Effect of Increasing Horizontal Shareholding with Index Funds on Competition and Market Prices – Investigation by Agent-Based Model –

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***Abstract*—Recently, some empirical studies have argued that "horizontal shareholding" (or "common ownership") lessens competition among companies and prevents industries from growing. In particular, index funds horizontally shareholding have become the largest shareholders and has become a subject of greater debate. In this study, I built an artificial market model, a kind of agent-based model, and investigated the effect of increasing horizontal shareholding with index funds on competition and market prices. My result shows that even when the holding ratio of index funds is not that high, the funds lessen competition. Moreover, when the value of a company successful at competition grows, its market price grows more than the company value (overshoots) and the company becomes overvalued; then, the number of shareholders who encourage competition decreases and the company loses competitive power. Alternately, when the value of a company unsuccessful at competition drops, its market price falls deeper than the company value (overshoots) and the company becomes undervalued; then, the number of shareholders who encourage competition increases, and the company gains competitive power. My simulation result indicated that such a mechanism balances competitive powers among corporations. Growing index funds may possibly weaken this mechanism.**

I. Introduction

Recently, some empirical studies have argued that "horizontal shareholding" (or "common ownership"), in which an investor holds all companies that are competitors in one industry, lessens competition among companies and prevents industries from growing [1]–[3]. Usually, investors encourage a company to compete with other companies because investors earn more when the stock price of the company rises if the company is successfully competitive among others in the industry. However, horizontal shareholders have different economic incentives from investors holding one company because even if one company that a horizontal shareholder holds is successfully competitive, the investors always also hold the losing companies. Therefore, they earn from the winning company but always also take a loss from the losing companies. For horizontal shareholders, the incentive to encourage holding companies to compete is very weak. Moreover, it seems that there are some cases in which they can earn more if they make holding companies avoid competition through reducing the prices of goods to keep the profit margin of the companies.

In particular, index funds horizontally shareholding, where a manager expects a return the same as a market index, e.g., the Dow Jones industrial average, and replicates the components of the index, have become the largest shareholders and has become a subject of greater debate because, recently, the assets of index funds have increased heavily [1].

In the United States, the index fund industry is dominated by the biggest three asset management companies, and they constitute the largest shareholder with 40% of all listed United States companies and hold 15% of all shares of listed companies [1]. This means they are horizontally shareholding heavily. Azar et al. [2] used 14 years of quarterly panel data to estimate that airline ticket prices in the United States are 3–7% higher because of horizontal shareholding, compared with a counterfactual world in which companies are separately owned. Fichtner et al. [1] analyzed data on shareholder voting and argued that shareholders tend to influence the management of companies through private engagements rather than public discussion, such as shareholder voting.

Elhauge [3] argued that recent horizontal shareholdings are already illegal under current antitrust laws, and such shareholding can help explain why economic inequality has risen in recent decades as shown by Piketty [4][1]. He also recommended that big funds should be restricted to investing in only one company for each industry.

However, there are many arguments against this [5], [6], and there are also answers to the arguments against [7], so no conclusion has been reached yet. Moreover, such empirical studies cannot make conclusions because they cannot handle very complex mechanisms, such as how horizontal shareholding affects business strategies and market prices. In particular, they cannot directly investigate the "positive feedback" process, as Fig. 1 shows, such as how stock trading changes the shareholder composition. The trading leads to changes in the business strategy of companies, the intrinsic value of companies (fundamental value), the stock price, and traders' decisions. Such discussion on the mechanism of positive feedback is very difficult when using only the results

[1]The reason Piketty [4] gives for the rise in economic inequality differs from horizontal shareholding.

of empirical studies. Empirical studies cannot be conducted to investigate situations that have never occurred in actual financial markets, such as ones in which index funds are more than present. Furthermore, because so many factors cause price formation in actual markets, an empirical study cannot be conducted to isolate the direct effect of changing the distribution of investor types on price formation.

