Journal of Simulation (2017) 11, 128–136

www.palgrave.com/journals

Relative wealth concerns, positive feedback, and financial fluctuation

Joohyun Kim[1] and Duk Hee Lee[2*]

[1]Naveen Jindal School of Management at the University of Texas at Dallas, 800 W Campbell Rd, Richardson, TX 75080, USA; and [2]School of Business and Technology Management, College of Business, Korea Advanced Institute of Science and Technology, Daejeon, Korea

Recent studies have shown that imitation and adaptation are the dominant mechanisms of a positive feedback loop that leads to a dramatic amplification of stock prices. In this research, relative wealth concerns have been taken into account as the primary origin of the positive feedback effect. Specifically, relative wealth concerns alongside wealth inequality would change the risk attitude of each stock-trading agent to catch up with their peers' wealth, by imitating and adapting their trading strategies. We simulate an artificial stock market via an agent-based modeling approach, which allows us to observe what happens to each agent's relationships, providing a more insightful view than the traditional economic model. This research demonstrates how relative wealth concerns can affect today's financial mechanism, by means of positive feedback effects.

Journal of Simulation (2017) **11**(2), 128–136. doi:10.1057/s41273-016-0005-1; published online 31 August 2016

Keywords: relative wealth concerns; positive feedback effect; risk attitude; wealth inequality

1. Introduction

In 2008, we suffered a dramatic change in asset prices, particularly, real estate price and stock price. From the great depression to the recent IT bubble, there were many exceptional financial fluctuations, even though the magnitudes of impact varied. However, we perceive that the shocks of economic crises are getting worse, and the periods of occurrence are getting shorter compared to the past. Therefore, what causes a financial bubble and crash? Recently, uncovering the underlying mechanisms of financial crises has been a hot issue, specifically dealing with the origins of bubbles and crashes. Even though many studies have been published to reveal the fundamental mechanism of complex stock market phenomena, we still have not reached a satisfactory conclusion that can completely explain the origin of financial crises (Sornette, 2003; Harras and Sornette, 2011).

In times past, many researchers have suggested that an overly optimistic expectation of returns in the future causes an instability within a stock market (Sornette, 2003; Kindleberger and Aliber, 2005; Shefrin, 2005). Recent research in this field has often regarded the stock market as a complex system, and the interaction of agents as the paramount factor in growing instability. In particular, some studies have developed models by considering heterogeneous agents that can update their belief about returns according to market conditions, and psychological trading style (Gaunersdorfer, 2000; Huang *et al*, 2010). Chiarella *et al* (2006) extended agents' heterogeneous trading styles in the financial market, to take into account not only wealth dynamics, but also separated assets as nonrisky assets and risky assets. Boschi and Goenka (2012) focused on how the behaviors of agents affect the contagion of financial crises via relative risk-aversion concepts, which allows us to understand why agents attempt to hold risky assets, and why the positive feedback effects of risk premium occurs.

From the perspective of positive feedback effects, Harras and Sornette (2011) suggested that imitation and adaptation are the principal mechanisms of a positive feedback effect that amplifies a dramatic increase in stock prices. Through this literature, we believe that we should focus on complexity theory, such as positive feedback effects, in order to properly explain atypical financial fluctuations.

Unfortunately, based on previous research, it is not sufficient to fathom why the positive feedback effects in the stock market occur. Of course, these phenomena could arise from individual relationships. However, we should recognize the role of the social environment when these phenomena occur. That is to say, the positive feedback effects emerging from autonomous relationship among agents can be amplified by certain satisfied social conditions. Finally, we have not only studied an individual approach, but also social environment conditions, to understand the underlying mechanism of positive feedback effects, which can cause exceptional financial fluctuations.

First, we suggested that relative wealth concerns can play a major role in explaining the occurrence of positive feedback effects from the individual viewpoint. DeMarzo *et al* (2008) developed an analytical model to explain the financial bubble mechanism, based on the concept of relative wealth concerns.

*Correspondence: Duk Hee Lee, School of Business and Technology Management, College of Business, Korea Advanced Institute of Science and Technology, Daejeon, Korea.
E-mail: dukheelee@kaist.ac.kr

In this concept, an investor's utility depends not only on their return, but also on the wealth of their peers (Gomez *et al*, 2010). To match the wealth of their peers, investors choose to imitate the portfolios of wealthy peers, inducing a herd effect, and causing an aggregated impact on equilibrium prices (DeMarzo *et al*, 2008; Cole *et al*, 1992, 2001). However, there are some disadvantages of DeMarzo's model, which is that the model assumes agents to be fully rational, who can therefore obtain the fundamental value of stock by crossing demand and supply. In the model presented in this paper, however, our agents do not consider the fundamental value of the stock price, but instead focus on the future increasing or decreasing direction of the stock price, in order to make a profit by buying stocks before they rise and selling stocks before they fall (Harras and Sornette, 2011).

In order to make a solid bridge between relative wealth concerns and stock trading, we took into account the concept of risk attitude. Much literature on behavioral finance has revealed the principle of the driving force for stock-trading behavior as five key points, such as "investment horizon, confidence, control, risk attitude, and personalization of loss" (Wood and Zaichkowsky, 2004). More specifically, in this research, we only focused on how changeable risk attitude affects financial fluctuations by means of positive feedback effects. We separated three types of risk attitudes: (i) risk seeking, (ii) risk neutral, and (iii) risk averse—which are changeable, depending on the investor's relative wealth concerns (Hillson and Murray-Webster, 2007). According to the investor's risk attitude, the investor reveals various trading behaviors, which also allow us to observe how exceptional financial fluctuations emerge.

