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RESEARCH PAPER

Modeling the Market Dynamics from a Behavioral Perspective

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Abstract

Psychological studies on decision-making under uncertainty have shown that investors have systematic errors and behavioral biases in decision-making. Thus, market prices are more determined by psychological factors rather than the fundamental variables. In addition, standard asset pricing models based on rational expectations and homogeneity have problems cannot satisfactorily explain the dynamics and volatile nature of financial markets. So an important challenge of the financial theory in recent years is to construct models which have more consistencies with as many financial stylized facts that cannot be explained by traditional models. In this sense, the present study use Agent-based computational approach and more specifically Artificial Stock Market to modeling the market dynamics from a behavioral perspective. The purpose of this study is to point out a possibility that behavioral bias, specially anchoring feature of investors explains most number of financial stylized facts and plays an important role in price formations of financial markets. The results capture great kurtosis and asymmetry of return distribution. Moreover, by using agent-based simulations, the paper also provides a better representation of price dynamics in the financial market.

Keywords: Behavioral Finance, Financial Market Anomalies, Behavioral Bias, Anchoring Effect, Agent-Based Modeling, Artificial Stock Market.

JEL Classification: G40, G41, C63.

Introduction

Traditional financial theories have been based on rational investors and on market efficiency hypothesis, which posits that market prices fully reflect all available information (Fama, 1970). In traditional models, rational use of information, their decision making is based on utility function with beliefs, calculated via optimal statistical procedures. Thus, the representative investor is an individual who acts as an expected utility maximize and adheres to the axioms of rational choice theory. These assumptions play an important role in determinants of asset prices, risk attitudes and portfolio management (Rekik et al., 2014). However, in recent years, theories of traditional finance have faced the challenge that cannot explain many of the facts of financial markets, including market anomalies. In recent decades, many phenomena have been observed in various world stock exchanges. excess volatility of asset prices, fluctuations in trading volume, bubbles, financial crisis, price crashes, calendar effects, scale and week effect, all show market inefficiencies and the lack of expected relationship between price and fundamental variables that contradict the EMH. (Golarzi and Ziacchi, 2014). Statistical properties which are commonly observed in return distributions of financial assets are called financial stylized facts. Especially, the phenomena that traditional

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financial models have never been able to explain are often called ‘‘anomalies’’ or ‘‘puzzles’’ and attract special attentions by researchers. An important challenge of the financial theory in recent years is to construct more sophisticated models which have consistencies with as many financial stylized facts that cannot be explained by the traditional models. If the sophisticated model can be constructed, then it means that crucial elements of price formation in financial markets are detected. Hence, to provide models which explain financial stylized facts has been the most important subject in modern financial theory (Shimokawa et al., 2006). In explaining market anomalies, researchers have argued that some financial phenomena can be better explained by employing models in which some agents in the economy are not entirely rational, or in some models, agents make choices that are incompatible with maximizing the expected utility. Simon (1991) has emphasized the importance of bounded rationality, taking into account the limited ability of agents to adapt optimally. Frijns et al. (2010) mention a demise of the efficient market hypothesis (EMH). Behavioral finance provides an alternative theory regarding financial markets. Based on experimental psychology literature, behavioral finance considers that cognitive biases could affect asset prices. In the field of behavioral finance, researchers set psychological biases underlying the behavioral explanations on the observed security price behavior (Kahneman and Tverskey, 1979, 1982; Shefrin and Statman, 2000; Barberis and Thaler, 2002). In fact, individuals are thought to make judgments under uncertainty because limited time and cognitive resources lead them to apply behavioral biases such us herding, loss aversion, anchoring and other behavioral biases by investors’. It seems evident that psychology plays an important role in financial markets and deserves through investigation. The effects of behavioral finance can be viewed as another answer to unrealistic assumptions of the Efficient Market Hypothesis. Psychological studies on decision-making under uncertainty have shown that investors have systematic errors and behavioral biases in decision-making. Thus, market prices are most determined by psychological factors rather than the fundamental ones. In this sense, the present study use Agent-based computational approach and more specifically artificial Stock Market modeling to modeling the market dynamics from a behavioral perspective. The purpose of this study is to point out a possibility that behavioral bias, specially anchoring feature of investors explains vast number of financial stylized facts and plays an important role in price formations of financial markets. The reason for considering agent-based computational models for this study is that we cannot understand market outcomes through the eyes of a single representative type of rational agents. In agent-based models, the market is filled with heterogeneous, bounded rationality agents with different expectation and behaviors. This bottom-up method involves large numbers of interacting agents with the “rule of thumb” trading strategies, and the aggregation of simple interactions at the micro level (investors' behavior) may generate sophisticated structure at the macro level (the fluctuation of asset prices). A relatively novel approach for studying the link between individual investors’ behavior and financial market dynamics, based on agent-based methodology, has become known as Artificial Financial Markets. These are often computational models of financial markets, and are usually composed of a number of heterogeneous and bounded rational agents, interacting through some trading mechanism, while possibly learning and evolving. According to this approach, markets are seen as complex dynamical systems consisting of heterogeneous learning, bounded rationality heterogeneous agents. Both approaches, agent-based models and behavioral finance, complement each other and could be used together as agent based approach framework could serving as a useful theoretical tool for verification of findings from behavioral finance. LeBaron (2005) argues that “Agent-based technologies are well suited for testing behavioral theories" and anticipates that “The connections between agent-based approaches and behavioral approaches will probably become more intertwined as both fields progress”. The complementarities of behavioral finance research and the agent-based methodology have been recognized in the literature as a nascent field of research with many opportunities ahead. Takahashi and Terano (2003), Hoffmann et al. (2007) and Mathieu et al. (2010) are counted as rare examples of agent-based papers that pursue the idea of explicit accounting for behavioral theories in financial market simulations. In Takahashi and Terano (2003), the focus is on overconfidence and loss aversion, while Hoffmann et al. (2007) focus on social dimensions of investor behavior. Barberis and Thaler (2003) and Scheinkman et al. (2004) mention overconfidence, De Grauwe and Grimaldi (2006), Boswijk et al. (2007) and Kukacha et al. (2013) suggest market sentiment, and Chiang et al. (2007) and Chiarella et al. (2003) put stress on herding behavior.

