Relationship between Trader Types and Their Long-run Wealths in an Artificial Financial Market

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Abstract

In this paper, we study the long-run wealth distribution regarding different trading strategies in an artificial stock market. An artificial stock market is designed consisting with two broad types of agents, "rational traders" and "imitators. Rational traders trade to optimize their short-term income and they invest based on their expectation on both trend follow and reverse of it. We also include imitators, i.e., traders that mimic behavior of the majority of rational traders. We investigate the performances of various traders by changing the ratio of rational traders and imitators. In the region where rational traders are in the minority, they can come to dominate the market, in that they eventually have a high share of wealth. On the other hand, in the region where rational traders are in the majority and imitators are in the minority, imitators can come to dominate the market. We conclude that the survival in a finance market is a kind of the minority game at the meta-level between rational traders and imitators.

1 Introduction

Economists have long asked whether traders who misperceive the future price can survive in a competitive market such as a stock or a currency market. The classic answer, given by Friedman, is that they cannot. Friedman argued that mistaken investors buy high and sell low, as a result lose money to rational trader, and eventually lose all their wealth.

Shleifer and his coleagues questioned the presumption that traders who misperceive returns do not survive. Since noise traders who are on average bullish bear more risk than do investors holding rational expectations, as long as the market rewards risk-taking such noise traders can earn a higher expected return even though they buy high and sell low on average. The relevant risk need not even be fundamental: it could simply be the risk that noise traders' asset demands will become even more extreme tomorrow than they are today and bring losses to any investor betting against them. Because Friedman's argument does not take account of the possibility that some patterns of noise traders' misperceptions might lead them to take on more risk, it cannot be correct as stated. But this objection to Friedman does not settle the matter, for

expected returns are not an appropriate measure of long run survival. To adequately analyze whether noise traders are likely to persist in an asset market, one must describe the long run distribution of investors' wealth, not just the level of expected returns.

Understanding if there are winning and losing market strategies and determine their characteristics is an important question from the point of view of investors and regulators alike. On one side, it seems obvious that different types of investors exhibit different investing behavior which is, at least partially, responsible for the time evolution of market prices. On the other side, it is difficult to reconcile the regular functioning of financial markets with the coexistence of different types of investors. If there is a consistently winning market strategy than it is reasonable to assume that the losing traders disappear in the long run. It was Friedman who first advanced the hypothesis that in the long run irrational investors cannot survive as they tend to lose wealth and disappear. Offering an operational definition of rational investors, however, presents conceptual difficulties as all investors are boundedly rational. No agent can realistically claim to have the kind of supernatural knowledge needed to formulate rational expectations. The fact that different types of traders with different trading strategies prone to forecast errors can coexist in the long run is a fact that still requires an explanation.

In this paper we take an approach in considering the long run distribution of wealth. We examine how traders with various trading strategies affect prices and the long run accumulation of the wealth. We show that mimic traders as a group might survive and come to dominate rational investors in wealth when the proportion of imitators is much less than that of rational traders. Generally, in a market where rational traders are minority, we found that they could win and accumulate their wealth, whereas in a market where rational traders become majority, they lose and imitators win and accumulate their wealth.

2 An Agent-based Financial Market

The variety of applications, the different types of learning mechanisms used in such applications and the different types of markets that one could simulate suggest a rich field of research. However, all this flexibility and freedom comes at a cost. One of the main criticisms to agent based markets is the large number of parameters and the tuning needed to get "realistic price behavior". In some situations, small changes in the parameter settings could lead to significant changes in the market's behavior, both quantitatively and qualitatively. For any results to be creditable, changes in the parameters settings must not lead to significantly different results.

In recent economic and finance research, there is a growing interest in marrying the two viewpoints, that is, in incorporating ideas from social sciences to account for the facts that markets reflect the thoughts, emotions, and actions of real people as opposed to the idealized economic investors who under lies the efficient markets and random walk hypotheses. A real investors may intend to be rational and may try to optimize his or her actions, but that rationality tends to be hampered by cognitive biases, emotional quirks, and social influences. The behaviors of financial markets is thought to result from varying attitudes towards risk, the heterogeneity in the framing of information, cognitive errors, self-control and lack thereof, regret in financial decision making, and the influence of mass psychology. Assumptions about the frailty of human rationality and the acceptance of such drives as fear and greed are underlying the recipes developed over decades by so-called technical analysis. There is growing empirical evidence of the existence of herd or "crowd" behavior in speculative markets. Herd behavior is often said to occur when many people take the same action, because some mimic the actions of others. The term "herd" obviously refers to similar behavior observed in animal groups. Other terms such as "flocks" or "schools" describe the collective coherent motion of large numbers of self- propelled organisms, such as migrating birds and gnus, lemmings and ants. In recent years, physicists have shown that much of the observed herd behavior in animals can be understood from the action of simple laws of interactions between animals.

