Analyzing the Effectiveness of Investment Strategies through Agent-based Modelling: Overconfident Investment Decision Making and Passive Investment Strategies

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Abstract—This article analyzes the effectiveness of investment strategies through agent-based modeling. In this analysis, we will focus on the performance of a passive investment strategy (which is one of the most popular investment strategies in the asset management business) under conditions where overconfident investors trade. As a result of intensive experimentation, it was concluded that overconfident investors could achieve a positive excess return in the market where there are no passive investors. However, our agent-based simulation shows that overconfident investor could not survive in a market where passive investors exist. These results suggest the effectiveness of a passive investment strategy. The results are of both academic interest and practical use.

Keywords-Finance; Agent-based Modelling; Behavioral Economics; Overconfidence; Asset Management.

I. INTRODUCTION

The financial system plays a significant role in society and the economy. The role of investors providing capital to companies has become more important than ever. Financial markets contribute to efficient capital allocation, and a great amount of research regarding financial markets has been carried out.

In the last years, there has been rising interest in a field called behavioral finance, which incorporates psychological methods in analyzing investor behavior. There are numerous arguments in behavioral finance that investors' decision making bias can explain phenomenon in the financial market which until now had gone unexplained. Such arguments often point out the limit of arbitrage and the existence of systematic biases in decision-making [12][23][24][32]. Behavioral finance has examined a wide range of phenomena in the market and among investors, drawing a number of provocative conclusions. There are, for example, studies which suggest that overconfident investors could survive in the market.

Market efficiency is a central hypothesis of traditional financial theory. Indeed, the efficiency of the market lies at the heart of traditional financial theory. For example, in the Capital Asset Pricing Model (CAPM), one of the most popular asset pricing theories, equilibrium asset prices are derived on the assumption that markets are efficient and investors rational [21]. CAPM indicates that the optimal investment strategy is to hold a market portfolio. Since it is very difficult for investors to get an excess return in an efficient market, it is assumed to be difficult to beat a market portfolio even if the investment strategy is firmly based on public information. A passive investment strategy, which tries to maintain an average return using benchmarks based on market indices, is consistent with traditional asset pricing theories and is considered to be an effective method in efficient markets.

With this background in mind, the purpose of this research is to analyze the performance of overconfident investors in a market where passive investors exist. To address this problem, we have employed agent-based modeling in this analysis [2][3][7][8]. Agent based modeling is an effective method of analyzing the relationship between Micro-rules and Macro-behavior. Agent-based modeling is an attempt to explain the macro-behavior of systems by local rules. As a result of applying this model to Social Science, it has been found that a variety of different macro-behaviors emerge bottom-up from local micro-rules. Agent-based modeling has many applications, and none more suitable than for the creation of an artificial market. For example, Arthur et al. [1] analyse the market under conditions where heterogeneous investors trade and concluded that complex conditions emerge. Using agent-based modeling, Takahashi et al. [25] found that irrational traders could survive in the market. Takahashi [29] suggests that the combination of behavioral biases and financial constraints causes a significant deviation from fundamental values. Analyses which attempt to replicate realistic market conditions and dynamics present a greater challenge to the researcher than traditional forms of research. Due to the efficacy of this type of advanced analysis, there is a greater demand for research conducted employing these kinds of models. There is, therefore, a need for analyses using this more current approach, in addition to original methods. Agent-based modeling is making an increasingly valuable contribution to financial research.

The next section describes the model used in this analysis. Section III shows the results of the analysis. Section IV summarizes this paper.