The rest of the study is organized as follows. Section (2) presents our research model. In this section we explain our basic asset pricing model, the agents' expectations formation and the price adjustment mechanism. The model can be seen as a simple extension of typical noisy rational expectation models to the case where anchor bias exists. In section (3) results are displayed. Section (4) contains the concluding remarks.

Model and Methodology

A novel bottom-up approach to studying and understanding stock markets comes from the area of computational finance as artificial financial markets (or, more specifically, as artificial stock markets). Agent-based artificial financial markets can be mathematical or computational models, and are usually comprised of a number of heterogeneous and bounded rationality agents, which interact through some trading mechanism, while possibly learning and evolving. These models are built for the purpose of studying agents' behavior, price discovery mechanisms, the influence of market microstructure, the reproduction of the stylized facts of real-world financial time-series (e.g. fat tails of return distributions and volatility clustering). As the present study uses Agent-based simulation and especially the artificial stock market, it is necessary to formulate the market mechanism and the behavior of market agents mathematically. The following describes these steps.

The model used in this study is based on the artificial market simulated by Bertella et al. (2017). In the trading environment of our artificial stock market N trader decide between two investment options**:**

(A)Risk free asset with constant interest rates r and infinite elastic supply

(B) Risky asset paid at the beginning of each period, a dividend which follows a First order autoregressive process AR (1) (Beretta et al., 2017):

$$d_t = \bar{d} + \rho\left(d_{t-1} - \bar{d}\right) + \mu_t \tag{1}$$

Where:

$\mu_t \sim N\left(0, \delta_\mu^2\right)$, $1 < \rho$<-1 ، d_{t-1} dividend at the previous period, $\bar{d}$ mean of the dividend and t is the time index.

Agents Preferences

The agents have identical constant absolute risk aversion (CARA) with a utility function of wealth as below (Bertala et al., 2017):

$$U\left(W_{i,t}\right) = -e^{-\lambda w_{i,t}} \tag{2}$$

Where $W_{i,t}$ is the wealth of agent i at time t and λ is the degree of risk aversion.