An artificial market model, which is a kind of agent-based model, is the only way to directly investigate positive feedback. The model can also handle situations that have never occurred, such as ones in which index funds are more than present, and can isolate the direct effect of changing the distribution of investor types on price formation. These are strong advantages for an artificial market simulation. The effects of distribution and of several changing regulations have been investigated by using these simulations [8]–[11].

Not only academies but also financial regulators and stock exchanges have recently become interested in agent-based models, such as artificial market models for investigating financial markets. Indeed, an article in Science by Battiston et al. [12] stated that "since the 2008 crisis, there has been increasing interest in using ideas from complexity theory (using network models, agent-based models, and so on) to make sense of economic and financial markets," and an article in Nature by Farmer and Foley [13] stated that "such (agent-based) economic models should be able to provide an alternative tool to give insight into how government policies could affect the broad characteristics of economic performance, by quantitatively exploring how the economy is likely to react under different scenarios."

Many studies have investigated the effects of kinds of investors on price formation and the effects of several changing regulations and rules by using artificial market simulations [10]. Indeed, the effects of market makers and index funds were investigated by using these simulations [14]. Mizuta and Horie [15] modeled agents who reflect the characteristics of investors who trade infrequently on the basis of the fundamental price (fundamental investors), and they investigated the effects of active agents on market price formation and whether they make a market more efficient or not by using the model. They succeeded in figuring out the mechanism of how active funds impact market prices and in proving that active funds trading infrequently is not inconsistent with making a market efficient. However, no simulation study has been done to investigate the effect of increasing horizontal shareholding with index funds on competition and market prices.

In this study, I implemented a competition model, in which horizontal shareholding changes the business strategy of companies and lessens competition among companies, into the artificial market model of Mizuta and Horie [15]. I investigated the effect of increasing horizontal shareholding with index funds on competition and market prices.

II. Artificial Market Model

In this study, I expand the artificial market model of Mizuta and Horie [15], which is not only simple enough but has also succeeded in replicating the characteristics of fundamental investors in real financial markets, to a two-stock market model.

The simplicity of the model is very important for this study because unnecessarily replicating macro phenomena leads to models that are over-fitted and too complex, and such models would prevent us from understanding and discovering the mechanisms that affect price formation because the number of related factors would increase [16]. I explain the basic concept for constructing our artificial market model in Appendix A.

A. Agent Model

The number of all agents is N. First, half of all agents $N/2$ have one share of stock, and the other half have cash C_0. C_0 is constant for all agents. The agents who have one share of stock always place a sell order for one share, and the agents who have no stock always place a buy order for one share. Therefore, the agents never have two or more shares and never have a short position (negative number of shares). The number of shares and buy or sell of orders are determined automatically, so the agents should determine only an order price. The changes in the fundamental prices with the "competition model" as mentioned in the following section only cause there to be a correlation between two stocks, and agents determine the order prices for each stock dependently.

This simplification makes it easier to interpret the simulation results since the types of agents only differ in terms of how an order price is determined, and this allows us to build a model of agents who trade infrequently. In the following sections, I explain the rules for determining an order price for each type of agent.

1) Fundamental Agent: I modeled fundamental agents who reflect the characteristics of fundamental investors that trade infrequently in real financial markets. A long time is needed for market prices to converge with the fundamental price. Therefore, fundamental investors must endure bad times and wait for profit patiently. Fundamental investors endure such bad times and earn more.

The number of fundamental agents is $N_{\mathbf{P}}$. The order price of an agent j at time t, $P_o^{t,j}$ is

$$P_o^{t,j} = P_f \exp(d\sigma^j \pm m(\mu^j + 1)), \tag{1}$$

where d and m are constant, and σ^j is determined by random variables that follow a standard normal distribution for each agent j. μ^j is determined by random variables that are uniformly distributed in $(0, 1)$ for each agent j. The $\pm$ gives $-$ in the case of a buy order and $+$ in the case of a sell order (see also Fig. 2).