II. MODEL

A computer simulation of the financial market involving 1000 investors was used as the model for this research. Shares and risk-free assets were the two types of assets used, along with the possible transaction methods. Several types of investors exist in the market, each undertaking transactions based on their own stock evaluations [1][13][28][30][31]. (see Fig. 1). This market was composed in three major stages; (1) generation of corporate earnings, (2) formation of investor forecasts, and (3) setting transaction prices. The market advances through repetition of these stages (see Fig. 2).
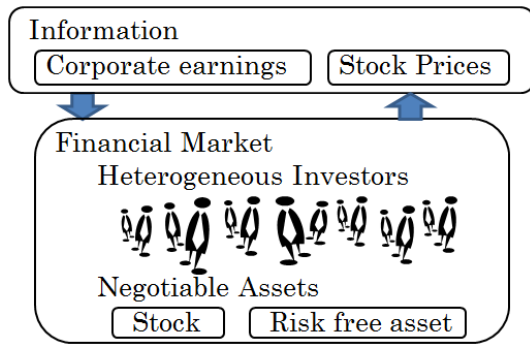
Figure 1. Basic architecture of financial market simulator
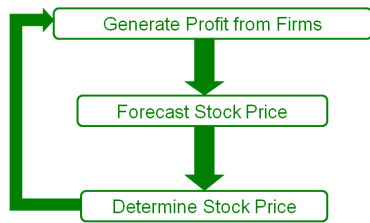

Figure 2. Simulation steps of market transactions

The following sections describe negotiable transaction assets, modeling of investor behavior, transaction price setting, and rules of natural selection in the market.

A. Negotiable assets in the market

This market has both risk-free and risk-associated assets. There are risk-associated assets in which all profits gained during each term are distributed to shareholders. Corporate earnings (y_t) are expressed as $y_t = y_{t-1} \cdot (1 + \varepsilon_t)$. However, they are generated according to the process of $\varepsilon_t \sim N(0, \sigma_y^2)$ with share trading being undertaken after the public announcement of profits for the term [5][19]. Each investor is given common asset holdings at the start of the term with no limit placed on debit and credit transactions (1000 in risk-free assets and 1000 in stocks). Investors adopt the buy-and-hold method for the relevant portfolio as a benchmark to conduct decision-making by using a one-term model. The buy-and-hold method [20] is an investment method to hold shares for medium to long term.

B. Modeling investor behavior

Each type of investor handled in this analysis is organized in Table I. This analysis covers most major types of investor [6][24]. The investors can be classified into two categories: active investors (Type 1-4) and a single passive investor type (Type 5). Active investors in this market evaluate transaction prices based on their own forecasts of market movements, taking into consideration both risk and return rates when making decisions. Passive investors employ a buy-and-hold strategy [14]. A passive investment strategy is one of the most popular investment strategies in the asset management business. Each active investor determines the investment ratio

(w_t^i) based on the maximum objective function $(f(w^i t))$, as shown below [10][15].

$$f(w_t^i) = r_{t+1}^{int,i} \cdot w_t^i + r_f \cdot (1 - w_t^i) - \lambda(\sigma_{t-1}^i)^2 \cdot (w_t^i)^2. \quad (1)$$

Here, $r_{t+1}^{int,i}$ and σ_{t-1}^i in the eq. (1) express the expected rate of return and risk for stocks as estimated by each investor i. r_f indicates the risk-free rate. w_t^i represents the stock investment ratio of the investor i for term t. λ shows degree of investor risk aversion. The value of the objective function $f(w_t^i)$ depends on the investment ratio (w_t^i). The investor decision-making model here is based on the Black/Litterman model that is used in the practice of securities investment [4][16][17][18].

The integrated expected rate of return for shares is calculated as follows [4]:

$$r_{t+1}^{int,i} = \frac{c^{-1}(\sigma_{t-1}^i)^{-2}r_{t+1}^{f,i} + (\sigma_{t-1}^i)^{-2}r_t^{im}}{c^{-1}(\sigma_{t-1}^i)^{-2} + (\sigma_{t-1}^i)^{-2}}. \quad (2)$$

Here, $r_{t+1}^{f,i} \quad r_t^{im}$ in the eq. (2) express the expected rate of return, calculated from short-term expected rate of return, and risk and gross current price ratio of stocks respectively. c is a coefficient that adjusts the dispersion level of the expected rate of return calculated from risk and gross current price ratio of stocks [4].