Another condition to consider is the viewpoint of social environment, specifically the wealth inequality of agents, which has been implemented into this research. According to many studies on this topic, the distribution of wealth is inclined to follow the power law empirically (Pareto, 1897; Ding and Wang, 2007; Levy and Solomon, 1997; Klass *et al*, 2007). Econophysicists have also tried to explain why the distribution of wealth follows the power law (Chatterjee and Chakrabarti, 2007; Cottrell *et al*, 2009). This topic, however, is beyond the scope of this research. Thus, we should only borrow the concept of wealth distribution to embody a more realistic social environment. In particular, the notion of relative wealth concerns and wealth inequality have dealt with the input parameters in our research. Furthermore, it is extremely difficult to represent complex phenomena, such as positive feedback effects, by using a traditional economic model, because we would not clearly describe the relationship between the individual investor and social conditions. Thus, we should find an alternative method for our research.

In the past, economic researchers often used statistical and mathematical methods to model economic fluctuations, which had some critical disadvantages, since real social phenomena are extremely complex, making it very difficult to represent these phenomena by using an analytical method (Gilbert and Terna, 2000). For instance, econometrics can effectively predict trends as long as something changes slightly. However, they failed to predict exceptional changes, and dynamic stochastic general equilibrium models suppose perfect market conditions (Farmer and Foley, 2009). In addition, some researchers have considered the concept of information cascades to explain the effect of positive feedback in financial fluctuation. Bikhchandani *et al* (1992) suggested an analytical model for information cascades in the financial market with a fixed asset price. An information cascade can occur when the imbalance of trading decisions is greater than a certain threshold. Otherwise, Avery and Zemsky (1998) built a model in a financial market where the asset price is flexible by a market maker. Cipriani and Guarino (2005) supported the aforementioned researches through a laboratory financial market. This study showed that information cascades should occur with fixed asset prices when the imbalance of decisions among traders is significant. However, in the process of information cascades, there is a critical assumption that a true fundamental price of an asset exists and agents' decisions are made by given exogenous information (Harras and Sornette, 2011).

However, in our agent-based model (ABM), agents can endogenously adapt their decisions based on the past correctness of information from neighborhood and public news without considering the fundamental value of the asset. If the credibility of information increases, the agent's trading decisions are more susceptible, resulting in the occurrence of positive effects. ABM is a system modeling technique, which uses a collection of autonomous decision-making individuals called 'agents', who make their decisions based on simple rules (Bonabeau, 2002; Chen, 2010). Using this method, we can construct an artificial stock market and find implications as to why the exceptional financial fluctuation occurs, by observing interactions between agents and adaptation of agents' trading decisions (Malek and Ezzeddine, 2011). Finally, we present the result of an artificial market process and interaction between these agents, demonstrating that relative wealth concerns not only cause a positive feedback effect in the dynamics of financial fluctuations, but also explain why wealth inequality could amplify the positive feedback effect, by offering social conditions that can incite relative wealth concerns among agents.

2. Model

2.1. Model background and hypothesis

In this research, we construct an artificial stock market based on ABM, and use a modification of Harras and Sornette's (2011) model. There are a fixed number of agents and a single stock on the stock market. In our model, agents cannot obtain more liquidity, and our artificial stock market does not allow the inflow and outflow of agents. For each time step, agents can decide on the stock order amount. Also, each agent has different levels of trading conviction, and there is heterogeneity among the agents as to how they weigh this information. Thus, there are various demands for stocks in the artificial stock market.

Unlike Harras and Sornette (2011)' model, all agents take into consideration the relative wealth of their connected agents in this research. By considering their peers' wealth, agents' risk attitudes are also revised. As a result, we can observe various investment portfolios in the stock market. Furthermore, by increasing the propensity among the agents for imitating others' investment strategies, we can observe the same direction of investment decisions in the market, which causes the emergence of patterns, such as positive feedback trading behavior. Of course, this phenomenon can occur when social inequality is adequate for inciting an agent's relative wealth concerns. That is to say, if the society is apparently fair about wealth distribution, nobody would hope to match their peers' wealth by imitating others' trading strategies, because there are only limited incentives to reduce the wealth difference.

Based on these sequential mechanisms, we establish our hypothesis that agents' risk attitudes are changed according to their relative wealth concerns, by comparing their peers' wealth and their wealth. Furthermore, wealth inequality is a paramount factor for the occurrence of positive effects, because a severe polarization of wealth distribution would intensify the propensity of relative wealth concerns among agents. As a result, we can observe an extraordinary financial fluctuation, such as the financial crisis. Lastly, we summarize, in Appendix Table A1, the input variables, output variables, internal variables, and parameters. We also note that the notations for the variables and parameters follow Appendix Table A1 in this research.

