=1}^{m+n} c_i(t) + [p(t) - p_{market}(t)] \sum_{i=1}^{m+n} q_i(t) \tag{18}$$

if $S(t) > 0$, there will be a lump sum tax imposed on all agents. If $S(t) < 0$, new agents will be added into the economy and their agent type (informed, uninformed, rational, or irrational) will identical to the most successful agent.

6.5 Parameters

Simulations enable modelers to construct multiple scenarios. Parameters dictate the overall structure of the model. Table 1 provides some of the general parameters of the model; specific parameters related to the design of the individual irrational agents will be provided in the future.

Table 1. Model Parameters

Parameters	Descriptions
Number of period	• Total number of periods in simulation
Total number of agent	• Give the number of informed and uninformed agents
Rational agent percentage	
Initial number individual shares	• All agents are assumed to have the same number of stocks initially. Individual initial wealth is the sum of initial cash and the initial security asset value
Initial stock price	
Initial cash for informed agents	
Initial cash for uninformed agents	
Individual absolute risk aversion	• All agents possess the same preference in risk
Fixed asset rate of return	• Interest rate remains constant for all periods
Variance of ε	• Variables that dictate the actual market and expected individual prices.
Mean of ε	
Variance of α_1	
Mean of α_1	
Variance of α_2	
Mean of α_2	

7. CONCLUSION AND FUTURE DIRECTION

This research encompasses areas in economics and finance, psychology and human behavior, and agent modeling and artificial intelligence. This paper lays down the framework of the market structure; the next phase of the project is to design and implement the agents. Individual agent behavior will be applied by specific algorithm.

Part of the appeal of using the simulation approach is that we can model multiple agent behaviors that resemble the real-life traders. The goal is to learn about the potential market performance in the presence of aggregation of individual behaviors.

So far, this research has laid down a market framework with simple agents. The next focus is to build more detailed irrational agents. Some of the irrational agents can be easily modeled by incorporating simple rules in them. A few of the irrational agent examples are:

• *Momentum agents:* They form their expectation of prices based solely on the movement of past prices. As a result, private market information does not affect their decisions.

• *Noise agents:* They form their price expectation randomly based on uniform distribution. The boundary of the distribution sets up the "randomness" range in the expectation.

• *Generic agents:* They form their price expectation based on the market information they receive. Informed agents make decisions based on more market information than the uninformed agents because they receive more private market information.

• *Learning agents:* They are the extension of generic agents that possess certain "intelligence" with the ability to "remember" past information. This type of agent is important in cases where the distribution of the information that constitutes the actual market price is different than the distribution of the private information received by the agents. By forming their price expectation based on past public market information and current private information, they can slowly learn about the distribution of the signals. One easy way to implement this is to average out past and current information to form price expectation. Other ways include using genetic algorithms to learn about the distribution of the market information.

- *Overconfident agents:* They "over-weigh" their private market information they receive from the market. This can be implemented by assuming they underestimate noise variance while other agents do not. As a result, they are over-weighing their private market information.

Two approaches can be used to implement adaptive or dynamic elements into the model. One is by considering the agent behaviors described above as potential trading strategies of the agent. Classifier systems and genetic algorithms can be applied to agents to "learn" the more effective strategy or combination of strategies. Another approach is to assume that each agent displays only one type of behavior defined above. An ineffective agent is eliminated from the market and replaced by an agent that belongs to the same type as the wealthiest agent. We will use the latter approach for now and may apply the first approach in the future.

We are currently designing specific agents, and hopefully we will have the results soon.

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