The short-term expected rate of return $(r_t^{f,i})$ is obtained where $(P_{t+1}^{f,i}, y_{t+1}^{f,i})$ is the equity price and profit forecast for term $t + 1$ is estimated by the investor, as follows: $r_{t+1}^{f,i} = ((P_{t+1}^{f,i} + y_{t+1}^{f,i})/P_t - 1)$.

The price and profit forecast $(P_{t+1}^{f,i}, y_{t+1}^{f,i})$ includes the error term $(P_{t+1}^{f,i} = P_{t+1}^{f,typej} \cdot (1 + \eta_t^i), y_{t+1}^{f,i} = y_{t+1}^{f,typej} \cdot (1 + \eta_t^i)$, where $\eta_t^i \sim N(0, \sigma_n^2))$ reflecting that even investors using the same forecast model vary slightly in their detailed outlook. The stock price $(P_{t+1}^{f,i})$, profit forecast $(y_{t+1}^{f,i})$, and risk estimation methods are described in the following paragraph.

The expected rate of return obtained from stock risk and so forth is calculated from stock risk (σ_{t-1}^i), benchmark equity stake (W_{t-1}), degree of investor risk aversion (λ), and risk-free rate (r_f), as follows [22]: $r_t^{im} = 2\lambda(\sigma_{t-1}^i)^2 W_{t-1} + r_f$.

1) Stock price forecasting method: The fundamental value is estimated by using the discounted cash flow model (DCF), which is a well known model in the field of finance. Fundamentalists estimate the forecasted stock price and forecasted profit from profit for the term (y_t) and the discount rate (δ) as $P_{t+1}^{f,typej} = y_t/\delta, y_{t+1}^{f,typej} = y_t$.

Forecasting based on trends involves forecasting the next term's stock prices and profit through extrapolation of the most recent stock value fluctuation trends. Stock price and profit of the next term are estimated from the most recent

TABLE I. LIST OF INVESTOR TYPES

No.	Investor types
1	Fundamentalist
2	Forecasting by past average (most recent 10 days)
3	Forecasting by trend (most recent 10 day)
4	Latest Price
5	Passive investor

trends of stock price fluctuation (a_{t-1}) from time point $t-1$ as $P_{t+1}^{f,typej} = P_{t-1} \cdot (1 + a_{t-1})^2, y_{t+1}^{f,typej} = y_t \cdot (1 + a_{t-1})$.

Forecasting based on past averages involves estimating the next term stock prices and profit based on the most recent average stock value.

C. Risk Estimation Method

Stock risk is measured as $\sigma_{t-1}^{s,i} = s_i \cdot \sigma_{t-1}^h$. In this case, σ_{t-1}^h is an index that represents stock volatility calculated from price fluctuation of the most recent 100 steps, and s_i is the degree of overconfidence. The presence of a strong degree of overconfidence can be concluded when the value of s_i is less than 1, as estimated forecast error is shown as lower than its actual value. The investors whose value of s_i is less than 1 tend to invest more actively. For example, when such investors predict that stock prices will increase, they invest more in stock than ones whose value of s_i is 1.

D. Determination of transaction prices

Transaction prices are determined as the price where stock supply and demand converge $(\sum_{i=1}^M (F_t^i w_t^i)/P_t = N)$. In this case, the total asset (F_t^i) of investor i is calculated from transaction price (P_t) for term t, profit (y_t) and total assets from the term $t-1$, stock investment ratio (w_{t-1}^i), and risk-free rate (r_f), as $F_t^i = F_{t-1}^i(w_{t-1}^i(P_t + y_t)/P_{t-1} + (1 - w_{t-1}^i)(1 + r_f))$.

E. Natural Selection in the Market

Investors who are able to adapt to and, hence, profit from the market as it fluctuates will remain in the market and their position will grow stronger. Conversely, investors who are unable to do this will drop out of the market. Such a pattern is very suggestive of what might be termed Natural Selection in the market. The driving force behind this Natural Selection is the desire for cumulative excess profit [9]. Two aspects of this pattern are of particular interest: (1) the identification of investors who alter their investment strategy, and (2) the actual alteration of investment strategy [25].