The most important design question faced in market building comes in the representation and structure of the actual trading agents. Agents can vary from simple budget constrained zero intelligence agents to sophisticated genetic programming models. This variation in design is due to the fact that trading agents must solve a poorly defined task. Given that there are many ways to process this past data, there must be as many ways to construct trading agents. The simplest and most direct route is to model agents as well defined dynamic trading rules modeled more or less as strategies used in the real world. This method can lead to very tractable precise results, which gives incites about the interactions between trading rules?

Many markets of this type assume that the trading strategies will continue without modification, although the wealth levels under their control may be diminishing to zero. This leaves some open questions about co-evolutionary dynamic with only a limited amount of new speciation. A second critique is that agents in these markets do not operate with any well defined objective function. There is some usefulness to having well defined objective functions for the agents. There may be important tradeoffs involved which only a model with well defined objective functions can answer.

The second most important part of agent-based markets is the actual mechanism that governs the trading of assets. Once one leaves the relatively simple world of equilibrium modeling, it is necessary to think about the actual details of trading. This can be both a curse and a blessing to market designers. On the bad side it opens up another poorly understood set of design questions. However, it may have the beneficial effect of allowing one to study the impact of different trading mechanisms, all of which would be inconsequential in an equilibrium world.

This has been interpreted as evidence that as a forecaster age, evaluators develop tighter prior beliefs about the forecaster's ability, and hence the forecaster has less incentive to herd with the group. On the other hand, the incentive for a second-mover to discard his private information and instead mimics the market leader increases with his initial reputation, as he strives to protect his current status and level of pay. In a practical implementation of a trading strategy, it is not sufficient to know or guess the overall direction of the market.

There are additional subtleties governing how the trader is going to enter (buy or sell) the market. For instance, A trader will want to be slightly ahead of the herd to buy at a better price, before the price is pushed up for the bullish consensus. Symmetrically, she will want to exit the market a bit before the crowd, that is, before a trend reversal. In other words, she would like to be a little bit contrarian by buying when the majority is still selling by selling when the majority is still buying, slightly before a change of opinion of the majority of her "neighbors" This means that she will not always want to follow the herd, at least at short time scales. At this level, Anne cannot rely on the polling of her "neighbors" because she knows that they, as well as the rest of the crowd, will have similar ideas to try to out guess each other on when to enter the market. More generally, she ideally likes to be in the minority when entering market, in the majority while holding her position, and again in the minority when closing her position.

3 Design of an Artificial Market

3.1 A Market Mechanism and Performance Measures

One of the most important part of agent based markets is the actual mechanism that governs the trading of assets. In most agent based markets they assume a simple price response to excess demand. Most markets of this type poll traders for their current demands, sum the market demands, and if there is an excess demand, increase the price. If there is an excess supply they decrease the price. Simple form of this rule would be where D(t) and S(t) are the demand and supply at time t respectively. The agent is

maintaining the stock and the capital in the artificial market model in this research. The agent loses the capital by obtaining the stock and gets it by selling off the stock.

It explains fluctuations in the value of stocks as follow: The unit of handling of the stock is assumed to be one unit.

<A Stock Price Model >

The basic model is to assume that the stock price reflect the excess demand, which h is governed as

$$P(t) = P(t-1) + \chi[N_1(t) - N_2(t)] \tag{3.1}$$

where P(t) is stock prices at time t, $N_1(t)$ is a number of agents to buy and $N_2(t)$ is a number of agents to sell respectively at time t, χ is a constant. This expression implies that "the stock price is a n function of the excess demand", and the price rises when there are more agents to buy, and it descend when more agents to sell it.

<A Stock Volatility >

We define the price volatility as

$$v(t) = \{P(t) - P(t-1)\} / P(t-1) \tag{3.2}$$

where P(t) is stock prices at time t.