2.2. An agent's decision

In this model, agents develop their stock-trading decisions based on three pieces of information at each time step: (i) public information; (ii) information from their peers; and (iii) private information. Using the three aforementioned sources of information, the opinion of agent i at time t, $\omega_i(t)$, consists of the weighted sum (Harras and Sornette, 2011):

$$\omega_i(t) = c_{1i}(t)\sum_{j=1}^{J} k_{ij}(t-1)E_i\left[s_j(t)\right] + c_{2i}u(t-1)n(t) + c_{3i}\varepsilon_i(t). \tag{1}$$

To be specific about Equation (1), $\omega_i(t)$ represents the opinion of agent i at time t, which consists of three parts: the first part is information from their peers; the middle part is public information; and the last part is private information. Via Equation (1), agents digitize their trading decisions, and then compare these values with their trading conviction factor ($\underline{\omega_i}(t)$) at every time step. $k_{ij}(t)$ and $u(t)$ represent the credibility of peer information and public information, respectively. In addition, $E_i[s_j(t)]$ represents the expected action by the neighbors, where $s_j(t)$ represents the direction (buy or sell) of agent j. Through this summation, agent can predict the action of its neighbors and reflect this information in its own decision-making. $n(t)$, $\varepsilon_i(t)$ are public information and private information, respectively, chosen randomly according to a Gaussian distribution, with unit variance at each time step. Therefore, this information offers positive signs and negative signs to agents, according to statistical distributions. Thus, the consecutive coincidences of information signs can lead to the development of homogeneous stock trading among agents, at the inception of positive feedback effects.

The values ($c_{1i}(t)$, c_{2i}, c_{3i}) represent not only the heterogeneity of an agent i's trading style, but also the weight of each piece of information. These factors can affect stock-trading decisions significantly, since these factors signify the agents' preference for different sources of information. While c_{2i} and c_{3i} are chosen randomly from the intervals $[0, C_2]$, respectively, $[0, C_3]$, the weight of the neighbor's information $c_{1i}(t)$ is determined by the ratio of the agent's wealth to the sum of their neighbor's wealth, multiplied by the inherent propensity of relative wealth concerns:

$$c_{1i}(t) = \frac{\sum_{j=1}^{J} \text{Wealth}_j(t-1)}{\text{Wealth}_i(t-1)} \times \log \gamma_i, \tag{2}$$

where γ_i represents the propensity of relative wealth concerns of agent i, and γ_i follows the uniform distribution on the interval $[1, \Gamma]$ at inception. From Equation (2), we can observe that the weight of the neighbor's information $c_{1i}(t)$ would increase when the gap between the agent's wealth and their peers' wealth increases, or when the propensity of the relative wealth concerns of the agent increases.

In particular, to weigh up peer information excessively indicates that each agent would not pay attention to the signals of public and private information. As a result, indiscriminate imitations of peers' trading decisions occur, leading to de-individualized and unidirectional trading behaviors within the market group. We have considered this phenomenon as the positive feedback effect in this study.

Each agent has a heterogeneous risk attitude—risk averse, risk tolerant, or risk seeking—determined by $c_{1i}(t)$. First of all, the propensity of investment is determined by risk attitude. After deciding risk attitude, agents follow the trading conviction factor and investment ratio by considering their risk attitude. The risk-seeking propensity has a more aggressive trading style than the other attitudes. Thus, if the number of risk seekers increases because of wealth inequality, many agents invest stocks unreasonably by only imitating peers' trading decisions to match peers' wealth. These phenomena can amplify the financial fluctuation. On the other hand, if most investors' risk propensity is risk averse, it is extremely difficult to observe the amplified financial fluctuation, since there is not vigorous trading in the artificial stock market.

Also, the risk attitude decides the propensity of investment; more specifically, the trading conviction factor $\underline{\omega_i}(t)$ and investment ratio $g_i(t)$ are chosen as shown in Table 1 (Hillson and Murray-Webster, 2007):

The trading conviction factor and investment ratio significantly affect the trading decisions; if the agent's opinion $\omega_i(t)$ is greater than $\underline{\omega_i}(t)$, then the agent buy stock. However, if the agent's opinion $\omega_i(t)$ is less than $-\underline{\omega_i}(t)$, then the agent sells the stock. In cases where neither is true, agent does not trade at all at time t. Also, $g_i(t)$ represents the amount of stock an agent tries to trade by considering its assets. Higher $g_i(t)$ indicates that the agent attempts to trade a large portion of its assets, whereas lower $g_i(t)$ indicates the opposite.

Agents decide their trading strategies at every time step as following steps. First, they compare the weighted sum from Equation (1) with their trading conviction. Using this comparison, they determine the trading decision, either buying, selling, or holding. In particular, risk seekers have a lower trading conviction, and try to trade stocks more than other propensities of risk attitude. On the contrary, risk-averse agents have a higher trading conviction; thus, they hope to maintain their assets without any trading.

In addition, they also determine their trading volumes after deciding whether to buy, sell, or hold. $s_i(t)$ represents a trading direction and $v_i(t)$ determines a trading volume by considering risk attitude. Then, the agents' trading strategies are transmitted to the market clearing system by multiplying $s_i(t)$ by $v_i(t)$. As a result, the sum of trading orders is considered as the demand for stock, and the market clearing system decides the next step for the stock price by using it.