Each investor must decide whether he should change investment strategies based on the most recent performance of each 5 term period (after 25 terms have passed since the beginning of market transactions). The higher the profit rate obtained most recently is, the lesser the possibility of strategy alteration becomes. The lower the profit, the higher the possibility becomes. (In the actual market, evaluation tends to be conducted according to baseline profit and loss.) Specifically, when an investor could not obtain a positive excess profit for the benchmark portfolio profitability, they are likely to alter their investment strategy with the probability below:

$$p_i = \min(1, \max(-100 \cdot r_i^{cum}, 0)). \tag{3}$$

Here, however, r_i^{cum} in the eq. (3) is the cumulative excess profit for the most recent benchmark of investor i. Measurements were conducted for 5 terms, and the cumulative excess profit was calculated as a one-term conversion. For example, if excess profit over a 5 term period is 5 %, a one term conversion would show this as a 1 % excess for each term period.
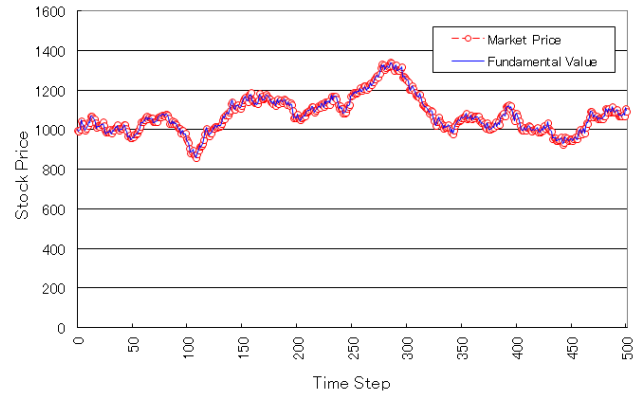

Figure 3. Price Transitions (Fundamentals)

When it comes to deciding on a new investment strategy, an investment strategy that has a high cumulative excess profit for the most recent five terms (forecasting type) is 'naturally' more likely to be selected. Where the strategy of the investor i is z_i and the cumulative excess profit for the most recent five terms is r_i^{cum}, the probability p_i that z_i is selected as a new investment strategy is given as $p_i = e^{(a \cdot r_i^{cum})}/\sum_{j=1}^M e^{(a \cdot r_j^{cum})}$. Selection pressures on an investment strategy become higher as the coefficients' value increases. Those investors who altered their strategies make investments based on the new strategies after the next step.

III. RESULTS

The first set of results is from a model in which no passive investors are analyzed. The second set presents a situation in which passive investors are present.

A. Case 1: No Passive Investors

At first, this section analyzes a situation where all investors make investment decisions based on fundamental values (Table 1, Type 1). Fig. 3 shows the transitions of transaction prices. The horizontal axis in the graph shows time steps and the vertical axis shows stock prices. Two transitions are shown: Fundamental values and transaction prices, and it can be seen that transaction prices are consistent with fundamental values throughout the entire transaction period. These results are consistent with traditional financial theory. Looking at transitions in the degree of overconfidence, a strengthening degree of overconfidence can be seen in the behavior of the remaining investors as market transactions move forward (Fig. 4). These results suggest that there is something going on in the market which allows overconfident investors - with their biases in investment decision-making - to survive. This would be in clear contradiction of traditional financial theory.