The fundamental agents determine order prices $P_o^{t,j}$ by depending not on the latest market price P^{t-1} but on the fundamental price P_f, which is the intrinsic value of a company. The agents do not know P_f but try to estimate it. $d\sigma^j$ is the ratio of the difference between P_f and the estimated fundamental price to P_f. Active funds generally want to buy (sell) at a sufficiently lower (higher) price than their estimated fundamental prices, and such a sufficient difference in prices is called the "margin of safety" [17]. $m(\mu^j+1)$ is the ratio of the margin of safety to the estimated fundamental price.

The order price $P_o^{t,j}$ does not depend on either the latest nor historical market prices. This leads to the behavior of fundamental agents not depending on their profit even though they are experiencing bad times for their investments. Therefore, fundamental agents can represent the feature of fundamental investors that endure bad times and wait for profit patiently.

2) Technical Agents: The number of technical agents is $N_{\mathbf{T}}$. They adopt a momentum strategy.

The order price of an agent j at time t, $P_o^{t,j}$, is

$$P_o^{t,j} = P^t \frac{P^t}{P^{t-tm^j}}, \tag{2}$$

where tm^j is a natural number determined by random variables uniformly distributed in $(1, tm_{\mathbf{max}})$ for each agent j, and $tm_{\mathbf{max}}$ is a constant. The technical agents decide the order price the same as the expected price; this leads to the expected return being $\ln(P_o^{t,j}/P^t)$. In the momentum strategy, they expect that the expected return, $\ln(P_o^{t,j}/P^t)$, will equal the historical return, $\ln(P^t/P^{t-tm^j})$. This leads to equation (2).

Previous studies showed that such technical agents are needed to replicate the price formations observed in real financial markets [9](see also Appendix B). This is the reason I introduced the technical agents.

3) Noise Agents: The number of noise agents is $N_{\mathbf{N}}$. The order price of an agent j at time t, $P_o^{t,j}$, is

$$P_o^{t,j} = P^t \exp(\eta\sigma^{t,j}), \tag{3}$$

where η is constant, and $\sigma^{t,j}$ is determined by random variables that follow a standard normal distribution for each time t and agent j. In this study, I handle a stock traded at a high enough volume. I introduced noise agents to supply enough liquidity. If there are no noise agents, order prices sometimes are inclined to lean to one side heavily, and this leads to orders not being matched. Also, in real financial markets, there are many such liquidity suppliers [18].

B. Price Determination Model

After all agents determine an order price, the market price P^t is determined by a "call auction" [19], where the numbers of sell/buy orders at prices lower/higher than P^t are matched. In a call market, buy and sell orders are grouped together and then executed at specific times rather than executed one by one continuously. The market price is determined at the crossing point of supply and demand curves. The supply (demand) curve is a cumulative number of orders that sellers (buyers) want to sell over (buy under) a price.

C. Competition Model

Both fundamental prices P_f are changed or not changed according to their shareholder composition every time Δt passed. I call what fundamental price is changed the "occurrence of competition." Competition happens only when time t can be divided by Δt. At that time, the number of agents holding only stock 1 n_1, those holding stock 2 n_2, and those holding both stocks n_b are counted for every time from $t-\Delta t$ to t. When the frequency at which n_1 is largest among n_1, n_2, n_b is larger than those of n_2 and n_b, the fundamental price of stock 1 is increased by δP_f, and that of stock 2 is decreased by δP_f. When the frequency is that at which n_2 is largest, the opposite holds. When the frequency is that at which n_b is largest, both fundamental prices are not changed (competition does not occur).

Fig. 1. Positive feedback process in horizontal shareholding

This is modeling for the following phenomena. Investors who hold only one stock earn more when the holding company competes with another company and the fundamental price rises. Therefore, the investors encourage the company to compete with another company. Alternately, for investors who hold both stocks even when one company competes with another company and earns money when the fundamental price rises, they always hold the stock of the other company and lose when the fundamental price decreases. Therefore, the investors have no economic incentive to encourage companies to compete. As I mentioned in the introduction, that horizontal shareholders have different economic incentives from separate investors has become a subject of greater debate.