2.3. Market clearance

After all the agents have decided on their stock orders, the new *stockprice* is determined by a price-clearing system (Cottrell *et al*, 2009)

$$\log(\text{stockprice}[t]) - \log(\text{stockprice}[t-1]) = \frac{D(t)}{\lambda}, \tag{3}$$

$$D(t) = \frac{1}{N}\sum_{i=1}^{N} s_i(t)v_i(t). \tag{4}$$

Equation (3) shows how to decide the stock price. $D(t)$ is the demand for the stock orders by combining each agent's trading decisions.λ represents the market depth which can control the variation in stock price. When the *stockprice* has been determined, $\text{cash}_i(t)$ and $\text{stock}_i(t)$ are updated by the following equations:

$$\text{cash}_i(t) = \text{cash}_i(t-1) - s_i(t)v_i(t)\text{stockprice}(t), \tag{5}$$

$$\text{stock}_i(t) = \text{stock}_i(t-1) + s_i(t)v_i(t). \tag{6}$$

2.4. Adaption

All agents can also consider their past performance, which acts as feedback for their next step decision. In particular, each agent estimates the value of three types of information after determining the new stock price from the correlation of the source's prediction and the excess demand in the market. Through these actions, the agents are able to adapt their strategy to the current market regime by using the following equations:

$$u(t) = \beta \cdot u(t-1) + (1-\beta)n(t)\frac{D(t)}{\lambda \cdot \sigma(t)}, \tag{7}$$

$$k_{ij}(t) = \beta \cdot k_{ij}(t-1) + (1-\beta)E_i[s_j(t)]\frac{D(t)}{\lambda \cdot \sigma(t)}, \tag{8}$$

$$\sigma^2(t) = \frac{1}{t}\sum_{l=1}^{t} D(l)^2 - \left(\frac{1}{t}\sum_{l=1}^{t} D(l)\right)^2. \tag{9}$$

$u(t)$ and $k_{ij}(t)$ represent the credibility of public and neighborhood information, respectively. β represents the memory discount factor, which can control how much to reflect on the previous value of $u(t)$ and $k_{ij}(t)$. If $\beta = 0$, agents do not consider the previous value, meaning that agents only focus on the performance of the current step. Otherwise, if $\beta = 1$, agents do not pay attention to the feedback sign; the credibility of public and neighborhood information is fixed as an inherent condition.

Equation (9) shows the volatility of excess demand ($\sigma^2(t)$) in this artificial market. It also affects the credibility of information. If the volatility increases, it affects the credibility of information source negatively, since the agent would deal with this information as a lower reliability source. By considering the correlation between predictions of each type of information and the sign of excess demand, $u(t)$ and $k_{ij}(t)$ are accumulated or dissipated. Public information, in

Table 1 Risk attitude for agents

	Criteria	$\underline{\omega_i}(t)$	$g_i(t)$
Risk seeking	$c_{1i}(t) > \text{TP}_{\text{ST}}$	RA_S	IR_S
Risk tolerant	$\text{TP}_{\text{TA}} < c_{1i}(t) < \text{TP}_{\text{ST}}$	RA_T	IR_T
Risk averse	$c_{1i}(t) < \text{TP}_{\text{TA}}$	RA_A	IR_A

particular, announced the favorable condition or unfavorable condition of a stock, based on stochastic distribution. Thus, if the coincident streak of same direction information is announced, $u(t)$ would increase, and the credibility of public information would be a significant factor in developing the agent's trading decision. However, it has an upper limit to mature the positive feedback effect, because the direction of public information is changed abruptly, owing to its stochastic characteristic.

In contrast, $k_{ij}(t)$ can be increased without any upper bounds if the direction of peers' decisions is consistent with the direction of stock price. Therefore, the credibility of neighborhood information can be amplified when adjacent peers predict the direction of stock price properly. In addition, when agents' $k_{ij}(t)$ exceed a certain (but unknown) point, agents would not pay attention to other information sources; they only focus on imitating peers' trading decisions, which signify the positive feedback effects. We can, therefore, forecast when the positive feedback effect will occur, by measuring the average of $k_{ij}(t)$ among agents. If the average of $k_{ij}(t)$ increased exceptionally, the society of artificial stock market is located in a certain excitable region that can cause amplified positive feedback effect.

In summary, agents adapt continuously to the current market, which leads to positive feedback owing to the agent's imitation characteristics, which, in turn, result in an unsustainable stock price.

3. Results

3.1. Initial conditions

An agent-based model is needed to design appropriate assumptions to describe the real phenomena by considering the model's simplification. In this simulation, we have a few fixed numerical assumptions and other assumptions, as shown in Table 2. Due to the inherent nature of modeling, it is crucial to have well-reasoned numerical assumptions that sets the foundation in ABM. In this paper, such numerical assumptions were derived through rigorous trials, where we found a reasonable combination of numerical assumptions that produced the results best representative of expected scenarios.