Similar results are seen when there are equal numbers of four types of investors (Table 1, Type 1-4). Figs. 5-7 show these results. Fig. 5 shows the transitions of transaction prices and Fig. 6 shows the transitions of the numbers of each type of investor. Fig. 7 shows the transition in the degree of overconfidence and shows that investors with a strong degree of overconfidence tend to survive in the market even under these conditions. These results further support the suggestion
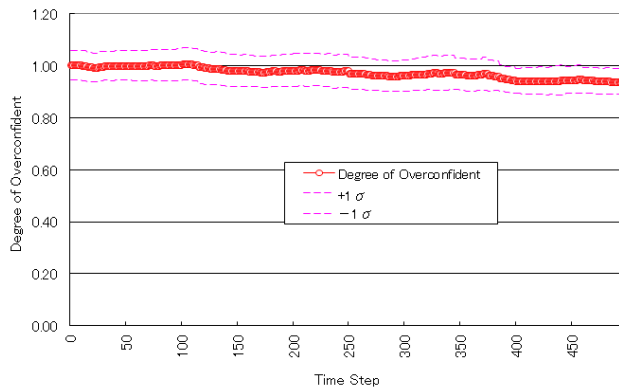
Figure 4.   Transition of degree of overconfidence (Fundamentals)
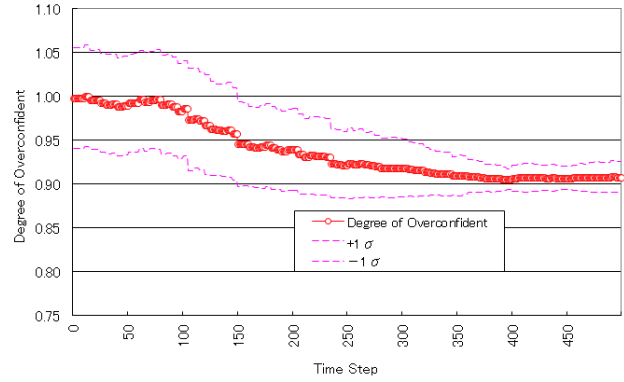

Figure 5.   Price Transitions (Fundamentals, Latest, Trend, Average)

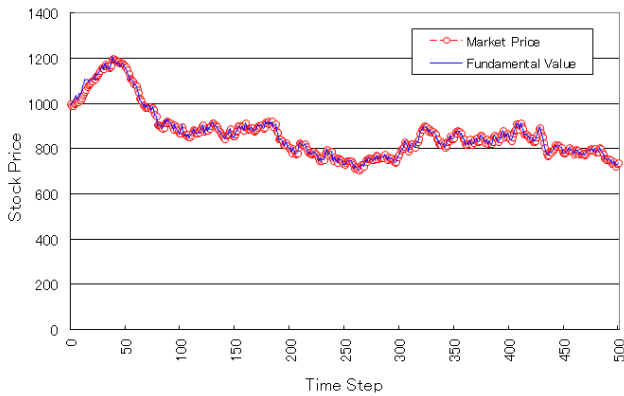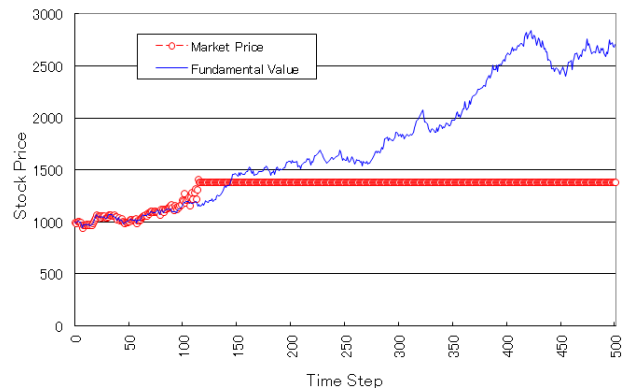Figure 7.   Transition of degree of overconfidence (Fundamentals, Latest, Trend, Average)

Figure 8.   Price Transitions (Fundamentals, Passive)

that overconfident investors can survive in the market. For details of the influence of overconfident investors, refer to [27].