Each agent i has the same initial wealth W_0. For the other time periods, the value of total wealth of agent i at subsequent time t is determined to be (Beretta et al., 2014):

$$W_{i,t+1} = x_{i,t}(p_{t+1} + d_{t+1}) + (1 + r)\left(W_{i,t} - p_t x_{i,t}\right) \tag{3}$$

Where $W_{i,t}$ is the wealth of agent i in the period t, $x_{i,t}$ is the number of stocks sought by agent i, p_t is the stock price in period t, d_t is the dividend of stock at time t, and r corresponds to the fixed interest rate of the risk free asset.

In this model, each trader tries to optimize the allocation of his wealth between risky assets and risk free assets. Thus, the problem facing each agent at each time period is to maximize the expected utility of their wealth:

$$\max E(U(W_{i,t+1}))$$
$$\text{s.t } W_{i,t+1} = x_{i,t}(p_{t+1} + d_{t+1}) + (1 + r)(W_{i,t} - p_t x_{i,t})$$

Taking into consideration the utility function of wealth defined in (2), and assuming that the price and expected dividend of the agents for a stock over the next time period are normally distributed with mean $E_{i,t}(p_{t+1} + d_{t+1})$ and variance$\sigma^2_{i,t,p+d}$ the expected utility of wealth can be written in terms of the mean and variance of the possible outcomes. Hence:

$$E[U(W_{t+1})] = -\int e^{-\lambda W_{i,t+1}} f(W_{i,t+1}) dw$$
$$= -e^{-\lambda[E(W_{i,t+1}) - \lambda\sigma^2/2]}$$

According to the maximization problem, the number of stocks demanded by agent defined as $x_{i,t}$ is (Beretta et al., 2014):

$$x_{i,t} = \frac{E_{i,t}(p_{t+1} + d_{t+1}) - p_t(1 + r)}{\lambda\sigma^2_{i,t,p+d}} \tag{4}$$

In the above expression, $E_{i,t}$ is the best forecast of agent i at time t. It is the essential elements in the stock market, and $\sigma^2_{i,t,p+d}$ is the conditional variance of the returns specified as the GARCH model:

$$\sigma^2_{i,t,p+d} = (1 - \theta)\sigma^2_{i,t-1,p+d} + \theta[p_t + d_t - E_{i,t-1}(p_t + d_t)]^2 \tag{5}$$

Where parameter θ determines the weight placed on the most recent square error as opposed to the weight placed on past square errors. This parameter is of primary importance, the more weight agents give to recent deviations, the more their behavior will become noisy and their trading more volatile.

After determining the optimum number of stocks demanded by agent i at each time period, the dynamics for determining the market price is as follows. Designating $b_{i,t}$ to be the number of stocks agent i wants to buy at time t, and $o_{i,t}$ the number of stocks agent I wants to sell at time t, we find that

$$b_{i,t} = \begin{cases} x^*_{i,t} - x_{i,t-1} & x^*_{i,t} \geq x_{i,t-1} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$o_{i,t} = \begin{cases} x_{i,t-1} - x^*_{i,t} & x^*_{i,t} \leq x_{i,t-1} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Moreover, aggregate demand (B_t) and supply (O_t) are obtained from the following equations:

$$B_t = \sum_{i=1}^{N} b_{i,t} \tag{8}$$

$$O_t = \sum_{i=1}^{N} o_{i,t} \tag{9}$$

Here, N is the number of agents.

Price Mechanism

Calculating stock market price in the period t is based on supply and demand, so that if the demand for the purchase is higher than the demand for sale, the price will increase in the subsequent period and if it is lower, the price will decrease. In order to calculate the market price, a price modifier equation is used (Market impact function by Farmer & Joshi (2002)), based on the difference between (B_t-O_t). The specification of this function allows the market price to be always positive.

$$p_t = p_{t-1} e^{\frac{B_t - O_t}{\beta}} \tag{10}$$

β is an important parameter in price equation and its adjusting. As the low value of β leads to a slow adjustment of the price, and its high value leads to severe fluctuations in price behavior.

Finally, the stock return rate in time t is defined as follows:

$$H_t = \frac{p_t - p_{t-1} + d_t}{p_{t-1}} \tag{11}$$

Which shows the rate of return on stocks in the artificial financial market consists of two elements: the capital gain and dividend (Beretta et al., 2014; 2017).

