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Research Article

Understanding How Short-Termism and a Dynamic Investor Network Affects Investor Returns: An Agent-Based Perspective

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The unexplained and inconsistent behavior of financial markets provides the motivation to engage interdisciplinary approaches to understand its intricacies better. A proven approach is to consider investors as heterogeneous interacting agents who form information networks to inform their investment decisions. The rationale is that the topology of these networks has contributed to a better understanding of the erratic behavior of financial markets. Introducing investor heterogeneity also allows researchers to identify the characteristics of higher performing investors and the implications of investors exhibiting short-termism, a feature recognized by some as detrimental to the performance of the economy. To address these topics, an agent-based artificial stock market is implemented, where investors utilize various information sources, including advice from investors in their network, to inform their investment decisions. Over time investors update their trust in their information sources and evolve their network by connecting to outperforming investors—Oracles—and discarding poor advisers, thereby simulating the evolution of an investor network. The model's most significant finding is uncovering how the market's behavior is materially affected by the time-horizon of investors, with short-term behavior resulting in greater volatility in the market. Another finding is the reason why short-term investors generally outperform their long-term counterparts, particularly in more volatile environments. By providing significant insights into the formation of an investor network and its ramifications for market volatility and wealth creation (destruction), this paper provides crucial clues regarding the empirical data that needs to be collected, assessed, and tracked to ensure policymakers and investors better understand the dynamics of financial markets.

1. Introduction

Since the inception of equity markets, investors have attempted to enhance their wealth by investing their capital into these markets. However, the inconsistent behavior of equity markets has meant that most investors have failed to master them and achieve their investment goals. The dominant theory, at least until the 2000s, was that investors should accept that financial markets behave in an efficient manner, resulting in asset returns matching a Gaussian distribution as a consequence of a random-walk process ([1, 2]). The basis of the efficient market approach, as encapsulated in the Efficient Market Hypothesis (EMH) [3], is that a representative rational agent has timely access to all necessary information, correctly evaluates that information, and makes the optimal investment decisions, thereby ensuring that prices reflect the most recent and relevant information. However, the financial pricing models related to the principle of efficient markets have been found to provide only a rough approximation of financial returns and have failed to explain outlying events [4]. Further, two critical implications stem from the EMH: prices are always right, and no investor can outperform the market over the long-term on a risk-adjusted basis [5].

While there is some supporting evidence that on average investors have been unable to outperform the market ([6–8]), evidence does exist that some investors (represented in this paper as Oracles) have achieved and maintained a material positive performance differential over the market ([9, 10]). Two possible determinants of investment performance considered in this paper are the tendency of investors to trade and the investment horizon of investors. Barber and Odean [11] highlight opposing explanations regarding the observed levels of trading, with the theory most relevant to this paper being that excess trading occurs because investors have a short-term focus and this leads to excessive speculative trading [12] which, in turn, results in inferior wealth generation [11]. Alternatively, when faced with volatile markets, it has been found that it is optimal for investors to employ short-term trading strategies [13].

Regarding the return characteristics of financial markets, these have been found to demonstrate a specific set of stylized facts that contradict the EMH-based Gaussian models. Kaldor [14] originally defined stylized facts as stable patterns that emerge from multiple empirical data sources after abstracting from the minutia of the evidence. The utility of stylized facts is that they enable the researcher to build a model capable of identifying, explaining, and communicating critical observations that require a scientific explanation without having the burden of explaining all the variations in the empirical evidence [15]. The vital stylized facts related to financial markets are excess volatility, the existence of large movements not supported by the arrival of new news; heavy tails, returns that exhibit heavy tails or fat tails; volatility clustering, large changes accompany further large changes; and volume/volatility clustering, trading volumes and volatility showing the same type of extended memory ([16, 17]). As expanded upon later, the utilization of these stylized facts has been instrumental in proving the utility of agent-based artificial stock markets.

Another vital characteristic of asset returns is that they have been found to match a power-law distribution over extended time intervals [18]. The existence of power-law returns provides the crucial insight that financial markets may operate as a complex adaptive system (CAS). Utilizing a CAS framework has become increasingly popular and relevant in attempting to understand the behavior of financial markets (for example, see [17, 19, 20]). Dependencies and the interaction between the various individual component of a CAS are deemed responsible for creating the macrolevel emergent outcomes [21], including extreme market movements. Allowing investors to interact with and receive information from other investors enables them to form an information network. The critical consequences of this process are that investor networks and financial networks in general have been found to be capable of affecting the behavior of the market ([22–24]), and they explain trading volumes and the performance of investors ([25, 26]). Critically, this analysis has not been, nor can it be, considered in the models underwritten by a representative agent approach.

The evidence on investment performance, trading volumes, and the non-Gaussian distribution of asset returns opens several compelling research questions. Specifically, issues arise regarding what makes high-performing investors unique, including how do they utilize various information sources to determine their investment decisions; how often do they trade; and what are the consequences of other investors attempting to replicate their strategies? These questions are addressed in this paper, by linking heterogeneous interacting investors with different investment horizons across a dynamic network, with trading information flowing across the network.

Unlike the return profile of financial markets, there is yet to emerge a definitive agreed-upon set of empirically grounded theories regarding the role of investor networks. This issue is most likely due to the rapid development of the research field and the initial and ongoing difficulty in accessing timely data to assess both the static and dynamic characteristics of these networks. The findings of Ozsoylev and Walden [25] are utilized to establish a level of empirical validation for the model presented in Section 2. Of most significance is that the investors with the highest connectedness will earn the largest profits from trading more aggressively, and the market's price volatility will be highest in an environment where the investor network exhibits an intermediate level of connectedness and lowest in markets with higher or lower levels of connectedness. The latter suggests that a scale-free topology will exhibit the highest volatility, a theory confirmed in various agent-based models (ABMs) (see [22, 27, 28]).

The standard analytical tools that underlie much of the conventional financial market analysis become redundant in the realm of a CAS [29]. ABMs are a possible solution as they allow researchers to build simulations from a bottom-up perspective, with the agents interacting with and adapting to their environment. Another justification for utilizing agent-based modeling, even in the absence of empirical data, is that ABMs can guide data collection and illuminate core dynamics [30]. Alternatively, ABMs can uncover the dynamics responsible for generating the stylized facts of financial markets [31], as evidenced by the substantial insights achieved via agent-based artificial stock markets (as reviewed in [32, 33]). Notably, the original models explained a great deal without the use of networks [34]. Despite this, the inclusion of networks within this framework is becoming an established field of research because by introducing structural heterogeneity—which manifests itself as a network between investors [34]—new dynamics regarding the stylized behavior of financial markets have been uncovered (recent examples include [22, 28, 35–37]). The common theme of these network models is that they utilize exogenously imposed, static, stylized networks. Therefore, the research gains in this area have occurred without empirically supported network structures.