The reason only fundamental agents are counted in the competition model is reflected in the fact that, in real financial markets, only fundamental investors usually engage in the management of companies, and other type of investors, sometimes called "speculators," rarely do so.

D. Index Agent

Some fundamental agents initially holding both stocks (the number is $N_{\mathbf{F}}/4$) never trade any stocks. We call them "index agents." The number of index agents is N_{Fp}. As I mentioned in the introduction, index funds never select stocks and always hold all stocks of the components of the index.

III. Simulation Results

I set $N_{\mathbf{F}} = 400, N_{\mathbf{T}} = 100, N_{\mathbf{N}} = 1000, P_f = 10000, d = 0.05, m = 0.02, tm_{\mathbf{max}} = 100, \eta = 0.5, \Delta t = 100, and \delta P_f = 2500$. I compared the results of simulation runs for $N_{\mathbf{Fp}} = 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 = N_{\mathbf{F}}/4$. I ran all simulations until $t = t_e = 1000$. I explain the verification of these parameters in Appendix B. The model has only the necessary minimum parameters and rarely obtains arbitrary results.

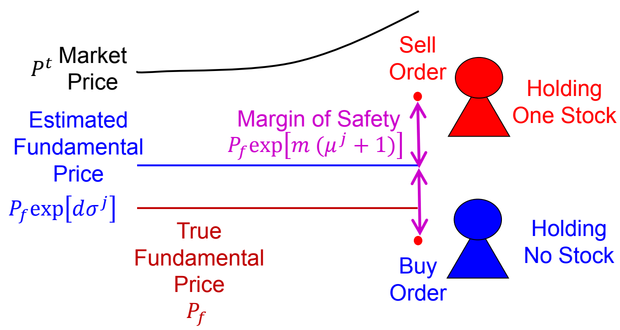

Fig. 2. Order prices of fundamental agents

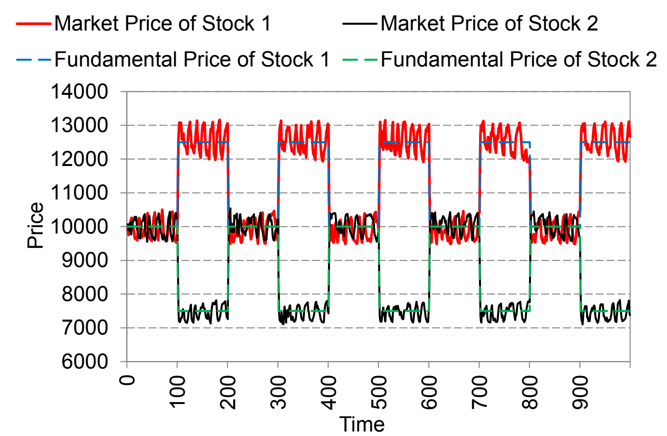

Fig. 3. Time evolution of market prices P^t and fundamental prices P_f for each stock when no index agent exists $N_{\mathbf{Fp}} = 0$