<Individual Wealth>

The stock one agent can buy and sell in one trading is one unit. We introduce a notional wealth $W_i(t)$ of agent i as follows.

$$W_i(t) = P(t)*\Phi_i(t)+C_i(t) \tag{3.3}$$

where Φ_i is the number of assets held and C_i is the amount of cash held by agent i.

It is clear from equation that an exchange of cash for assets at any price does not in any way affect the agent's notional wealth. However, the point is in the terminology :the wealth $W_i(t)$ is only notional and not real in any sense. The only real measure of wealth $C_i(t)$, the amount of capital the agent has available to spend. Thus, it is evident that an agent has to do a "round trip"(i.e.buy(sell)an asset then sell(buy)it back) to discover whether a real profit has been made.

<The Profit Rate >

The coefficient is actually used for the value of this normal distribution putting it. Next, it explains the rate of profit that becomes the standard of loss and gain.
The rate of profit of agent i is shown with γ_i, and $\gamma_i(t)$ at time t is

$$\gamma_i(t) = W_i(t)/ W_i(0) \tag{3.4}$$

The mode of dealing and the rate of profit are as mentioned above defined, Which agent is obtaining a higher profit is clarified by the simulation.

3.2 Modeling of Trader Types

For modeling purposes, we have (rational traders) who make rational decision in the following stylized terms: If they expect the price goes up then they will buy, and if they expect the price goes down then they will sell right now. But what happens if every trader behaves the same way? Suddenly, some noises or disturbances are introduced exogenously. Given this uncertainty, the individually is modeled to behave differently.

One body of research has sought to explain the data with aggregate models in which a representative agent solves this optimization problem. If the goal is simply to fit the data, it is not unreasonable to attribute to agents the capacity to explicitly formulate and solve dynamic programming problems. However, there is strong empirical evidence that humans do not perform well on problems whose solution involves backward induction. For this reason, these models fail to provide a realistic account of the phenomenon.

The model we describe will not invoke a representative agent, but will posit a heterogeneous population of individuals. Some of these will behave "as if" they were fully informed optimizers, while others will not.

The traders who enters the market forecasts, and has dealings over stock prices by various techniques. It is a linear forecast of past price data, and a forecast by information from media like news etc. The type of a investor is described from the difference of the forecast method.

(i) Fundamentalist

Fundamentalist decide investment attitude form various economic indicators etc.

(ii) Chartist

Investor who uses analysis technique for requesting present value from movement of past price chart.

(iii) Noise trader

The investor who behaves by the strategy based on the being seemed it economic information when it is a speculator or a technical index and it relates though known by

various names.

In this paper, traders are segmented into two types depending on their respective trading behavior: rational traders(chartist) and imitators. Rational traders further classified into two types: momentum and contrarian traders. In this section, we introduce two population-types which have been already described in the literature and which represent more realistic trading behaviors. The aim is twofold: first, we want to study the behavior of these stylized populations in a realistic environment characterized by limited resources and a market clearing mechanism; second, we want to address the important issue about the existence or not of winning strategies.

(1) Rational traders (Chartists)

The successful traders will sell if the price is going down and buy if the price is going up. We now distinguish rational traders into two types: momentum and contrarian traders.

<Momentum traders>

The momentum trader is a trend follower who makes decision depending on the trend of past prices. The momentum trader speculates that if prices are raising, they will keep raising, and if prices are decreasing, they will keep decreasing.

<Contrarian traders>

The contrarian traders are structured in the same way as the momentum traders. The difference consists in their trading behavior. A contrarian trader speculate that, if price is raising, it will stop raising soon, and will decrease, so it is better to sell near the maximum, and vice versa.

(2) Imitators

Traders may have incorrect expectations about the price movements. For such misperceptions, imitators who do not affect prices may earn higher payoff than rational traders. Each imitator has a unique social network with rational traders. Within this individual network, if the majority of rational traders buy then she also buys or the majority of rational traders sells then she also sells. It is now widely held that mimetic responses result in herd behavior and that the properties of herding crucially arise in financial markets.

Heterogeneity turns up repeatedly as a crucial factor in evolving many systems and organizations. But the situation is not always simple as saying that heterogeneity is desirable and homogeneity is not good. It is the remaining basic question in many fields: what is the right balance between heterogeneity and homogeneity? When

heterogeneity is significant, we need to be able to show the gains from heterogeneity. However, the analysis of a collective of heterogeneous agents becomes to be difficult, and it is often intractable.