Model of Agent Behavior

Agent-based models allow us to use a range of methods when determining the expectations and trading strategies used by different groups of agents. This capability in agent-based models is the most distinguishing feature. In this study, the artificial stock market includes N agent (trader), classified into two groups: fundamental investors and non-fundamental investors (noise traders). The expectations of the agents of $E_{i,t}(P_{t+1}+d_{t+1})$ are determined by a series of simple and predetermined rules. The interaction between different groups of agents with different behavioral rules can affect market behavior in general.

The rules that agents use to shape their expectations and the behavioral bias affecting their decisions, explained in more details:

Fundamental Traders

Fundamentalist agents estimate the future value of the stock by using the future discounted dividend flow model (the Gordon model). In this trading strategy the risky asset value forecast is based on its fundamental value derived from the expected dividend paid by the stock. The agents note the value of a stock dividend paid in the current period and, based on this value, assume the stock dividend will grow at a constant rate:

$$E(d_{t+1}) = d_t(1+g) \tag{12}$$

Using the future discounted dividend flow model, the expected future price of a stock is defined to be:

$$E(p_{t+1}) = \frac{d_t(1+g)}{k-g} \tag{13}$$

Where g is the growth rate of dividends and k is the discount rate.

Using the above expressions we can obtain the value of $E_{i,t}(P_{t+1}+d_{t+1})$ which is then used to determine the optimum volume of stocks to be purchased by agent i at each time period (Beretta et al., 2017).

Non-fundamental Traders

Non-fundamental investors or noise trades are irrational investors who believe that the asset price is not determined by economic fundamentals only, but it can be partially predicted using simple technical trading rules, extrapolation techniques or taking patterns observed in the past prices into account. In this study, the focus is on a group of non-fundamentalists, the anchoring, tending to rely (anchor) heavily on some of the information at the time of decision-making. Anchoring heuristic establishes that people often make their decision making process on elements or conditions of reference point (Brav and Heaton, 2002). According to this behavioral bias, the expectation method used by investors who are subject to anchoring behavior can be expressed as follows (Rekik et al., 2014):

$$E(p_{t+1}) = p_t.\left(1 + React_{Anchoring}\right) \tag{14}$$

$$E(d_{t+1}) = d_t.\left(1 + React_{Anchoring}\right) \tag{15}$$

where $React_{Anchoring}$ is the reference point of anchor and is calculated based on the trader's[1] memory length (m), as follows:

$$React_{Anc} = (1-k).[1/m\sum_{i=1}^{m}[\frac{(p_{t-i}+d_{t-i})}{p_{t-i-1}} - 1]] + k[\frac{1}{m\sum_{i=1}^{m}[\frac{p_{t-i}}{p_{t-i-1}} - 1]}] \tag{16}$$

K is the parameter measuring the weight of prior belief and the value is between 1>k>1.2. Finding the anchor point shows how individuals tend to focus on specific information and less weight to other information that can be useful in analyzing investor behavior.

Simulation Results and Analysis

After determining the main elements constituting the artificial financial market, the computational simulations can be carried out. The artificial stock market is designed and written in C#. This software is suitable for the implementation of agent-based models because it creates simulations in discrete time, and results are expressed as a series of values for each variable of the model. The computational simulations are executed according to the following steps:

1. At the beginning of each period t, the dividend value d_t is generated.
2. The agents then make their predictions in terms of stock price and dividend for the next time period $E_{i,t}(P_{t+1}+d_{t+1})$ .The agents can be fundamentalists or non-fundamental, depending on the rules they use for their predictions.
3. After the expectations of the future price and dividend of the stock are defined, the number of stocks demanded by the agents at time period t.
4. The buy and sell stock orders by the agents are determined.
5. The buy and sell stock orders are added to the market.
6. The market price of the stock is then adjusted to reflect the surplus stock demand in the market.
7. After the market price of the stock for time period t is defined, the agents' asset portfolio and the wealth level for the current time period are updated. The perceived variance of returns is also updated for use in the next time period. The information on both the aggregate behavior of the market and the individual behavior of the agents is recorded for later analysis.