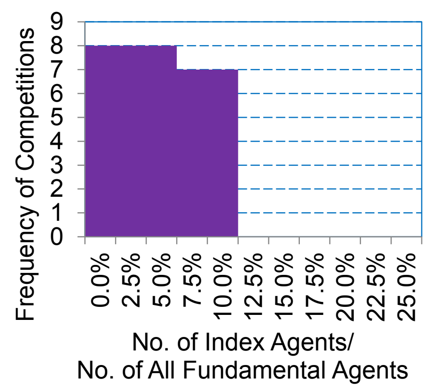

Fig. 4. Frequency of competitions for various $N_{\mathbf{Fp}}/N_{\mathbf{F}}$

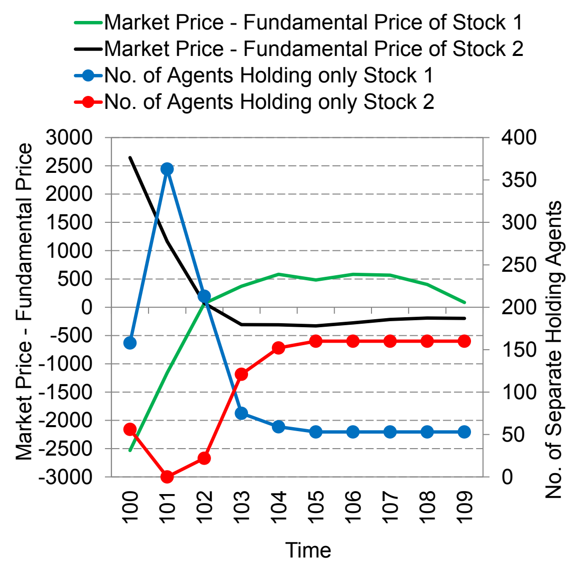

Fig. 5. Time evolution (expanding from $t = 100 - -110$) of market price minus fundamental price of each stock and number of agents holding only stock 1 or 2 when no index agent exists $N_{\mathbf{Fp}} = 0$

Fig. 3 shows the time evolution of market prices P^t and fundamental prices P_f for each stock when no index agent exists $N_{\mathbf{Fp}} = 0$. The fundamental prices changed many times, and competition occurred frequently. Furthermore, the two companies won alternately, and this implies that there is a mechanism that balances competition powers among corporations. Fig. 4 shows the frequency of competitions for various $N_{\mathbf{Fp}}/N_{\mathbf{F}}$. When $N_{\mathbf{Fp}}/N_{\mathbf{F}} > 12.5\%$, competition never occurred. The result shows that even when the existing ratio of index funds is not that large, the funds lessen competition.

Fig. 5 shows the time evolution (expanding from $t = 100 - -110$) of the market price minus the fundamental price of each stock and the number of agents holding only stock 1 or 2 when no index agent existed $N_{\mathbf{Fp}} = 0$. At $t = 100$, competition occurred, causing the fundamental price of stock 1 to rise and that of stock 2 to fall. Due to the rise of the fundamental price of stock 1, stock 1 was bought, and the number of agents holding only stock 1 increased by time $t = 102$ when the market prices of stock 1 converged with the fundamental price of stock 1. After that, the market prices of stock 1 rose higher and then overshot the fundamental price[2]. Therefore, within the overshooting, the number of agents holding only stock 1 was lower than that of stock 2.

As Fig. 6 shows, when the value of a company successful at competition grows, its market price grows more than the company value (overshoots), and the company becomes overvalued; then, the number of shareholders who encourage competition decreases, and the company loses competitive power. Alternately, when the value of a company not successful at competition drops, its market price falls deeper than the company value (overshoots), and the company becomes undervalued; then, the number of shareholders who encourage competition increases, and the company gains competitive power. My simulation result indicated that such a mechanism balances competition powers among corporations. Growing index funds may possibly weaken this balancing mechanism.

[2]Previous empirical studies showed that such overshooting occasionally occurs, and some previous simulation studies with artificial market models discussed the mechanism of such overshooting [20], [21].

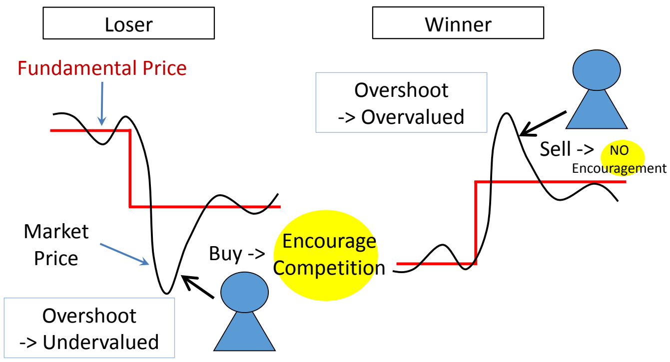

Fig. 6. Mechanism balancing competition powers among corporations

IV. Conclusion and Future Work

In this study, I implemented a competition model, in which horizontal shareholding changes the business strategy of companies and lessens competition among companies, in the artificial market model of Mizuta and Horie [15]. I investigated the effect of increasing horizontal shareholding with index funds on competition and market prices.