4 Trading Rules of Traders

In this section we describe a trading rule of each trader type discussed in the previous section.

<Rational Traders (Chartists)>

Rational traders observe the trend of the market and trade so that their short-term payoff will be improved. Therefore if the trend of the markets is “buy”, this agent’s attitude is “sell”. On the other hand, if the trend of the markets is “sell”, this agent’s attitude is “buy”. As can be seen, trading with the minority decision creates wealth for the agent on performing the necessary trip, whereas trading with majority decision loses wealth. However, if the agent had held the asset for a length of time between buying it and selling it back, his wealth would also depend on the rise and fall of the asset price over the holding period. However, the property that the purchaser (seller) can be put in a single deal and bought (clearance) is one unit, so the agent who cannot buy and sell it when the number of the purchaser and seller is different exists.

(1)When buyers are minority

The agent cannot sell it even if it is selected to sell it exists. Because the price falls in the buyer's market still, it is an agent that sells who is maintaining a lot of properties. The agent who is maintaining the property more is enabled the clearance it.

(2) When buyers are majority

The agent cannot buy it even if it is selected to buy it exists. Because the price rises, being able to buy is still an agent who is maintaining a lot of capitals. The agent who is maintaining the more capital is able to purchase it.

The above trading behavior is formulated as below. We use the following terminology:

N: Number of agent who participate in markets.

$N_1(t)$: Number of agent who buy at time t.

$R(t)=N_1(t)/N$: The rate of agents to buy at time t . (3.5)

We also denote the estimated rate of buy of agent i at time t as

$$R_F(t)=R(t-1)+\varepsilon_i \tag{3.6}$$

where ε_i ($-0.5 < \varepsilon_i < 0.5$) is the rate of bullishness and timidity of agent i , which differs depending on rational traders. In a population of rational traders ε is normally distributed .

<A trading rule of a rational trader>

(1) If $P_F(t)<0.5$, then sell

(2) If $P_F(t)>0.5$, then buy (3.7)

If ε_i is large, this agent has tendency to "buy", and it is small, the tendency to "sell" is high.

<Imitators>

Imitators observe the behaviors of rational traders. If the majority of rational traders "buy", then imitators also "buy", on the other hand, if the majority of rational traders "sell" then they also "sell". We can formulate the imitator's behavior as follows.

$R_F(t)$: The ratio of rational traders to buy at time t

$P_I(t)$: The estimated value of $R_F(t)$ by imitator j

$$P_I(t)= R_F(t-1)+\varepsilon_j \quad (3.8)$$

where ε_j ($-0.5< \varepsilon_j<0.5$) is the rate of bullishness and timidity of imitator j which differs depending by each imitator. In a population of imitators ε is also normally distributed .

<A trading rule of imitator>

(1) If $P_I(t)>0.5$, then buy

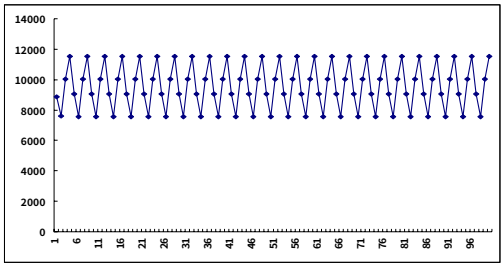
(2) If $P_I(t)<0.5$, then sell (3.9)

5 Simulation Results

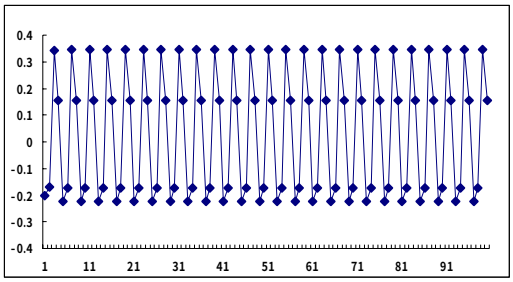
We consider a artificial stock market consists of 2,500 traders in total and simulate markets behavior by varying the ratio of rational traders and imitators. We also investigate the long-run accumulation of wealth of each type of traders.