In all the simulations, the artificial market consists of 100 agents and each run is for 5,000

1. Takahashi and Truno (2003) distinguish between non fundamental agents, categorizing them according to the length of memory when they analyze the price history of a stock and make a forecast.

time steps. Each agent is allowed only five stocks during each time period. Short selling of up to five stocks is permitted. These restrictions are kept uniform in artificial financial markets so that replication of the results is more realistic. Table (1) shows the values used for the model parameters. We specify the initial values on the basis of configurations exhibited in several artificial financial markets; among them are the ones suggested by Arthur et al. (1996), Lovric (2011), and Farmer and Joshi (2002). We keep the same initial parameter values in all of these simulations

Table 1. Parameters of the Model

Parameter value	Parameter	Parameter value	Parameter
0.10	r	100	N
2000	β	4	$\bar{d}$
0.5	λ	4	d_{t-1}
100	$w_{t-1,i}$	0.95	ρ
22	$E_{i,t-1}(p_{t+1}+d_{t+1})$	0	$mean\ \mu_t$
4	$\sigma^2_{i,t-1,p+d}$	0.0742	$var\ \mu_t$
1	$x_{i,t-1}$	20	p_{t-1}
0.25	k	0.015	g
		0.01	$\boldsymbol{\theta}$

Source: Research finding.

In the next step, we describe the computer simulations and discuss the results. The simulations are carried out as follows:

1: (Homogeneous market with 100% of fundamental traders) - In the first simulation, all traders in the market are homogeneous and of fundamental type and take the same principle (cash flow model) to form their expectations. They decide based on fundamental values. The results of this simulation are considered as a reference for comparison with the results of subsequent simulations.

2: the heterogeneous market comprises 50% of fundamental traders and 50% anchors with a memory length of m=5.

3: The homogeneous market contains 100% of anchor traders with a memory length of m=5.

Figures (1) and (2) compare the evolution of the stock price with the reference case (in which there are only fundamentalists). The evolution pattern of the stock price differs entirely from that of the reference case. Thus the presence of behavioral heterogeneity in the market may explain the excess volatility and systematic deviations of the asset prices from their fundamental values.

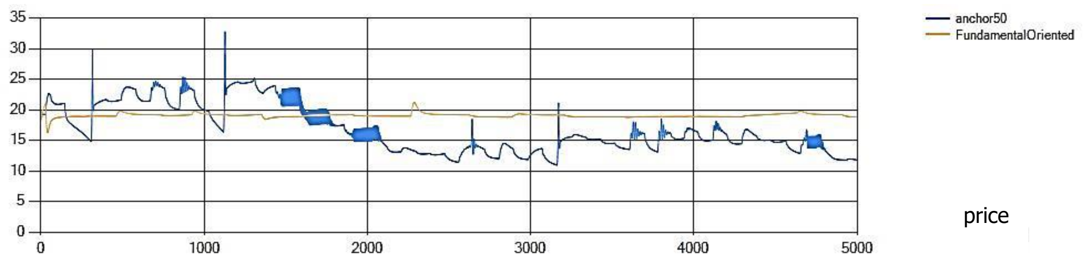

Figure 1. Evolution of Prices in the Case where 50% of the Traders are Anchor
Source: Research finding.

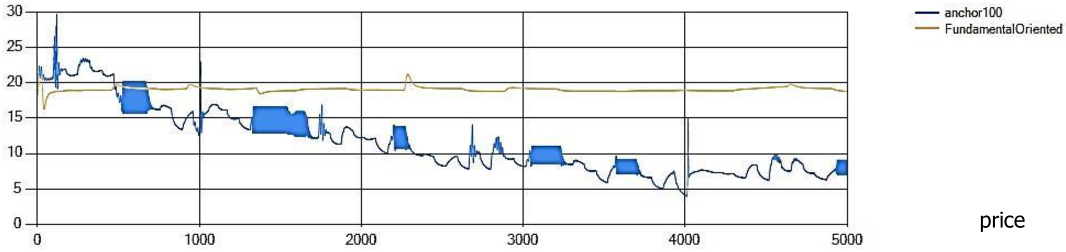

Figure 2. Evolution of Prices in Case where 100% of the Traders are Anchor
Source: Research finding.

According to the charts, when the market has agents with anchor behavioral bias, it is seen that market prices vary from fundamental prices. According to Brav and Heaton (2002) and Rekik et al. (2014), this cognitive bias may influences price formation on financial market so that it can give rise to the phenomena of under reaction to new information received by investors.