The result shows that even when the holding ratio of index funds is not that much, the funds lessen competition. Moreover, when the value of a company successful at competition grows, its market price grows more than the company value (overshoots), and the company becomes overvalued; then, the number of shareholders who encourage competition decreases, and the company loses competitive power. Alternately, when the value of a company unsuccessful at competition drops, its market price falls deeper than the company value (overshoots), and the company becomes undervalued; then, the number of shareholders who encourage competition increases, and the company gains competitive power. My simulation result indicated that such a mechanism balances competition powers among corporations. Growing index funds may possibly weaken this balancing mechanism.

More detailed discussion will be for future work because investigating horizontal shareholding both empirically and through simulation has only just begun. The model in this study neglected many important processes, for example, the in- or out-flow of cash to index funds, so additional implementations of such processes in the model are future work.

For more detailed discussion, I should compare the simulation results with those from studies that use other methods, e.g., empirical studies and theoretical studies. An artificial market can deal with situations that have never occurred, such as index funds being more than present, and can isolate the direct effect of changing the distribution of investor types on price formation. These are strong advantages for an artificial market simulation; however, the outputs of these simulations may not be accurate or credible forecasts for actual markets. It is an important role for artificial market simulations to reveal the possible mechanisms that affect price formation through many runs to gain new insights; conversely, one limitation of artificial market simulations is that their outputs may, but not certainly, occur in actual financial markets.

TABLE I
Statistics of stock 1 when $N_{\mathbf{Fp}} = 100 = N_{\mathbf{F}}/4$

Standard deviation of return		1.25%
Kurtosis of return		1.29
	lag	
Autocorrelation coefficient for square return	1	0.22
	2	0.03
	3	−0.09

Appendix

A. Basic Concept for Constructing Model

An artificial market model, which is a kind of agent-based model, can be used to discuss investor distributions that have never been realized, can handle regulation changes that have never been made, and it can isolate the pure contribution of these changes to price formation [8]–[11]. These are the strong points of the artificial market simulation.

However, the outputs of this simulation would not be accurate or credible forecasts of the actual future. The simulation needs to reveal possible mechanisms that affect price formation through many simulation runs, e.g., searching for parameters or purely comparing the before/after of changes. The possible mechanisms revealed by these runs provide new intelligence and insight into the effects of the changes on price formation in actual financial markets. Other methods of study, e.g., empirical studies, would not reveal such possible mechanisms.

Indeed, artificial markets should replicate macro phenomena existing generally for any asset and any time. Price variation, which is a kind of macro phenomena, is not explicitly modeled in artificial markets. Only micro processes, agents (general investors), and price determination mechanisms (financial exchanges) are explicitly modeled. Macro phenomena emerge as the outcome interactions of micro processes. Therefore, the simulation outputs should replicate existing macro phenomena in order to generally prove that simulation models are probable in actual markets.

However, it is not a primary purpose for an artificial market to replicate specific macro phenomena only for a specific asset or a specific period. An unnecessary replication of macro phenomena leads to models that are over-fitted and too complex. Such models would prevent us from understanding and discovering mechanisms that affect price formation because the number of related factors would increase.

Indeed, artificial market models that are too complex are often criticized because they are very difficult to evaluate [9]. A model that is too complex not only would prevent us from understanding mechanisms but also could output arbitrary results by over-fitting too many parameters. It is more difficult for simpler models to obtain arbitrary results, and these models are easier to evaluate.

Therefore, I constructed an artificial market model that is as simple as possible and do not intentionally implement agents to cover all the investors who would exist in actual financial markets.