A downside to the previously mentioned network modeling approach is that it limits the analysis to assessing the behavior of investors across a predefined static network, thereby providing no insight into how the network evolves. However, research is now expanding toward explaining the dynamics responsible for influencing how a network's structure evolves. ABMs have proven to be a successful tool for understanding the dynamics of network formation [38], with this paper making a further contribution to the research field. Within the artificial stock market literature, there is a body of work, which forms the foundation for this paper, that implements models that endogenously evolve networks between investors (see [31, 39]). The central theme of these papers was to include dynamic learning, with investors attempting to connect with investment "gurus" (defined as agents with superior investment performance) to improve their investment performance. This dynamic resulted in the expectations of the general population becoming aligned with those of the gurus. An essential finding of the models was that the networks formed by the investors became highly interconnected through their shared connection to gurus, and matched a scale-free topology. This paper utilizes Oracles in a similar but not identical manner to gurus, hence the change of title for a superior investor.

This paper reports on the implementation of an agent-based artificial stock market model where investors determine their optimal information sources, including information coming from a dynamic investor network. The investor network evolves as investors adjust, at fixed intervals, the agents (advisers) from whom they receive advice. Agents also continually update the trust in their various information sources. In choosing their new advisers, investors seek out the better performing investors, known as Oracles. The intention of the process is for investors to enhance their investment performance by receiving the highest quality of information. Additionally, investors are divided into short- and long-term investors, to test the implications of considering more or less information and a differing decision threshold.

The intention of the paper is to assess the consequences, if any, at the market and agent level of connecting investors in a dynamic investor network and allowing them to utilize differing investment horizons. The specific research questions to be addressed at the market level are what are the implications of providing agents with the flexibility to select advisers; what form does the resulting investor network topology take; how long does it take the network to become stable, if at all; and what are the effects of allowing investors to take a myopic approach. At the agent level, the critical question relates to establishing whether specific agents are more successful in generating excess returns than others, and if so, what are their defining characteristics? In short, what are the attributes of an Oracle? The intention is to see if it is possible to grow a Warren Buffett (the Oracle of Omaha) in silico. The paper is structured as follows: Section 2 summarizes the implemented model with its results presented in Section 3, Section 4 provides a discussion of the results, and Section 5 concludes the paper.

2. Approach and Model Design

The contribution of this paper comes from two material changes to the model of Harras and Sornette [37] (H&S hereafter). This model has investors initiated with a unit of a risky and a risk-free asset and connected via a static lattice network. Investors are then continually provided with three sources of information: public, private, and trading intentions, that is, to buy, hold, or sell the risky asset, of their advisers (network links) to aid their own investment decision. Investors then adjust their trust in the various information sources based on its ability to correctly (or incorrectly) predict the movement of the risky asset's price. The trust updating and the new rewiring process provide the potential mechanism to feed a positive feedback loop which creates an asset bubble. The loop becomes more relevant as investors become aligned (herd) with one another as the trust in specific advisers grows. The justification for utilizing the H&S model as a foundation was that it provided a framework where information that affected investment decisions flowed across a network; considered the processes of adaptation and evolution adjusting trust in each of their information sources; showed that price movements were affected by how strongly neighbors influence an agent's investment decision; and generated asset returns that matched the stylized fact of fat-tailed returns.

Table 1: Agent decision thresholds.

Scenario	Action	Variable
$\omega_{ij}(t) > \overline{\omega}_j$	Buy	$a_{ij}(t) = +1$
$\omega_{ij}(t) < \overline{\omega}_j * -1$	Sell	$a_{ij}(t) = -1$
Otherwise	Hold	$a_{ji}(t) = 0$

Of the various changes, the most significant was allow investors, at varying intervals, to adjust their information network via a rewiring process. Via this process, the investors can select a higher quality adviser(s) (Oracles) as the simulation evolves. The work of Markose et al. [39] and Tedeschi et al. [31] motivated this functionality, with Section 2.2.1 detailing the modifications. The other alteration was to divide investors into two classes: long- and short-term investors. Section 2.2.2 provides the full details of this process: briefly stated, the extension relates to how investors assess the performance of their peers, update their trust in the various information sources, and make decisions. The intention is that a short-term investor will adjust trust more rapidly and be more reactionary in making trading decisions.

Sections 2.2 and 2.3 provide a brief description of the model and detail of the crucial changes. The model and an overview, design, and details (ODD) document [40], which details the model, is retrievable from http://tidy.ws/28jdyT. The rationale for providing both the model and ODD is that it allows for the replication of the results and dissemination of the model to motivate additional extensions. NetLogo 5.3 [41] was selected as the programming language to implement the model.

2.1. Model Background

Equation (1): The Precise Decision-Making Equation Used by Agents

$$\omega_{ij} = c_{1ij}\left(\sum_{k=1}^{K} nt_{jk}(t-1)\, E_{ij}\left[a_{ik}(t)\right]\right) + c_{2ij}\, pt_i(t-1)\, pi_i(t) + c_{3ij}\epsilon_{ij}(t) \tag{1}$$

Equation (1) is how investor j combines the three sources of information to determine the decision metric (ω_{ij}) for asset i. The decision metric, when compared against the investor's decision threshold ($\overline{\omega}_j$), determines whether the agents buy more, hold, or sell a proportion of their holding in the risky asset per Table 1. The information sources are the expected actions of their neighbors ($E_{ij}[a_{ik}(t)]$), public information ($pi_i(t)$), and private information ($\epsilon_{ij}(t)$). The public and private information sources are normally distributed stochastic variables with a mean of 0. Also, (1) details how additional variables weight the influence of each information

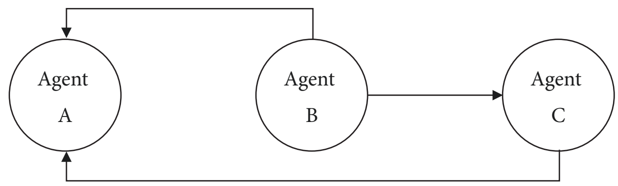

Figure 1: Stylized directed investor network.

source. For the public and network information, one set of the variables—the initial bias coefficients—remain fixed while the other variables—the trust coefficients—are updated to reflect the trust the investor has in each information source as they react to the market and the quality of the information. The fixed values are given by c_{1ij}, c_{2ij}, and c_{3ij}, while the variable coefficients are network trust (nt_{jk}) and public trust (pt_i). The fixed variables are uniformly distributed at initiation among the investors, with the lower limit being 0 and the upper limit determined by the user. By altering the upper limit of the initial bias (simplified to be read as c_1, c_2, and c_3) different model dynamics transpire. The parameter sweep of the implemented model includes values of c_1 ranging from 1 to 4, while the others remain fixed at 1. Once investors make their decision, trading occurs, with a new price endogenously determined for the risky asset. Investors utilize the pricing outcome to update various beliefs, including trust in their advisers (outbound network links).