As figures 1 and 2 show, the existence of traders with an anchor bias leads to a price bubble or crashes in some periods. The occurrence of bubbles and crashes can be related to the memory length of investors. When a very high dividend is realized, anchor investors switch to the risky asset, which creates a surge in the market price. Such a high capital gain entices them into further high exposure to the risky asset. However, as the memory window moves so that the initial jump in the price is forgotten and a low dividend is realized, they can shift back to the risk-free asset, which in turn causes a sudden drop in the price. As long as this market crash remains in their memory window, it reminds anchor investors to stay invested in the bond. After the crash is forgotten, there is an opportunity for a new bubble to start.

Table 2 and 3 show descriptive statistics of stock prices and stock return rates:

Table 2. Descriptive Statistics for Stock Prices

	100% fundamentalist	50% anchor-based	100% anchor-based
	Price	Price	Price
Mean	19.88064	16.84037	11.68856
Median	19.7251	15.63488	10.12453
Maximum	23.69369	32.79935	29.77369
Minimum	16.67214	10.97506	3.959091
Std. Dev.	0.504657	3.868746	4.746749
Skewness	0.295107	0.63789	0.807346
Kurtosis	0.059072	2.235192	2.704545
Jarque-Bera	1874.4604	460.9474	561.3593
Probability	0	0	0
Observations	5000	5000	5000

Source: Research finding.

Table 3. Descriptive Statistics of the Stock Return Rate

	100% fundamentalist	50% anchor-based	100% anchor-based
	Price	Price	Price
Mean	0.149299	0.272146	0.380227
Median	0.125025	0.254022	0.355733
Maximum	0.531738	0.773567	1.243301
Minimum	-0.06296	-0.0979	-0.21566
Std. Dev.	0.140546	0.189699	0.297389
Skewness	0.088607	0.336165	0.468242
Kurtosis	1.768215	2.535325	2.836382
Jarque-Bera	322.6457	139.1564	188.286
Probability	0	0	0
Observations	5000	5000	5000

Source: Research finding.

As the results show, by increasing the number of anchors, the market becomes more volatile. The greater the anchors participations, the greater the stock price fluctuations and the more extreme and periodic the fluctuations become. The impact of their actions is greater than the impact of the actions of fundamentalist agents. Moreover, with an increase in the number of anchors, the coefficient of skewness and the kurtosis also increase, showing that the distribution of price goes far away from the normal distribution, and the tail of the distribution becomes thicker. So price process which is endogenously generated through our model has consistencies with high kurtosis and asymmetry of return distribution. One can state that all of these characteristics, which are seen in the financial series of real markets, are due to heterogeneous behavior in the market and behavioral bias.

Conclusions

The present study use Agent-based computational approach and more specifically artificial Stock Market to modeling the market dynamics from a behavioral perspective. Behavioral finance provides a new way of analyzing financial markets. Many of stylized facts in a financial time series contradict the central theoretical proposition in finance, i.e., the efficient market hypothesis (EMH). The reason for considering agent-based computational models in this study is that we cannot understand market outcomes through the eyes of a single representative type of rational agents. In agent-based models, the market includes heterogeneous and bounded rationality agents with different expectations and behaviors. This bottom-up method involves large numbers of interacting agents with the “rule of thumb” trading strategies, and the aggregation of simple interactions at the micro level (investors' behavior) may generate sophisticated structure at the macro level (the fluctuation of asset prices). A relatively novel approach for studying the link between individual investors’ behavior and financial market dynamics, based on agent-based methodology, has become known as Artificial Financial Markets. These are often computational models of financial markets, and are usually composed of a number of heterogeneous and bounded rational agents, interacting through some trading mechanism, while possibly learning and evolving. According to this approach, markets are seen as complex dynamical systems consisting of heterogeneous learning, bounded rationality heterogeneous agents.

This paper finding based on the agent-based model simulation show that the anchor features of traders, which based on a psychological study about a decision making under risk, had consistencies with many observed facts in financial markets.

The results indicate:

1) With the increase in the number of anchor traders, the market becomes more volatile
2) In the market where there are heterogeneous traders with behavioral bias or unrealistic expectations, market anomalies, including price bubbles, are more evident.
3) The dominance of non-fundamental or noise traders in the market leads to an increase in risk based on the variance and fourth-order momentum (kurtosis).

Note that this work represents a simple exercise of behavioral finance using agent-based models to understand the effects of behavioral biases in financial markets. Actually this field is only in its infancy, and much remains to be done.

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