As Weisberg mentioned [16], “Modeling, (is) the indirect study of real-world systems via the construction and analysis of models.” “Modeling is not always aimed at purely veridical representation. Rather, they worked hard to identify the features of these systems that were most salient to their investigations.” Therefore, under different phenomena to focus on, good models are different. Thus, my model is good only for the purpose of this study and may be not good for other purposes. An aim of my study is to understand how important properties (behaviors, algorithms) affect the investigation of macro phenomena and play a role in the financial system rather than representing actual financial markets precisely.

B. Verification of Model

In many previous artificial market studies, the models were verified to see whether they could explain stylized facts, such as a fat-tail or volatility-clustering [8]–[11]. A fat-tail means that the kurtosis of price returns is positive. Volatility-clustering means that square returns have a positive autocorrelation, and this autocorrelation slowly decays as its lag becomes longer. Many empirical studies, e.g., that of Sewell [22], have shown that both stylized facts (fat-tail and volatility-clustering) exist statistically in almost all financial markets. Conversely, they also have shown that only the fat-tail and volatility-clustering are stably observed for any asset and in any period because financial markets are generally unstable.

Indeed, the kurtosis of price returns and the autocorrelation of square returns are stably and significantly positive, but the magnitudes of these values are unstable and very different depending on the asset and/or period. The kurtosis of price returns and the autocorrelation of square returns were observed to have very broad magnitudes of about $1 \sim 100$ and about $0 \sim 0.2$, respectively [22].

For the above reasons, an artificial market model should replicate these values as significantly positive and within a reasonable range as I mentioned. It is not essential for the model to replicate specific values of stylized facts because the values of these facts are unstable in actual financial markets.

Table I lists the statistics, standard deviation of returns, kurtosis of price returns, and autocorrelation coefficient for square returns of stock 1 when $N_{\mathbf{Fp}} = 100 = N_{\mathbf{F}}/4$. This shows that this model replicated the statistical characteristics, fat-tails, and volatility-clustering observed in real financial markets.

Disclaimer

Note that the opinions contained herein are solely those of the authors and do not necessarily reflect those of SPARX Asset Management Co., Ltd.

References

[1] J. Fichtner, E. M. Heemskerk, and J. Garcia-Bernardo, “Hidden power of the big three? passive index funds, re-concentration of corporate ownership, and new financial risk,” *Business and Politics*, vol. 19, no. 2, p. 298326, 2017. [Online]. Available: https://doi.org/10.1017/bap.2017.6

[2] S. M. C. Azar, Jose and I. Tecu, “Anti-competitive effects of common ownership,” *SSRN Working Paper Series*, 2014. [Online]. Available: https://ssrn.com/abstract=2427345

[3] E. Elhauge, “Horizontal shareholding,” *Harvard Law Review*, vol. 129, no. 5, p. 1267, 2016. [Online]. Available: https://harvardlawreview.org/?p=4185

[4] T. Piketty, *Le Capital au XXI^e siècle*. Éditions du Seuil, 2013.

[5] D. O’Brien and K. Waehrer, “Athe competitive effects of common ownership: We know less than we think,” *SSRN Working Paper Series*, 2017. [Online]. Available: http://ssrn.com/abstract=2922677

[6] E. Rock and D. Rubinfeld, “Defusing the antitrust threat to institutional investor involvement in corporate governance,” *SSRN Working Paper Series*, 2017. [Online]. Available: http://ssrn.com/abstract=2925855

[7] E. Elhauge, “The growing problem of horizontal shareholding,” *SSRN Working Paper Series*, 2017. [Online]. Available: http://ssrn.com/abstract=2988281

[8] B. LeBaron, “Agent-based computational finance,” *Handbook of computational economics*, vol. 2, pp. 1187–1233, 2006. [Online]. Available: http://dx.doi.org/10.1016/S1574-0021(05)02024-1