2.2. Agent Classes

2.2.1. The Network. At initiation, the network is created by investors forming directed links to their nearest neighbors, thereby creating a lattice network. The user sets the number of immediate neighbors with the *Ring_M* parameter, with the number of advisers at initiation being double the setting for the *Ring_M* parameter. With directed links investors utilize outbound links to connect to the investors whom they wish to receive information from; therein, a chosen investor becomes an adviser, whom may ultimately be an Oracle. The information in this instance is the investment action (buy, hold, or sell) that the adviser intends to implement in the current time step (see (1)). Advisers will not seek information from those investors who connect to them. Figure 1 summarizes the various relationships where: Agent A (an Oracle) has two followers (Agent B and C) but does not seek information from any investors; Agent B has two advisers (Agent A and C) but has no followers; and Agent C has one adviser (Agent A) and one follower (Agent B).

The justification for this functionality is that investors (followers) become disciplines of Oracles and that Oracles maintain a disciplined investment approach. This point is illustrated by how the attendance at the annual Berkshire Hathaway—Warren Buffett's investment vehicle—annual meeting grew as his investment performance grew in status [42], while his investment style remained predicated on a concentrated value style [43]. In general, per Gergaud & Ziemba [43], there is no suggestion that their followers influence the investment decisions of star performers.

The more critical element of the model is how the rewiring process alters the advice network of the investors. The rewiring process occurs at intervals decided by the users, via the *rewire* variable. When the rewiring procedure is called, investors assess the trust they have formed in each of their advisers (their outbound directed links); their performance relative to the market; and their aggregate trust in the information they receive from their advisers. Table 2 summarizes the possible actions of an investor and the rationale for each behavior. The basis for the response is that investors are assessing their environment and then deciding the best course for improving their investment performance. Performance relates to the way an investor allocates their wealth between the risky asset and the risk-free asset. While the rewiring process occurs at discrete intervals, investors are updating their trust in their public and network information at each step. Therefore, investors may have little, or negative, trust in an individual adviser at the time of the rewiring process.

The implemented model has several differentiated network formation characteristics of the models of Markose et al. [39] and Tedeschi et al. [31]. The first is the use of a lattice network at initiation, as opposed to a random network. Crucially, this approach is consistent with Watts and Strogatz [44], who demonstrated how the critical elements of a small-world network (a network considered representative of most real-world networks [[45]])—a high clustering coefficient yet short average path length—evolved from lattice network. Utilizing a lattice network also allows for more accurate verification against the H&S framework. Additionally, the model rewires the network at discrete intervals while in the other models this process occurs in each period. The justification for this change is that investors do update their trust at each step so investors can essentially "cut" a link by not assigning weight to the available information from their advisers. The implemented model also allows for multiple outbound links from an investor, whereas Tedeschi et al. [31] have a single link per investor.

2.2.2. The Investors. To facilitate the introduction of two investor classes, the user sets the proportion allocated to the short- or long-term investor class. The introduction of the *%_longterm* variable facilitates this process. The investor's class has two effects: the amount of history the investor considers, and the distribution of the decision threshold value ($\overline{\omega}_j$). Utilizing past information, and how much of it, is a vital component in building artificial financial markets [46].

Table 2: Investor network behavior rationale.

Outperformed the market?	Positive Network Trust?	Action	The Rationale for the Behavior
Yes	Yes	Keep all advisers and add an Oracle	These investors judge that their advisers are a significant overall source of outperformance. Therefore, they are willing to overlook the individual performance of their advisers (noting that they already adjust their trust) in the rewiring process and merely look to add an Oracle in the expectation of improving their incoming information.
Yes	No	Do nothing	These investors are attributing their outperformance to the other information sources. That is, there is not a strong belief that advisers can aid performance. They have already adjusted the trust in each neighbor; thereby, they would be already ignoring the advice, so do not see the need for change.
No	Yes	Cut bad advisers and add an equivalent number of Oracles	These investors have underperformed but given the positive level of trust in their network information assume that removing poor advisers and adding Oracles will reverse their underperformance. This mechanism contrasts to outperformers who are prepared to forgive poor advisers.
No	No	Cut bad advisers without adding new advisers	These investors are effectively attributing their underperformance to their network information and to turn around their performance will cut ties with their advisers and not seek new advisers. In the extreme, these investors will only use public and private information.

The rationale is that short-term investors are deemed myopic in assessing all elements of the market ecosystem. Kay's [12] identification of the "hyperactivity" of the short-term investor provides the foundation for this approach.

The introduction of the $short\_term\_diff$ variable accommodates the two investor classes, with (2) illustrating how the variable affects the amount of history that an investor considers. Section 2.3.4 provides the details through (3) and (4) as to how investor i considers history through the memory weight variable α_i. With the time-scale by which past information continues to influence various metrics given by $1/|\ln(\alpha_j)|$, any positive value for $short\_term\_diff$ reduces the length of time that past performance affects current decision-making. For example, in the experiments reported in Section 3, the difference was set at .05, which is equivalent to 10 periods.

Equation (2): Determining an Investors' Memory Weight

$$\alpha_j = memory\_weight - short\_term\_diff \tag{2}$$

The next modification was the utilization of an exponential distribution, bounded between 0 and 2, to allocate the decision threshold variable ($\overline{\omega}_j$) from (1). For long-term investors, the distribution is 2 minus the value from the exponential distribution. Alternatively, short-term investors take the value generated by the exponential distribution, noting a value of 0 increased to 0.1. Therefore, short-term investors possess a lower trading threshold, due to the assumption that they have a higher propensity to act on the most recent information. A prima facie argument exists that this assumption will see short-term investors trade more. However, this result might not necessarily arise because short-term investors may struggle to maintain sufficient trust in any of their information sources, so they will become indifferent to trading.

2.2.3. The Risky Asset. The risky asset class encompasses a single asset i. The asset has a passive role, with its price movements being the primary variable of interest. Investors receive private and public information ($\epsilon_{ij}(t)$ and $p_i(t)$ respectively from (2)) about the asset at each step of the model. This information is in turn utilized to inform their decision-making process. Therefore, the information is broader than, yet not as specific as an earnings stream. This approach is consistent with the H&S framework, with the rationale of the method being that it will ensure that the dynamics reported in Section 3 relate solely to the behavior of the investors.