In this model, we take into account the wealth inequality among agents. We therefore embody the distribution of $\text{cash}_i(0)$ and $\text{stock}_i(0)$, following the Pareto law at inception (Ding and Wang, 2007; Raberto *et al*, 2003; Takayasu, 1990):

$$\text{wealth}_i(0) = \frac{i^{-\frac{1}{\alpha}} \cdot M}{\sum_{i=1}^{N} i^{-\frac{1}{\alpha}}} \tag{10}$$

$$\text{cash}_i(0) = \text{wealth}_i(0) \times 0.5, \tag{11}$$

$$\text{stock}_i(0) = \frac{\text{wealth}_i(0) \times 0.5}{\text{stockprice}(0)} \quad \text{for } i = 1, \ldots, N. \tag{12}$$

Equation (10) shows how to distribute agents' wealth by following the Pareto law (α). Even though agent's wealth is distributed with the sequential ordering in Equation (10), each agent is randomly assigned according to periodic boundary condition on grid space, thus giving rise to wealth inequality among agents. We fix the total initial market fund (M); however, the wealth distribution and the total market fund would be changed by stock transactions, according to the stream of time.

3.2. Threshold analyses

Phase transitions are the inherent characteristics of the Ising model, which supports the verification of the complexity simulation model. We checked whether our model follows the expected results based on our hypothesis using threshold analyses.

Figures 1 and 2 show the transition of maximum of $\langle k \rangle$, respectively. We first represented the relationship between Γ and Max.$\langle k \rangle$ by changing α in Figure 1. We can detect a phase-transition point where $\Gamma = 1.5$. In the region $\Gamma < 1.5$, the propensity of relative wealth concerns is lower; thus, agents do not weigh the neighbors' information, because there are few incentives to catch up with peers' wealth by imitating

Table 2 Fixed numerical assumptions and other assumptions in our simulations

Name	*Value*	*Description*
Step	500	The maximum of time steps
N	2500	The number of agents
M	7.5×10^6	The total initial market fund
β	0.8	The memory discount
λ	4.0	The market depth
C_2	1.0	The maximum value of c_2
C_3	1.0	The maximum value of c_3
stockprice(0)	10	The initial stock price
Space	50×50 grid space (periodic boundary condition)	
Neighborhoods	Von Neumann	
Initial locations	Random	
Updating	Sequential updating mechanism (random ordering)	

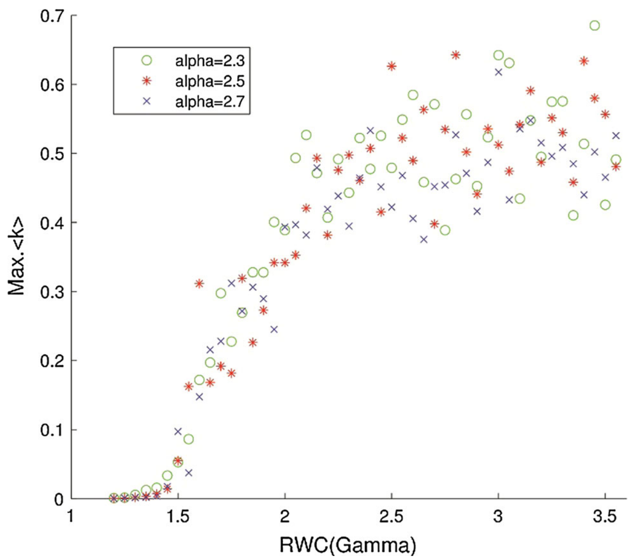

Figure 1 The transition of maximum of $\langle k \rangle$ according to Γ.

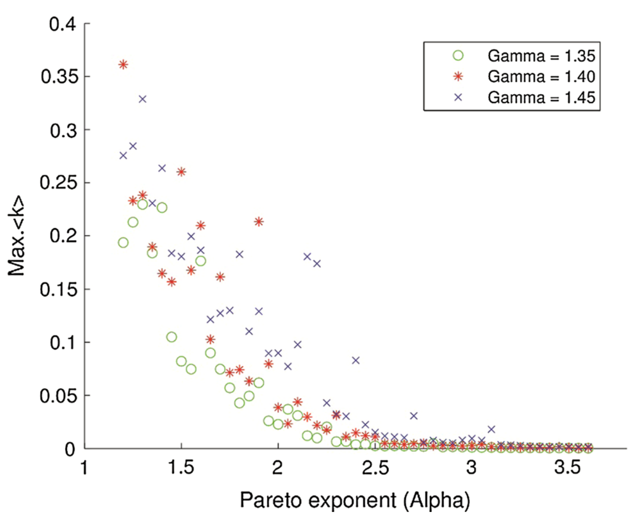

Figure 2 The transition of maximum of $\langle k \rangle$ according to α.

others' trading decision. However, in the region $\Gamma > 1.5$, agents changed their propensity excessively by weighing up peers' decision, thus amplifying the synchronized opinion among agents. Also, Max.$\langle k \rangle$ increases as α decreases as well, meaning that wealth inequality can amplify the imitation propensity in stock trading, causing positive feedback effects.

Figure 2 shows the relationship between Max.$\langle k \rangle$ and α by changing Γ. In this graph, we can also detect the phase-transition point where $\alpha = 2.0$. In the region $\alpha < 2.0$, agents can recognize the wealth gap by comparing peers' wealth. Thus, agents try to catch up with their cohort's wealth by imitating peers' trading decisions. In addition, Max.$\langle k \rangle$ increases as Γ increases, indicating that higher relative wealth concerns can lead to an excessive imitation of stock trades among agents.