B. Case 2: Passive Investors

1) Fundamentalists and Passive Investors: This section analyzes a situation where passive investors invest in the market. At first, this section analyzes the market where the
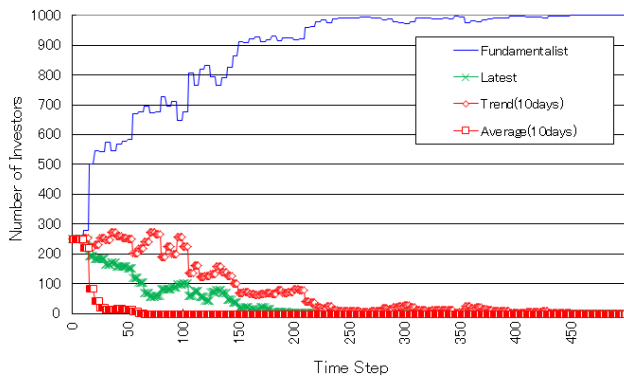

Figure 6.   Transitions of Number of Investors (Fundamentals, Latest, Trend, Average)

same number of fundamentalists and passive investors trade (Table 1, Type 1 and 5). Figs. 8, 9, and 10 show the transition of share prices, the number of investors, and the degree of overconfidence, respectively. Fig. 9 shows that, as time steps go, the number of passive investors increases. These results speak to the effectiveness of passive investment strategies. However, it is also the case that market prices reach a point where they begin to deviate from fundamental values (see Fig. 8). These latter result indicates possible drawbacks of passive investment strategies. As for the details of the analysis focusing on passive investment strategies, please refer to [26]. Yet from the data (see Fig. 10), a clear conclusion may be drawn: in this model overconfident investors do not survive, and a passive investment strategy is superior in its effectiveness.

2) Introducing extra investor types: This section analyzes the case where the same number of five types of investors including passive investors trade in the market (Table 1, Type 1-5). Figs. 11-13 show the results (Transitions of stock prices, number of investors and the degree of overconfident). Fig. 12 shows that passive investors survive in the market, and Fig. 11 shows that market prices reach a point where they begin to deviate from fundamental values, as is in the previous section. Fig. 13 shows that investors who survive in the market do not have a tendency towards overconfidence. These results also suggest the effectiveness of passive investment strategies. Although very simple, passive investment strategies
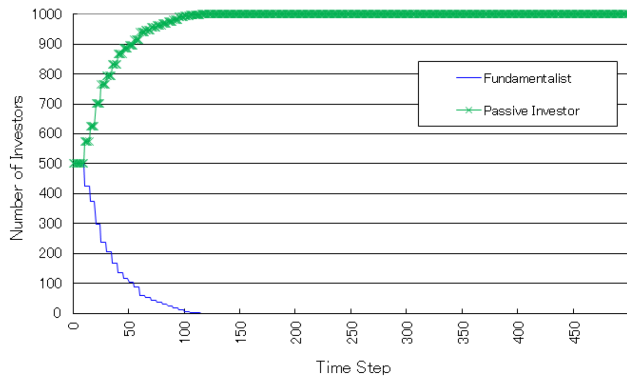
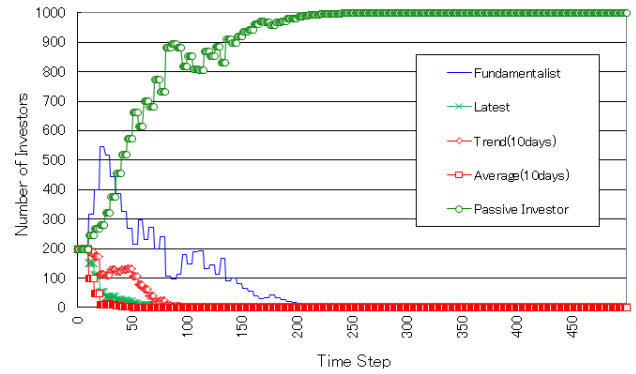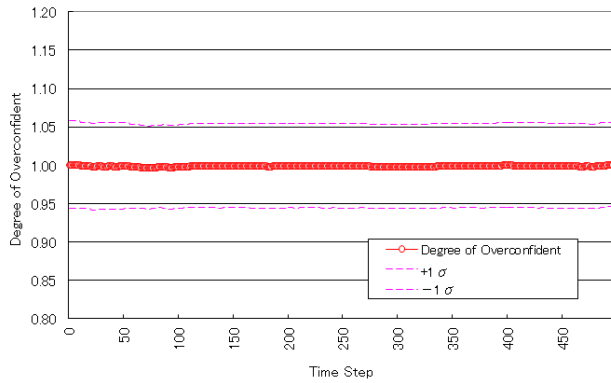Figure 9. Transitions of Number of Investors (Fundamentals, Passive)