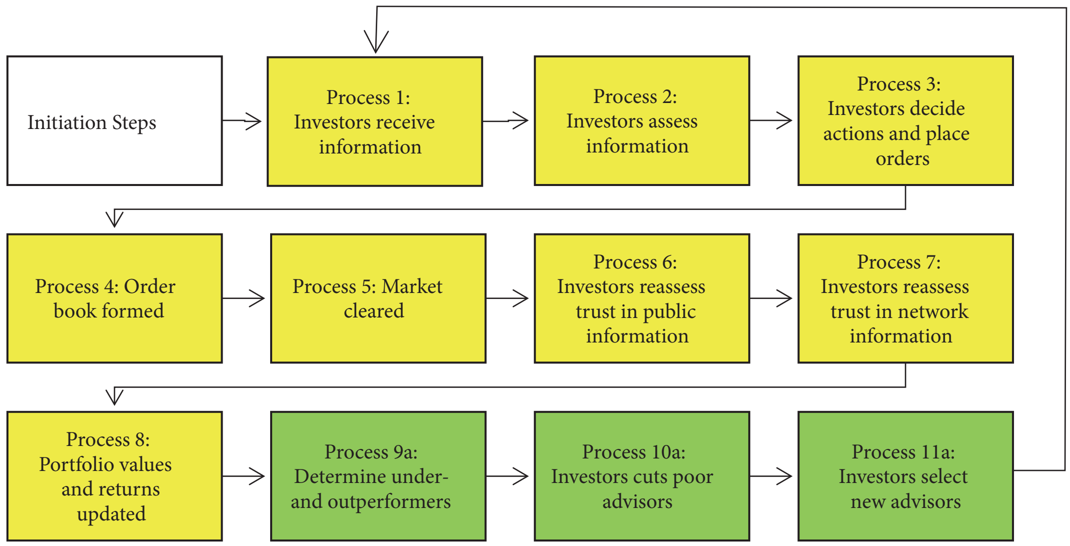

Figure 2: Representation of the model steps. Steps 9a to 11a only occur at the rewiring intervals.

2.3. Model Steps. Figure 2 details processes and the order of execution of various processes contained within a step of the model. A step in the model is assumed to be a day with some new material information arriving at each step, and daily price movements and trading decisions are a closer approximation of actual financial markets. Within a step, Process 1 to Process 7 (color-coded in yellow) are performed in a manner consistent with the model H&S. Processes 8a through 10a (color-coded in green) only occur when the step number matches, or is divisible by the *rewire* variable (set by the user); for example, if the *rewire* variable equals 500, the model will call the rewire procedure at steps 500, 1000, 1500, etc.

2.3.1. Receiving Information and Assessing Information (Processes 1 and 2). The first repeated process has investors receive information. Then they combine the information to decide their action for the step. Regarding private information (ϵ_{ij}), each investor's information comes from a normally distributed random-float with a mean of 0 and a finite variance (1 in this case). Equation (1) implies that a positive (negative) value provides an impetus to the investor to buy (sell) with a higher value, *ceteris paribus*, having a more material effect on the investment decision. Given the random nature of the private information, there should be no serial correlation between the private information of the investors. Public information for asset i (pi_i) at time t is generated in the same manner, except the population shares the same value. Investors will have varying inclinations toward following the data due to their independent trust (pt_i) in the source and their specific influence parameter (c_{2ij}).

To gather their network information, investors poll the intended actions of their advisers. The $E_{ij}[a_{ik}(t)]$ variable from (1) captures the expected actions of an investor's neighbors. The justification for following the actions of an adviser is that when an investor can only employ bounded rationality, it may become optimal to follow neighbors [46]. The information received from advisers is not weighted equally, with an investor consideration based on the trust in the given adviser (nt_{jk}) generated in the prior period *(t-1)*. Finally, each investor sum the weighted actions of their advisers before multiplying the value by their fixed influence term (c_{1ij}). Note that connecting with more advisers will increase the given investor's tendency to follow their network's behavior. In a similar vein to Markose et al. [39], by measuring the accumulated actions of the population, the herding tendency can be assessed, as reported in Figure 6.

2.3.2. Finalizing the Investment Decision (Processes 3 and 4). After determining their investment action, investors check they have the required resources to undertake the desired action and decide how much to trade. The need for the former comes from the assumption that there is no leverage or short-selling. Therefore, investors must have a positive balance of the risk-free asset at time t $(rf_j(t))$ to buy more of the risky asset and must hold a positive quantity of the risky asset $(holding_{ij}(t))$ if they intend to sell. If investors meet the requirements, they trade per Table 1. If an investor does not meet the trading requirements, the investor must sit out of the market. To determine the actual trading volume $(v_{ij}(t))$ of asset i at time t, the model utilizes the transaction ratio variable (tr). The user sets the *transaction_ratio* parameter at initiation, which is fixed and shared by all investors. Finally, to form the market book the orders of all the investors are accumulated.

2.3.3. Market Clearing (Process 5). This procedure clears the market and determines the risky asset's new price by processing the previously calculated market book. Within the agent-based artificial stock market literature, two alternate market-clearing processes exist, a market-maker and an auction market. In line with the H&S model, a market-maker model is employed. Tedeschi et al. [31] in contrast utilized an auction market, but their model implemented 150 investors in comparison to the 2,500 implemented in the H&S model. Farmer [47] provides a detailed rationale for the market-maker model, with the chief support being that the process ensures the market is not frozen due to gaps in the order book yet it can still accurately determine an appropriate price change based on the surplus (deficit) demand for the asset.

2.3.4. Trust and Portfolio Updating (Processes 6 - 8). Once investors become aware of their returns, they utilize the information to adjust the level of trust they have in the information provided by their network (nt_{jk}) and public sources (pt_j). With trust initiated 0, investors begin to build trust in a source if it provides the correct advice; that is, if the agent receives a buy (sell) signal from the information source and the price subsequently increases (decreases), then the weight (trust) increases. This updating process is the point at which the difference in the short- and long-term investors manifests itself.

Equation (3) is the process that investors utilize to update their public trust, while (4) is the mechanism by which investors revise their network trust. The essence of the two equations is the same, with the first term in the equation discounting the previous trust value variable by the variable α_i. However, per (2) this variable differs for the two investor classes. The second part of the equation adds the assessment of the immediately preceding information, which has been discounted by (1-α_i) after the $r_i(t)/\sigma_{ir(t)}$ term multiples it. From these equations, a lower value of α_i increases the influence of the most recent history. Crucially, the $r_i(t)/\sigma_{ir(t)}$ term normalizes the past return of an asset ($r_i(t)$) by the standard deviation of its past returns $\sigma_{ir}(t)$. H&S [37] provide the rationale: a more substantial change scaled by its volatility enhances trust to a higher degree.