(Case 1) The ratio of rational traders: 20% (imitators,80%)

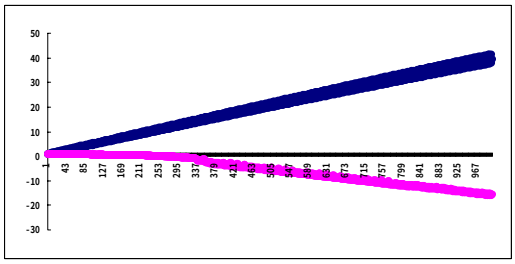
<Stock prices over time>



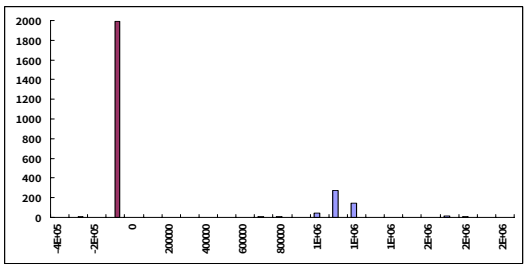
<Volatility>



<The profit rate >



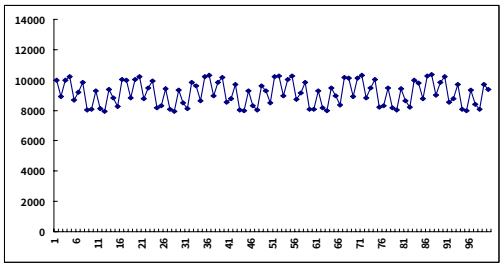
<The distribution of wealth>



In Case 1, stock prices vibrate greatly. It is thought that this is because imitator's ratio is large. As the ratio of Imitators is large, a lot of imitators run for buy when rising. And stock prices rise further. Moreover, about the rate of profit of both traders, while small number of rational traders are raising the great advantage, it is understood that the imitators is losing. Small number of rational traders greatly raise the profit, a lot of imitators are losing little by little.

(Case 2) The ratio of rational traders: 50%(imitators,50%)

<Stock prices over time>



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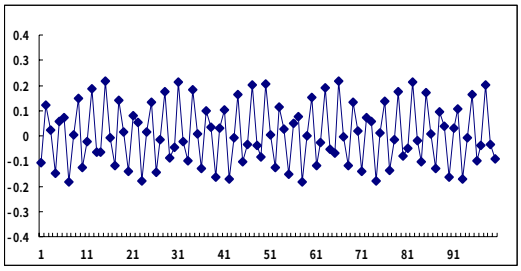
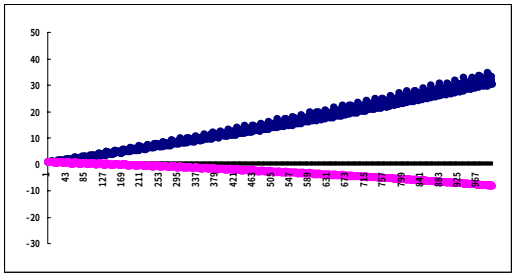
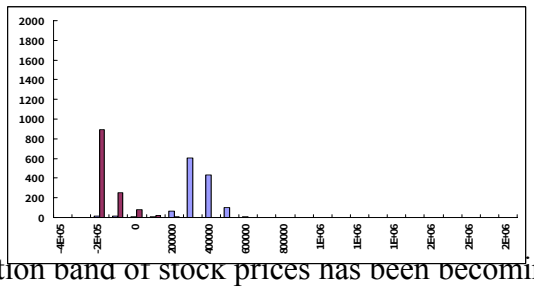


<The profit rate >



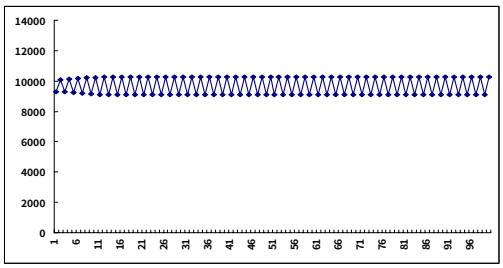
<The distribution of wealth>



In Case 2, the fluctuation band of stock prices has been becoming small compared with case1. About the rate of profit, rational trader is raising the profit , and the imitators is losing just like case1. However, understand from the assets distribution, rational trader who has small profit rate is increase.