3.3. Sensitivity analyses

A virtual experiment based on random seeds can be misleading if we try to simulate our model only once. Thus, we should find the particular patterns through repeated simulations, a statistically significant number of times (Axelrod, 1997; Rand and Rust, 2011). Also, owing to the variations inherent in our computer program model, we need to iterate our model many times to assess the impact of varying the input parameters on our output variables (Gilbert and Terna, 2000).

Table 3 shows the numerical assumptions in sensitivity analysis, which are the most suitable datasets from Jarque–Bera test (Jarque and Bera, 1980). Furthermore, in order to analyze the behavior of our system, we developed meta models based on regression analysis. We determined three types of dependent variables, consisting of the maximum value of *stockprice*, the maximum of $\langle k \rangle$, and the maximum of $\langle u \rangle$. Also, we chose the Pareto exponents α, Γ, TP_{ST}, and TP_{TA} as the independent variables.

In this paper, we fixed the range of the Pareto exponent to be between 1.5 and 3.5 because many other papers have shown empirically that the distribution of wealth follows the power law, with a Pareto exponent between 1.5 and 3.5 (Pareto, 1897; Ding and Wang, 2007; Levy and Solomon, 1997; Klass *et al*, 2007). The range of Γ is determined by considering the threshold analysis. We already revealed the transition points. Thus, we considered value sets of Γ over 1.5. TP_{ST}, and TP_{TA} affect the number of risk-averse, risk-tolerant, and risk-seeking agents. Thus, it is imperative to build the appropriate personnel organization with regard to risk attitude by adjusting TP_{ST}, and TP_{TA}. In this paper, by counting the number of risk-averse, risk-tolerant, and risk-seeking agents, respectively, we designed the experimental specification of sensitivity analysis, as shown in Table 4.

Also, we measured the maximum of stockprice(t), the maximum of $\langle k \rangle$, and the maximum of $\langle u \rangle$ for the sensitivity analyses, but we excluded values above 150 of *stockprice*, to prevent the distortion of the statistical results. These data take into account the dependent variables in the sensitivity analysis.

In order to clarify the relationship between input and output values, we performed the regression analysis. Table 5 shows the results of these analyses. First, in the maximum *stockprice* of the meta model, we can observe a negative coefficient of α, which implies that decreasing the polarization of the wealth distribution affects the *stockprice* negatively, owing to the decreasing probability of the occurrence of atypical financial fluctuations. In addition, Γ is a more significant coefficient than α, because the relative concern factor (γ_i) affects the weight of the neighborhood information directly ($c_{1i}(t)$). In particular, to weigh up the peer information arising from relative wealth concerns indicates that each agent would not pay attention to the signals of public and private information.

Table 3 Numerical assumptions in sensitivity analysis

Name	*Value*	*Description*
IR_S	0.10	The investment ratio of risk seeking
IR_T	0.04	The investment ratio of risk tolerant
IR_A	0.03	The investment ratio of risk averse
RA_S	0.75	The trading conviction factor of risk seeking
RA_T	3.00	The trading conviction factor of risk tolerant
RA_A	5.00	The trading conviction factor of risk averse

Table 4 The experimental design specification for sensitivity analysis

Input parameter	*Value*	*Description*
α	1.5, 2.0, 2.5, 3.0, 3.5 (5 cases)	The Pareto exponent
Γ	1.7, 1.8, 1.9, 2.0, 2.1 (5 cases)	The maximum value of each agent's γ
TP_{ST}	1.15, 1.20, 1.25 (3 cases)	The tipping point between risk seeking and tolerant
TP_{TA}	0.65, 0.70, 0.75 (3 cases)	The tipping point between risk tolerant and averse
Total cells	225 cells	$3^2 \times 5^2$ cases
Replications	30 times	–

Table 5 Regression for sensitivity analysis

Independent variable	*Maximum of* ⟨stockprice⟩	*Maximum of* $\langle k \rangle$	*Maximum of* $\langle k \rangle$
α	−0.115**	−0.275**	0.038
Γ	0.364**	0.238**	−0.150**
TP_{ST}	−0.082**	−0.048**	0.511
TP_{TA}	−0.019*	−0.024**	0.056
Adjusted R^2	0.153	0.135	0.003

p-value ** < 0.001, p-value *< 0.05

As a result, agents focus excessively on imitating peers' trading decision, thus amplifying the probability of not only positive feedback effects, but also extreme financial fluctuations in the artificial stock market.

In the maximum of a $\langle k \rangle$ meta model, we can observe a pattern similar to the aforementioned meta model. In these two cases, the p-values of α and Γ are less than 0.001, meaning that these variables affect the output variables significantly. Also, in absolute value terms, the coefficient of TP_{ST} is greater than TP_{TA}, which shows that an additional risk-seeking agent is able to affect the outputs with more impact than other propensity agents such as risk tolerant and risk averse. On the contrary, the maximum of $\langle u \rangle$ meta model shows the higher p value, meaning that public information cannot affect the output values significantly. That is, even if coincidental streaks of positive or negative public information occur, these by-chance events cannot lead to sufficiently positive feedback effects.

For all meta models, R-squared is even less than 0.2. However, we should not predetermine the validation of regression model based only on low values of R-squared. The aim of this research is not how appropriately the input parameters fit the trend of the virtual experiment results, but to reveal the paramount factors that affect stock prices and positive feedback effects. Thus, we should focus on the p-value and the coefficients of the independent variables, rather than on R-squared (Colton and Bower, 2002). In addition, the reason why this model has a lower R-squared value is that the computational model not only has a lot of internal variables based on statistical distributions, but also has a few outlying output values, as a result of exceptional financial fluctuations caused by positive feedback effects.