Equation (3): Public Trust Updating Process

$$pt_i(t) = \alpha_i pt_i(t-1) + (1-\alpha_i)\, pi_i(t-1) * \frac{r_i(t)}{\sigma_{ir}(t)} \tag{3}$$

Equation (4): Network Trust Updating Process

$$nt_{jk}(t) = \sum_{i=1}^{I} \alpha_i nt_{jk}(t-1) + (1-\alpha_i)\, E_{ij}\left[a_{ik}(t-1)\right] * \frac{r_i(t)}{\sigma_{ir}(t)} \tag{4}$$

The final process is for the model to update the portfolios of the investors to reflect the outcome of the market-clearing process. This process sees just the balance of the investors' holdings in the risky and risk-free assets adjusted.

2.3.5. Determining Under- and Outperformers (Process 9a). When the rewire procedure is called, investors undertake a detailed assessment of their performance. First, investors determine the value of the portfolio and calculate their return between the rewiring steps. Next, investors determine whether they have out-or underperformed their benchmark. The long-term investors compare the growth of their portfolio value to that of the markets since inception. In contrast, the short-term investors compare their most recent portfolio return against the return of the market since the last rewiring process. Investors consider themselves out (under) performers if they have exceeded or underperformed their relevant benchmark.

Next, the model selects the best-performed investors (Oracles) for each investor class. Given the difference in the performance criteria for the long- and short-term investors, there is a list of investors with the largest portfolio values and one with the largest returns since the last rewiring process. The user dictates the number of Oracles via the *Oracle_options* variable, with the identification details of the Oracles stored in a global list. It may be the case that the same investors are on both lists, but they are there on different criteria. The investors stored in these lists may be selected as advisers, as described in Section 2.3.6.

2.3.6. Cutting Poor Advisers and Selecting New Advisers (Steps 10a–11a). From Table 2 it is seen that underperformers (identified in Section 2.3.5) will cut poor advisers, defined as an adviser for whom the agent's trust level is negative. Once identified, the poor adviser is added to a list, named *stayorgo*. After reviewing all their advisers, the length of the *stayorgo* list is utilized to update the *p_new_ad* variable, whose purpose is to record the number of new advisers the investors may select in the next step. Having identified their poor advisers, the investor will cut the links to those advisers and remove them and their trust record from the relevant lists.

The initial process for investors to select a new adviser is to access the list of outperformers (Oracles) relevant to their subclass and choose at random the required number. An outperformer with overall positive trust in their network information will select one additional Oracle. For an underperformer with a combined positive level of trust in their network information, the number of Oracles selected comes from the value of their *p_new_ad* variable. Having selected an Oracle(s), the investors form a directed link to the Oracle, thus rewiring the network. New advisers have an initial trust level of 0.

3. Results and Findings

3.1. Experimental Settings and Result Summary. Table 3 provides a summary of the baseline settings and parameter changes utilized for the various experiments. The settings were chosen to ensure a level of consistency against Harras & Sornette [37] and Oldham ([23, 27]). These papers reported that as the variable that determines the inclination of the investor to be influenced by their network increases—denoted by c_1 (see (1))—the price series begins to experience increased periods of volatility. An elevated level of network influence ultimately results in a positive feedback loop between investors generating sufficient weight for "herding" to occur; that is, following the actions of their most trusted adviser becomes common practice within the

Table 3: Baseline parameter settings.

Variable	Settings
Time steps per run	2,999
Runs per setting	60
Number of investors (J)	2,500
Market depth (λ)	0.25
Transaction ratio (tr)	0.02
Memory for long-term investors (α)	0.95
Memory differentiation	0.05
Potential Oracles	10
Number of original neighbors	4
Network influence (the c_1 variable)	1,2,3,4
Percentage of short-term investors	0%, 25%, 50%, 75% & 100%
Rewiring intervals (time step)	250, 500, 1000, 1500

populations, and the price of the risky asset no longer moves randomly, per the arrival of private and public information. Asset bubbles also appear, noting that the catalyst for their collapse is that investors have insufficient funds to maintain their buying momentum. This loss of momentum impairs the positive feedback loop, and investors begin to lose trust in their neighbors' investment advice, meaning the population's investment strategies become less synchronized.

The research questions informed the design of the experiments presented in this section, with the essence of the analysis to understand how the system varies from the baseline results of Harras & Sornette [37]. Table 4 provides an overview of the main components of the two classes of experiments and a summary of the findings. In combination with Table 3, the reader should note that as each model run was 2,999 steps a final rewiring of the network did not occur; that is, for a rewiring set of 1,500 (250) the final rewiring occurred at step 1500 (2750). The rationale for this decision was to allow an analysis of the network and agent characteristics without the interference of a final rewiring process. The methodology put forward by Lee et al. [48] was utilized to decide the number of runs. The approach suggests that the number of runs should be such that the coefficient of variation for selected variables should demonstrate sufficient stability.

Time-series plots and summary statistics plots are utilized to present findings. The time-series plots provide a stylized temporal interpretation by using a LOESS smoothing technique. The benefit of this process is that clearly illustrates how each combination of parameters affects a given variable and removes unnecessary noise. Summary statistics plots—range plots or bar graphs—are utilized to illustrate the variation within a given set of parameters. Figure 3 through Figure 10 apply the same color-coding for the percentage of short-term investors in the ecosystem, with the variable of interest plotted on the y-axis. The facets for Figure 3 reflect the different levels of the network influence variable (c_1). Figures 4 through 10 utilize a facet grid, with the setting for network influence variable (c_1) described by the vertical facet and the rewiring setting represented by the horizontal facet. Additionally, the network influence variable facets have the prefix of (1) through (4), while the rewiring facets have the prefix of (a) through (e). Therefore, when referenced, a facet will be described by its coordinates; for example, facet b3 refers to a rewiring setting of 500 and a level of network influence equal to 3. Regarding the time-series plots, the x-axis indicates the time step of the simulation, and the y-axis is the variable of interest. Therefore, within a figure, each facet shares the same axes and is scaled consistently.

3.2. Detailed Results

3.2.1. Introducing Short-Term Investors. Figure 3 presents the stylized price dynamics of the various settings across time that are the result of introducing short-term investors without rewiring. The y-axis represents the range between the maximum and minimum price of the risky asset at each step from the multiple runs (60) of each experimental combination. Regarding validation, the ex-ante expectation was that a 50:50 mixture of short- and long-term investors would produce similar results to the original model. The results of facet 1 and facet 2 provide a level of confirmation for this hypothesis. However, from facet 3 and facet 4, it appears that a 25:75 mix of short- and long-term investors produces a comparable result.