(Case 3) The ratio of rational traders: 80%(imitators,20%)

<Stock prices over time>



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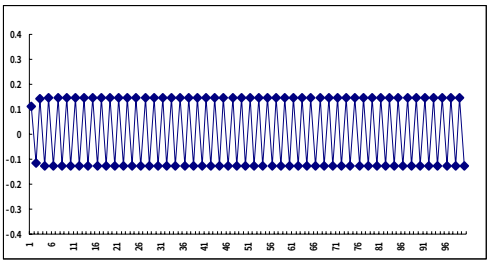

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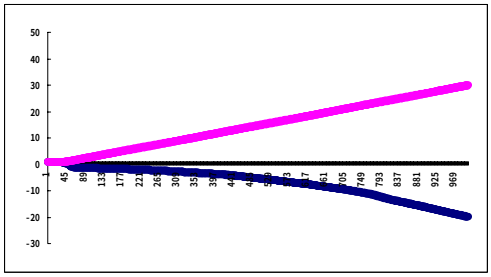
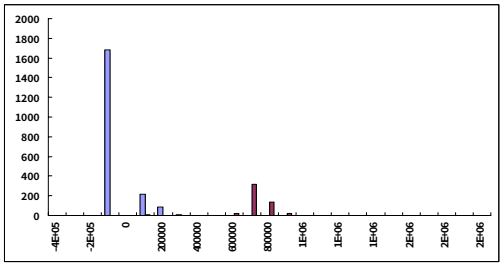


Rational trader

Imitators

<The distribution of wealth>



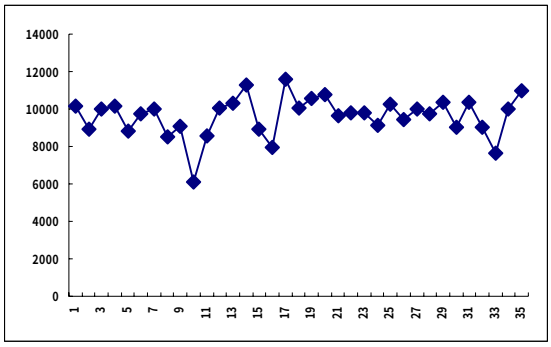
Rational trader

Imitators

In the Case 3, the fluctuation band of stock prices has been becoming small further. It is thought that this is because there are a lot of rational traders. Because there are a lot of rational traders, the market becomes efficient, the price doesn't change widely. In such an efficient market, A rational trader cannot raise the profit and Imitators can raise the profit.

(Case 4) The ratio of rational traders: Random between 20% and 80%.

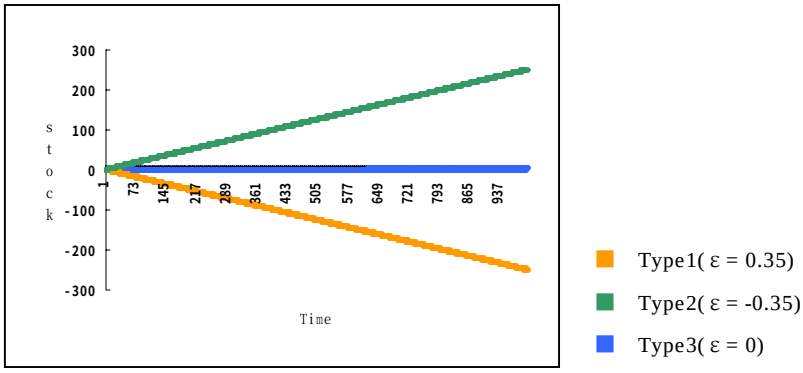
<Stock prices over time>



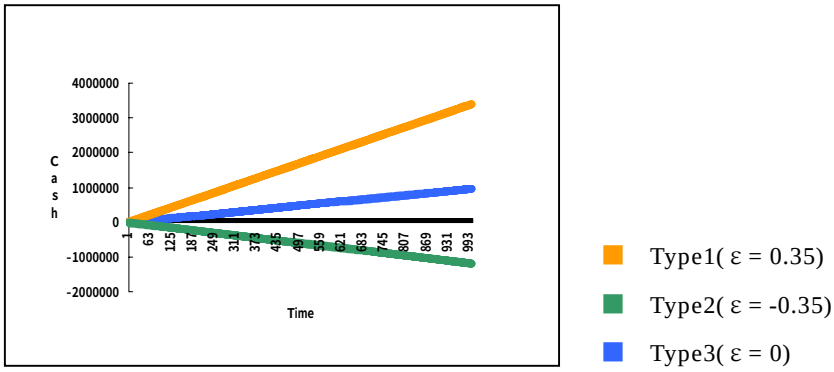
In Case 4 , we show the change of the stock price when ratio of rational traders was randomly changed between 20 to 80%.Because trader's ratio changes every five times, price fluctuations are random.