From these statistical analyses, we can infer that the polarization of the wealth distribution, and the relative wealth concerns of agents, would lead to positive feedback effects from the propensity to imitate, by increasing the credibility of others' opinions, in order to catch up with the peers' wealth, which has an effect on economic fluctuations. In other words, we can conclude that our hypothesis has reasonable credibility from various statistical indicators.

4. Discussion

This research looked into the question of whether relative wealth concerns can affect financial fluctuations, by adopting an agent-based modeling approach. Agents made their stock decisions based on three types of information. These decisions were accumulated in the stock market, and the stock price for the next step was determined by using a price-clearing condition. These sequential mechanisms occurred recurrently in the artificial stock market until the final step. Interestingly, we observed an emerging pattern, like extreme financial fluctuations, based on the spontaneous interaction among agents. We thus established the hypothesis of why these phenomena occur, and also suggested a rigorous model to bolster our hypothesis.

We established our proposed hypothesis that agents' risk attitudes are changed according to relative wealth concerns by comparing their peers' wealth and their wealth. Furthermore, we took into account wealth inequality as a paramount factor for the occurrence of positive effects because a severe polarization of wealth distribution would intensify the propensity of relative wealth concerns among agents.

We can now derive meaningful conclusions through sensitivity analyses. First, the polarization of the wealth distribution affects the behavior of agents. As wealth inequality worsens, agents recognize the gap of wealth between them and their peers. Therefore, they try to catch up with their peers' wealth by weighing up neighbors' information. In particular, if the Pareto exponent passes the phase-transition points by worsening the wealth distribution, we observe not only extreme financial fluctuations, but also positive feedback effects.

Second, the inherent propensity of relative wealth concerns also affects the occurrence of positive feedback effects significantly. Most agents would like to imitate others' decisions because of the incentives to increase their wealth. Thus, the inherent propensity of relative wealth concerns can amplify the behavior that weighs up the neighbors' information signal. In particular, if the propensity of relative wealth concerns is amplified, agents pay no attention to others' source of information, except for neighbors' information. As a result, agents imitate their peers' decisions excessively, which causes the positive feedback effects. Lastly, the number of risk-seeking agents also should be considered as important. Risk seekers attempt to trade excessively without considering their assets. Thus, the amount of trading increases abruptly if there are many risk seekers in the market. If the number of risk seekers increase, owing to unexpected conditions, such as worsening wealth inequality and amplifying the propensity of relative wealth concerns, many agents would speculate on the stock to catch up with their peers' wealth.

In summary, this research has allowed us to demonstrate how wealth inequality and relative wealth concerns can affect today's financial mechanism, by means of positive feedback.

Acknowledgments—This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (2014S1A3A2044459).

Statement of contributions Duk Hee Lee proposed the model, and Joohyun Kim analyzed the results of simulations. All the authors equally contributed to the preparation of the manuscript of the paper.

References

Avery C and Zemsky P (1998). Multidimensional uncertainty and herd behavior in financial markets. *American Economic Review* **88**: 724–748.

Axelrod R (1997). *Advancing the Art of Simulation in the Social Sciences.* Santa Fe Institute.

Bikhchandani S, Hirshleifer D and Welch I (1992). A theory of fads, fashion, custom, and cultural changes as informational cascades. *Journal of Political Economy* **100**: 992–1026.

Bonabeau E (2002). Agent-based modeling: Methods and techniques for simulating human system. *Proceedings of the National Academy of Sciences of the United States of America* **99**: 7280–7287.

Boschi M and Goenka A (2012). Relative risk aversion and the transmission of financial crises. *Journal of Economic Dynamics and Control* **36**: 85–99.

Chatterjee A and Chakrabarti BK (2007). Kinetic exchange models for income and wealth distribution. *The European Physical Journal B* **60**:135–149.

Chen S (2010). *Agent-Based Modeling for Wealth and Income Distribution*. Universita Politecnica delle Marche.

Chiarella C, Dieci R and Gardini L (2006). Asset price and wealth dynamics in a financial market with heterogeneous agents. *Journal of Economic Dynamics and Control* **30**: 1755–1786.

Cipriani M and Guarino A (2005). Herd behavior in a laboratory financial market. *American Economic Review* **95**: 1427–1441.

Cole HL, Mailath GJ and Postlewaite A (1992). A social norms, savings behavior, and growth. *Journal of Political Economy* **100**: 1092–1125.

Cole HL, Mailath GJ and Postlewaite A (2001). Investment and concern for relative position. *Review of Economic Design* **6**: 241–261.

Colton JA and Bower KM (2002). *Some Misconceptions About R Square*. Extraordinary Sense, International Society of Six Sigma Professionals.

Cottrell AF, Cockshott P, Michaelson GJ, Wright IP and Yakovenko V (2009). *Classical Econophysics*. 1st edn, Oxford: Routledge.

DeMarzo PM, Kaniel R and Kremer I (2008). Relative wealth concerns and financial bubbles. *The Review of Financial Studies* **21**: 19–50.