[9] S.-H. Chen, C.-L. Chang, and Y.-R. Du, “Agent-based economic models and econometrics,” *Knowledge Engineering Review*, vol. 27, no. 2, pp. 187–219, 2012. [Online]. Available: http://dx.doi.org/10.1017/S0269888912000136

[10] T. Mizuta, “A brief review of recent artificial market simulation (agent-based model) studies for financial market regulations and/or rules,” *SSRN Working Paper Series*, 2016. [Online]. Available: http://ssrn.com/abstract=2710495

[11] A. Todd, P. Beling, W. Scherer, and S. Y. Yang, “Agent-based financial markets: A review of the methodology and domain,” in *Computational Intelligence for Financial Engineering Economics (CIFEr), 2016 IEEE Symposium Series on Computational Intelligence on*, Dec 2016. [Online]. Available: https://doi.org/10.1109/SSCI.2016.7850016

[12] S. Battiston, J. D. Farmer, A. Flache, D. Garlaschelli, A. G. Haldane, H. Heesterbeek, C. Hommes, C. Jaeger, R. May, and M. Scheffer, “Complexity theory and financial regulation,” *Science*, vol. 351, no. 6275, pp. 818–819, 2016. [Online]. Available: http://science.sciencemag.org/content/351/6275/818

[13] J. D. Farmer and D. Foley, “The economy needs agent-based modelling,” *Nature*, vol. 460, no. 7256, pp. 685–686, 2009. [Online]. Available: https://www.nature.com/articles/460685a

[14] K. Braun-Munzinger, Z. Liu, and A. Turrell, “Staff working paper no. 592 an agent-based model of dynamics in corporate bond trading,” *Bank of England, Staff Working Papers*, 2016. [Online]. Available: http://www.bankofengland.co.uk/research/Pages/workingpapers/2016/swp592.aspx

[15] T. Mizuta and S. Horie, “Why do active funds that trade infrequently make a market more efficient? - investigation using agent-based model,” in *Computational Intelligence for Financial Engineering Economics (CIFEr), 2017 IEEE Symposium Series on Computational Intelligence on*, Nov 2017. [Online]. Available: https://doi.org/10.1109/SSCI.2017.8280798

[16] M. Weisberg, *Simulation and Similarity: Using Models to Understand the World*. Oxford Studies in the Philosophy of Science, 2012.

[17] B. Graham and J. Zweig, *The Intelligent Investor: The Definitive Book on Value Investing*. HarperCollins, 2003.

[18] T. Kurosaki, Y. Kumano, K. Okabe, and T. Nagano, “Liquidity in jgb markets: An evaluation from transaction data,” *Bank of Japan Working Paper Series*, no. 15-E-2, 2015. [Online]. Available: https://www.boj.or.jp/en/research/wps_rev/wps_2015/wp15e02.htm/

[19] TSE, *Guide to TSE Trading Methodology*. Tokyo Stock Exchange, 2015. [Online]. Available: http://www.jpx.co.jp/english/equities/trading/domestic/

[20] I. Yagi, T. Mizuta, and K. Izumi, “A study on the reversal mechanism for large stock price declines using artificial markets,” in *2012 IEEE Conference on Computational Intelligence for Financial Engineering Economics (CIFEr)*, March 2012, pp. 1–7. [Online]. Available: http://dx.doi.org/10.1109/CIFEr.2012.6327791

[21] T. Mizuta, S. Kosugi, T. Kusumoto, W. Matsumoto, K. Izumi, I. Yagi, and S. Yoshimura, “Effects of price regulations and dark pools on financial market stability: An investigation by multiagent simulations,” *Intelligent Systems in Accounting, Finance and Management*, vol. 23, no. 1-2, pp. 97–120, 2016. [Online]. Available: http://dx.doi.org/10.1002/isaf.1374

[22] M. Sewell, “Characterization of financial time series,” *Research Note, University College London, Department of Computer Science*, no. RN/11/01, 2011. [Online]. Available: http://finance.martinsewell.com/stylized-facts/