Change of Rational trader's property in Case1

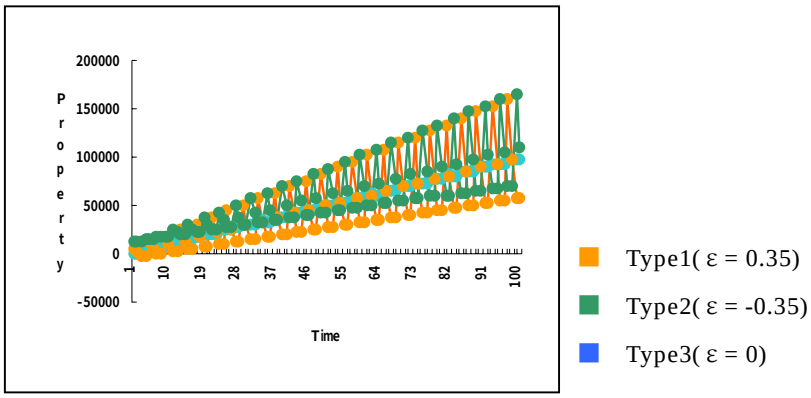
<Change in rational trader's stock >



<Change in rational trader's cash >



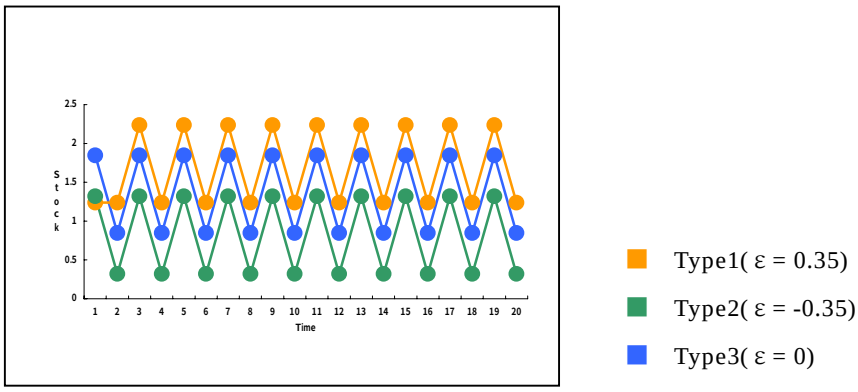
<Change in rational trader's property >



In Case1, rational trader has raised the profit. Type 1 sells the stock when stock prices are high. Type 2 buys the stock when stock prices are low.Type3 sells the stock when stock prices are high, and buys the stock when stock prices are low.