Ding N and Wang YG (2007). Power-law tail in the Chinese wealth distribution. *Chinese Physics Letter* **24**: 2434–2436.

Farmer JD and Foley D (2009). The economy needs agent-based modeling. *Nature* **460**: 685–686.

Gaunersdorfer A (2000). Endogenous fluctuations in a simple asset pricing model with heterogeneous agents. *Journal of Economic Dynamics and Control* **24**: 799–831.

Gilbert N and Terna P (2000). How to build and use agent-based models in social science. *Mind and Society* **1**: 57–72.

Gomez JP, Priestley R and Zapatero F (2010). *The Effect of Relative Wealth Concerns on the Cross-Section of Stock Returns*. Instituto de Empresa and Area of Economic Environment.

Harras G, and Sornette D (2011). How to grow a bubble: A model of myopic adapting agents. *Journal of Economic Behavior and Organization* **80**: 137–152.

Hillson D and Murray-Webster R (2007). *Understanding and Managing Risk Attitude*. 2nd edn, Aldershot: Gower Publishing, Ltd.

Huang W, Zheng H, and Chia WM (2010). Financial crises and interacting heterogeneous agents. *Journal of Economic Dynamics and Control* **34**: 1105–1122.

Jarque CM and Bera AK (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letter* **6**: 255–259.

Kindleberger CP and Aliber R (2005) *Manias, Panics, and Crashes: A History of Financial Crises.* 5th edn, New York: Wiley.

Klass OS, Biham O, Levy M, Malcai O and Solomon S (2007). The Forbes 400, the pareto power-law and efficient markets. *The European Physical Journal B* **55**: 143–147.

Levy M and Solomon S (1997). New evidence for the power-law distribution of wealth. *Physica A* **242**: 90–94.

Malek B and Ezzeddine A (2011). Agent-based approach to asset price fluctuations and excess volatility: An experimental investigation. *Middle Eastern Finance and Economics* **12**: 159–173.

Pareto V (1897). *Course dEconomie Politique.* Lausanne.

Raberto M, Cincotti S, Focardi SM and Marchesi M (2003). Traders' long-run wealth in an artificial financial market. *Computational Economics* **22**: 255–272.

Rand W and Rust RT (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing* **28**: 181–193.

Shefrin H (2005). *A Behavioral Approach to Asset Pricing*. 2nd edn, Boston: Academic Press.

Sornette D (2003). *Why Stock Markets Crash.* 1st edn, Princeton: Princeton University Press.

Takayasu H (1990). *Fractals in the Physical Science.* 1st edn, New York: Wiley.

Wood R and Zaichkowsky JL (2004). Attitudes and trading behavior of stock market investors: A segmentation approach. *Journal of Behavior Finance* **5**: 170–179.

Appendix

Table A1 The parameter specifications

Type	*Name*	*Description*
Input	α	The Pareto exponent
	Γ	The maximum value of each agent's propensity of relative wealth concerns
	$\mathrm{TP}_{\mathrm{ST}}$	The tipping point of risk attitude between risk seeking and risk tolerant
	$\mathrm{TP}_{\mathrm{TA}}$	The tipping point of risk attitude between risk tolerant and risk averse
Output	$\mathrm{stockprice}(t)$	The stock price at time t
	$\langle k(t)\rangle$	The average of the credibility of the neighbor's information among agents
	$\langle u(t)\rangle$	The average of the credibility of the public's information among agents
Parameter	*Step*	The maximum of time steps
	N	The number of agents
	M	The total initial market fund
	J	The number of neighbors
	α	The Pareto exponent
	β	The memory discount
	λ	The market depth
	c_{2i}	The weight of public information of agent i
	c_{3i}	The weight of private information of agent i
	C_2	The maximum value of each agent's c_2
	C_3	The maximum value of each agent's c_3
	γ_i	The relative wealth concerns of agent i
	IR_{S}	The investment ratio of risk seeking
	IR_{T}	The investment ratio of risk tolerant
	IR_{A}	The investment ratio of risk averse
	RA_{S}	The trading conviction factor of risk seeking
	RA_{T}	The trading conviction factor of risk tolerant
	RA_{A}	The trading conviction factor of risk averse
Internal variables	$c_{1i}(t)$	The weight of neighborhood information of agent i at time t
	$\omega_i(t)$	The opinion of agent i at time t
	$\underline{\omega_i}(t)$	The trading conviction factor of agent i at time t
	$\varepsilon_i(t)$	The private information of agent i at time t
	$n(t)$	The public information at time t
	$E_i[s_j(t)]$	The expected action of the neighbor j estimated by agent i at time t
	$s_i(t)$	The direction of the opinion of agent i at time t
	$v_i(t)$	The volume of trading of agent i at time t
	$u(t)$	The credibility of the $n(t)$ at time t
	$k_{ij}(t)$	The credibility of the $E_i[s_j(t)]$ at time t
	$\sigma(t)$	The volatility at time t
	$D(t)$	The excess demand in the market at time t
	$g_i(t)$	The investment ratio of agent i at time t
	$\mathrm{wealth}_i(t)$	The wealth of agent i at time t
	$\mathrm{cash}_i(t)$	The amount of cash of agent i at time t
	$\mathrm{stock}_i(t)$	The number of stocks of agent i at time t

Received 17 December 2014;
accepted 23 June 2016