The introduction of short-term investors produces several new dynamics, with the magnitude of these dynamics dependent on the composition of the ecosystem. The first observation, as illustrated in Figure 3 facet 1, is that it is only when the level of network influence exceeds 1 that there is any material change in the price dynamics. Next, when there is a high proportion of short-term investors, the system does not require the level of network influence to be as high for the system to show extreme price movements; Figure 3 facet 2 demonstrates this point. From Figure 3 facet 3 and facet 4 it is seen that a higher proportion of short-term investors leads to a more rapid expansion and deflation of the risky asset's price because it takes less time for the investors to form herds. Even a 25:75 combination is sufficient to increase price volatility as the long-term investors enter a buying herd. The final point of the initial analysis is the behavior of a population comprised entirely of long-term investors. From Figure 3, it is seen that under no circumstances does the price series become excitable. The conclusion drawn from this is that considering more price points and not being able to change advisers are sufficient to restrict the behavior of investors.

3.2.2. The Combination of Short-Term Investors and Rewiring. With the introduction of the dynamic network, there is the need to assess the dynamics of both the financial market and the investor network, more specifically, if, and in what form the investors evolve the topology of their network. The relevance of this outcome is that the topology of investor networks has been found to affect the behavior of the market materially [35]. The first stage of the analysis (Section 3.2.2.(1)) presents an assessment of the system's response to the conduct of the risky asset's price and the dynamic variables driving it. The second component

Table 4: Experimental design and result summary.

Model Setting	Key Components	Summary of Findings
Varying network influence (c_1) and short-term investors	The initial network for the investors is a lattice network. The parameters varied in the following manner: (i) network influence (c_1) $[1, 2, 3 \text{ and } 4]$; (ii) percentage of short-term investors [0%, 25%, 50%, 75%, 100%]	The introduction of the short-term investors resulted in greater volatility, and the earlier synchronization of investor strategies, meaning the system tipped into bubble territory earlier. Also, bubbles appeared under conditions that did not previously result in a bubble. Of note was that only a small percentage of short-term investors was required to increase the activity in the system.
Varying network influence (c_1), short-term investors, rewiring	As above with the exception that the investor network rewiring occurs in the following increments: (i) $[250,\ 500,\ 1000,\ 1500]$ steps, meaning rewiring occur: $[11,\ 5,\ 2,\ 1]$ times.	The rewiring process resulted in even more significant variations in the behavior of the system. This conclusion comes from previously dormant markets, those that contained only long-term investors, producing volatile behavior; thereby identifying the fact that the presence of Oracles can destabilize the market The wealth distribution was extremely skewed under the conditions responsible for severe price movements, with short-term investors gaining off long-term investors.

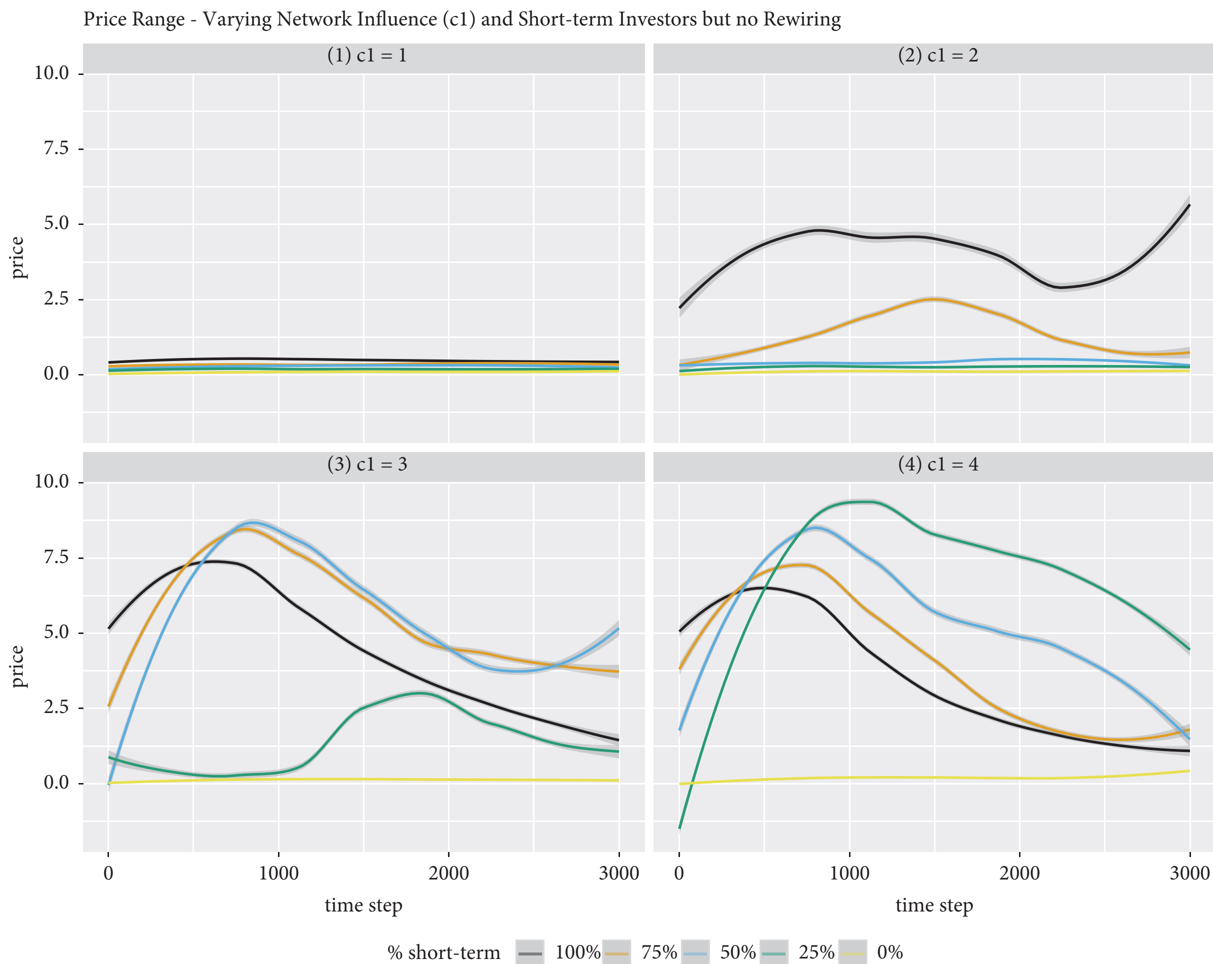

Figure 3: Temporal price behavior of the risky asset with no rewiring. The lines are prepared by applying a LOESS and represent the temporal evolution of the risky asset's price for the various combination of short- and long-term investors.