Figure 10. Transition of degree of overconfidence (Fundamentals, Passive)

show impressive flexibility, adaptability and resilience.

IV. SUMMARY

This article examines the effectiveness or otherwise of passive investment strategies, utilizing agent-based modeling. As a result of intensive experimentation, this paper confirms that a passive investment strategy is effective under conditions where overconfident investors invest. This conclusion is of interest in itself and merits further study. Future analyses will focus on examining the effect on markets of practical changes.

Figure 11. Price Transitions (Fundamentals, Latest, Trend, Average, Passive)

Figure 12. Transitions of Number of Investors (Fundamentals, Latest, Trend, Average, Passive)

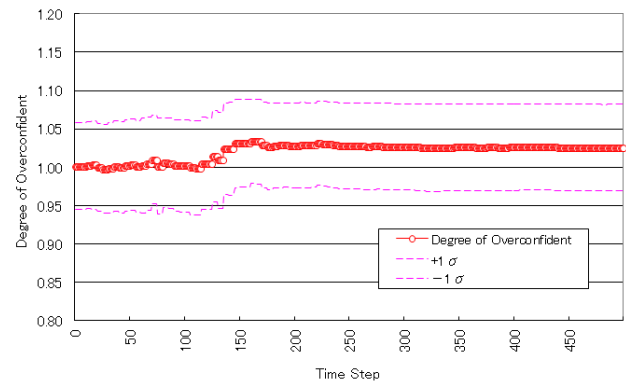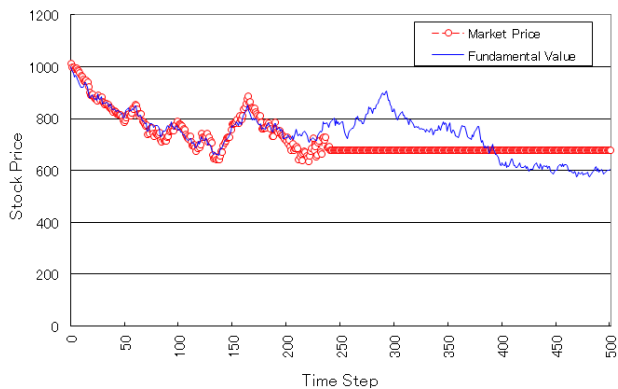Figure 13. Transition of degree of overconfidence (Fundamentals, Latest, Trend, Average, Passive)

This research focuses on passive investors and overconfident investors. A more detailed analysis would consider both types of investment behavior under more realistic market conditions. This is a matter for further research.

APPENDIX

This section lists the major parameters of the financial market designed for this paper. The explanation and value for each parameter is described.

M: Number of investors (1000)
N: Number of shares (1000)
F_t^i: Total asset value of investor i for term t ($F_0^i = 2000$: common)
W_t: Ratio of stock in benchmark for term t ($W_0 = 0.5$)
w_t^i: Stock investment rate of investor i for term t ($w_0^i = 0.5$: common)
y_t: Profits generated during term t ($y_0 = 0.5$)
σ_y: Standard deviation of profit fluctuation ($0.2/\sqrt{200}$)
δ: Discount rate for stock($0.1/200$)
λ: Degree of investor risk aversion (1.25)
σ_n: Standard deviation of dispersion from short-term expected rate of return on shares (0.05)
c: Adjustment coefficient (0.01)

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