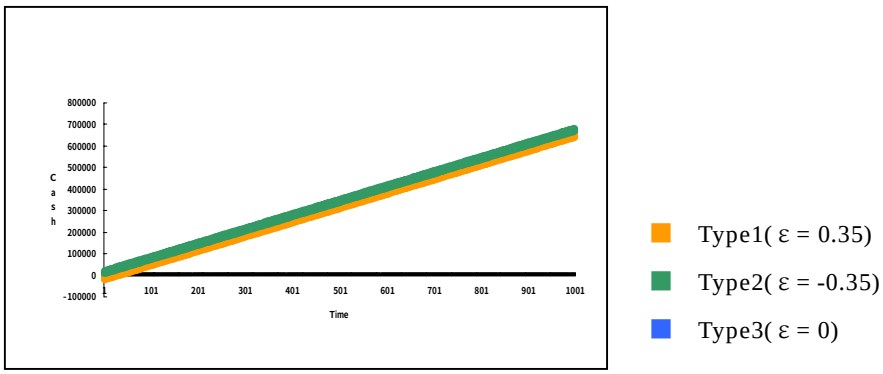
Change of Imitator's property in Case3

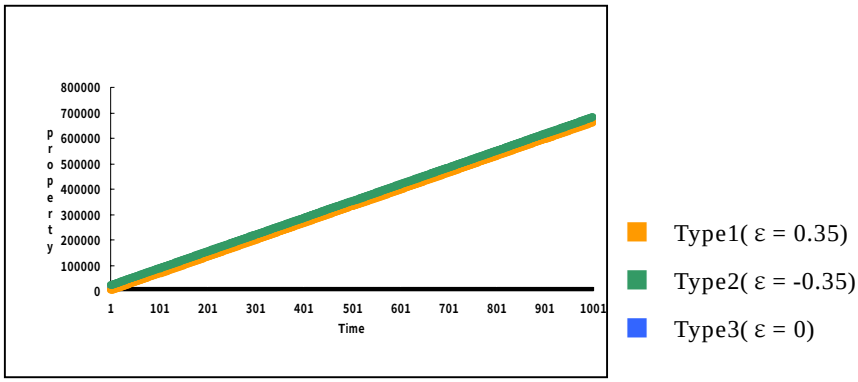
<Change in Imitator's stock >



<Change in Imitator's cash>

<Change in rational trader's property >





In Case3, Imitators has raised the profit. Imitators differs from a reasonable trader, each type bought when stock prices are low, sold when stock prices are high.

6 Implication of Simulation Results

The computational experiments performed using the agent-based modeling show a number of important results. First, they demonstrate that the average price level and the trends are set by the amount of cash present and eventually injected in the market. In a market with a fixed amount of stocks, a cash injection creates an inflation pressure on prices. The other important finding of this work is that different populations of traders characterized by simple but fixed trading strategies cannot coexist in the long run. One population prevails and the other progressively lose weight and disappear. Which population will prevail and which will lose cannot be decided on the basis of the strategies alone. Trading strategies yield different results in different market conditions. In real life, different populations of traders with different trading strategies do coexist. These strategies are boundedly rational and thus one cannot really invoke rational expectations in any operational sense. Though market price processes in the absence of arbitrage can always be described as the rational activity of utility maximizing agents, the behavior of these agents cannot be operationally defined. This work shows that the coexistence of different trading strategies is not a trivial fact but requires explanation. One could randomize strategies imposing that traders statistically shift from one strategy to another. It is however difficult to explain why a trader embracing a winning strategy should switch to a losing strategy. Perhaps market change continuously and make trading strategies randomly more or less successful. More experimental work is necessary to gain an understanding of the conditions that allow the coexistence of

different trading populations. As noted earlier, there are two broad types of agents and we designate them "rational traders (rational agents)" and "imitators The agents in our model fall into two categories. Members of one group (rational traders) adopt the optimal decision rules. If they expect the price goes up then they will buy, and if they expect the price goes down then they will sell right now. In order to introduce heterogeneity among strategic agents we also introduce some randomness for behavioral rules. The other group consists of imitators, who mimic rational traders of their social networks. The model we describe will not invoke a representative agent, but will posit a heterogeneous population of agents. Some of these will behave as if they were fully informed optimizers, while others will not.

7 Summary

There are two related theoretical issues. One is the connection between individual rationality and aggregate efficiency, between optimization by individuals and optimality in the aggregate. The second is the role of social interactions, and social networks in individual decision-making and in determining macroscopic outcomes and dynamics. Regarding the first, much of mathematical social science assumes that aggregate efficiency requires individual optimization. Perhaps this is why bounded rationality is disturbing to most economists: they implicitly believe that if the individual is not sufficiently rational it must follow that decentralized behavior is doomed to produce inefficiency. Experimental economics and psychology have now produced strong empirical support for the view that framing effects, as well as contextual and other psychological factors put a large gap between homo-sapiens and individuals with is bounded rationality. The question we pose in this paper is as follows: Does that matter and how does it matter? To answer these questions, we developed a model in which imitation in social networks can ultimately yield high aggregate levels of optimal behavior. Now, the fraction of agents who are rational in such an imitative system will definitely affect the stock markets. But the eventual (asymptotic) attainment *per se* of such a state need not depend on the extent to which rationality is bounded. Perhaps the main issue then is not how much rationality there is at the micro level, but how little is enough to generate macro-level patterns in which most agents are behaving "as if" they were rational, and how various social networks affect the dynamics of such patterns.

8 References

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