(Section 3.2.2.(2)) then assesses how investors rearrange themselves in their network.

(1) The Behavior of the Risky Asset's Price. Figure 4, which provides a facet grid of the price behavior of the risky asset, provides sufficient evidence that rewiring does have a positive effect on the price movements of the risky asset. The only condition to this statement is that the initial setting for the network influence parameter is greater than 1. This fact can be seen by the lack of activity in the price series in facets a1 through e1 when compared to the remainder of Figure 4. Therefore, short-termism may well be an irrelevant concern if investors can maintain a balanced perspective regarding where and how they assess the information. However, if investors are inclined to favor the information coming from advisers—seen with a c_1 variable setting higher than 1—and can select their advisers, many implications arise. The first implication is that a previously "nonvolatile" market environment—that is, where extreme price movements do not occur—becomes volatile. Facets a3 through e3 are clear indications of this, with the most obvious example being where there are no short-term investors. Facet e3 shows that with no rewiring and no short-term investors, the price series is dormant. In contrast, the remaining facets record material movements in the price immediately following the rewiring set, noting that the LOESS smoothing will spread the action before and after the actual rewiring step. More generally, when comparing the facets in column e to those of a through d, the effect that the rewire interval has on bringing forward the upward trajectory of the risky asset's price is evident.

Figure 5 provides a more specific illustration of the risky asset's price movement characteristics by illustrating the maximum draw-down and -up metrics. The draw-down (up) is calculated as the value of each consecutive uninterrupted downward (upward) streak of price reductions (increases) and represents the potential gains (losses) an investor can experience. The maximum is then the longest upward and downward streak. The advantage of these metrics is that the number of time steps in the simulation does not influence the magnitudes of these variables as they represent a specific subset of the data: that is, an uninterrupted streak of a price movement. Figure 5 plots the median maximum draw-down or -up with the standard deviation illustrated by the bars.

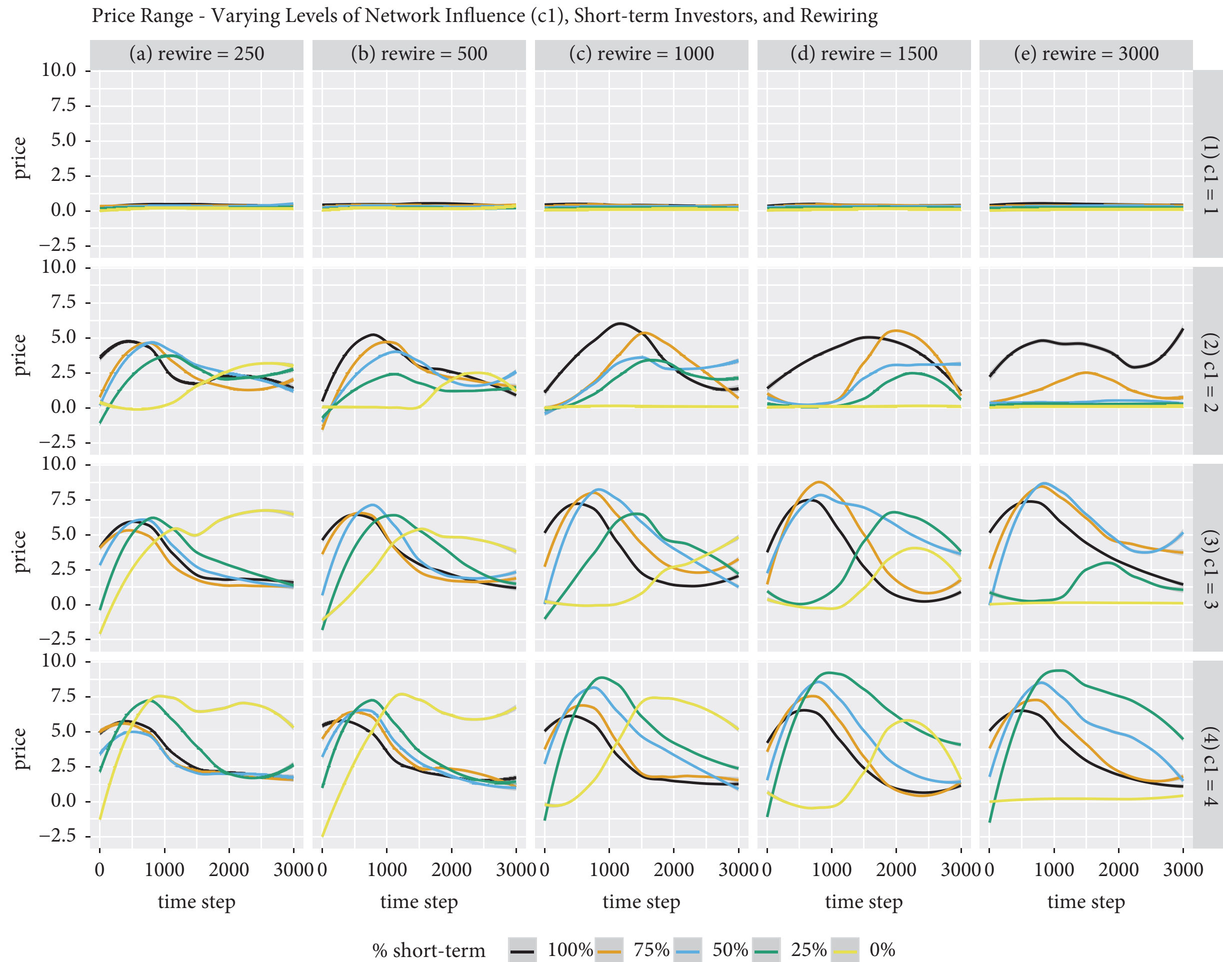

Figure 4: Temporal behavior of the risky asset's price with rewiring introduced. Facets now differentiate for the rewire and c_1 variables. The lines are prepared by applying a LOESS and represent the progression of the asset's price for the various combination of short- and long-term investors.

Consistent with the other findings, the rewiring interval and the network influence have a noticeable effect. This point can be seen with the points "jawing" open; that is, the gap between the maximum draw-down and -up increases as the interval decreases, with a scenario of no short-term investors being the anchor point. However, given the muted activity in facet 1, the results show that a higher initial level of network influence is required to instigate the positive feedback loop that results in the more extreme price movements.

The combined effects on the draw-down or -up variable of a shorter rewiring interval and a higher proportion of short-term investors are seen in facet rows 3 and 4. The first observation is that the jaws open farther, including some instances with no short-term investors experiencing material drawdowns and drawups (for example, facet a4 and b4), thus supporting the concept that even long-term investors can herd when given the ability to change advisers. The second observation is that jaws open in a linear fashion in facet row 3, while in facet row 4 the width of jaws is constant, except for when the rewiring process does not occur. This finding implies that the inclination of investors following neighbors, given by the c_1 variable, has a more significant effect than do the rewiring intervals.

Figure 6 provides an insight into how herding, instigated across the investor network, affects the pricing behavior of a risky asset. The herding coefficient—the proportion of the population undertaking the most common trading activity, thus excluding holding—captures both the inflation and deflation of an asset bubble. The main observation regarding the herding coefficient is that the collective behavior grows in the early stages of the simulation, peaks and then decline for the remainder of the simulation, thus mirroring the stages of an asset bubble. The mechanism that explains this process is that the positive feedback loop grows in influence as investors herd, before losing momentum as investors exhaust their investable funds. As the price momentum slows, investors begin to lose trust in their advisers, which eventually leads to some investors starting to leave the buying herd and decrease their holding in the risky asset. This dynamic ultimately creates a selling herd, thus extending the collective behavior, before the loss of any synchronized behavior in the population.

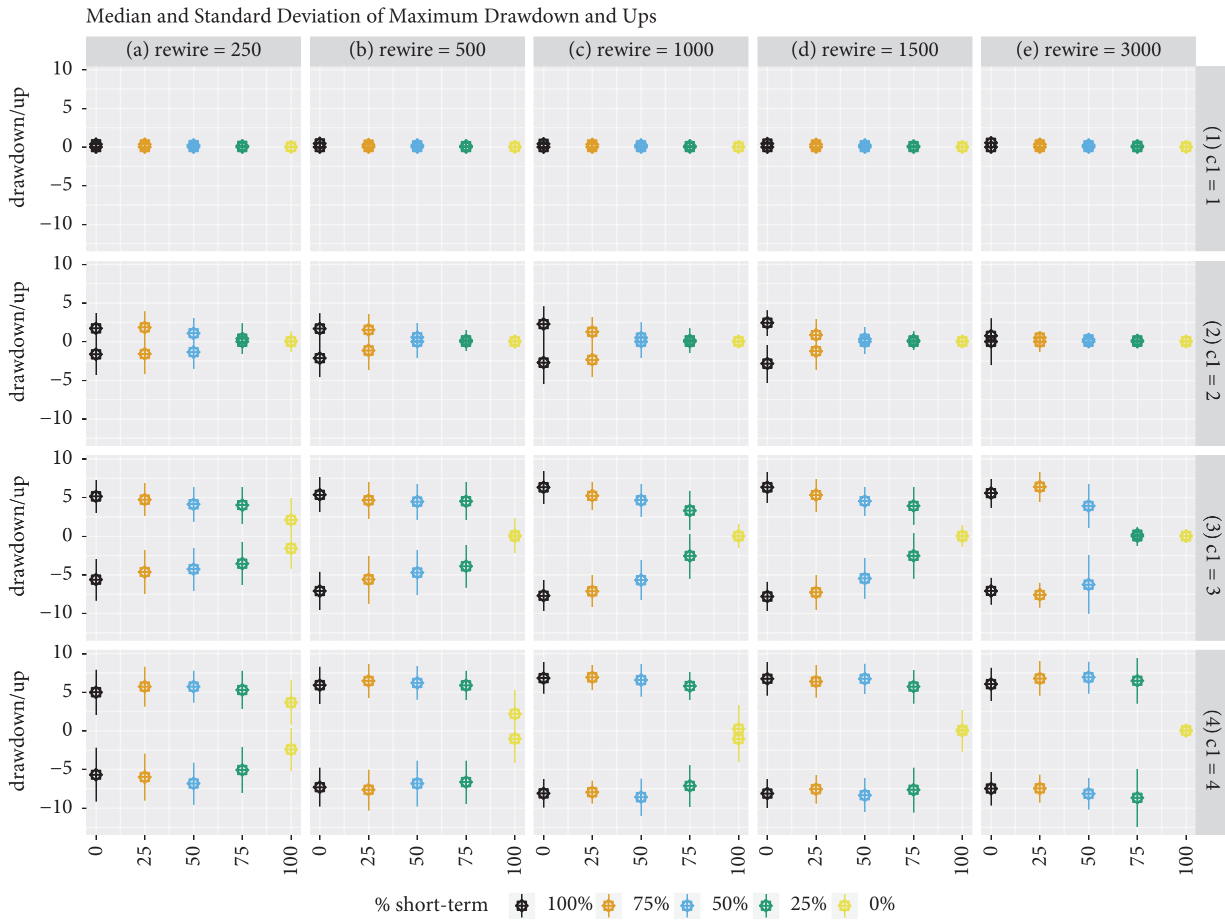

FIGURE 5: The maximum drawdowns and drawups recorded in the market across the various settings with rewiring. The boxes represent the median, while the lines represent the upper and lower maximums recorded for each combination.

Multiple implications arise from the analysis of how the interaction of investors of varying characteristics affects the behavior of the artificial stock market. The first is that a higher proportion of short-term investors will increase the volatility of the market because these investors are more reactionary and built trust in their advisers at an enhanced rate. The second is that by allowing investors to choose from whom they receive information hastens the building of trust and ultimately accelerates the realization of extreme price movements. The size and timing of these movements are also affected by the investors' preference for following advisers (the network influence variable). If investors do not prefer any information source, that is, $c_1 = c_2 = c_3 = 1$, these interactions become irrelevant.

(2) The Behavior of the Investor Network. This section establishes how the characteristics of the investors and the environment affect the evolution of the investor network topology. Ozsoylev and Walden [25] propose a theory regarding the importance of the topology of the network by explaining that markets would record higher volatility when there was an intermediate level of connectedness between investors, yet lower in markets with higher or lower connectedness. Therefore, if investors form a scale-free network, the volatility of the market should be higher. The rationale for this dynamic is straightforward, in that many investors would tend to follow the decisions of a few Oracles, resulting in a higher prevalence of herding and more substantial price changes.

A vital component in assessing the evolution of the network topology is the investment performance of the investors because as detailed in Section 2.2.1, it is essential to the rewiring process. Figure 11 splits the short and long-term investor results and represents the evolution of the median number of outperformers within each subclass. An observation is that long-term investors have difficulty outperforming over the entirety of the simulation, despite having some success in the early portion of the simulation. Additionally, a higher proportion of short-term investors accentuates the poor performance of long-term investors. The rationale for these points is that the short-term investors are early to join(leave) a significant price upswing(downswing) and first to exit(join) the downward(upward) correction. The opposite holds for long-term investors, who are "left without a chair when the music stops." These results imply that long-term investors will be less inclined to utilize their information network.

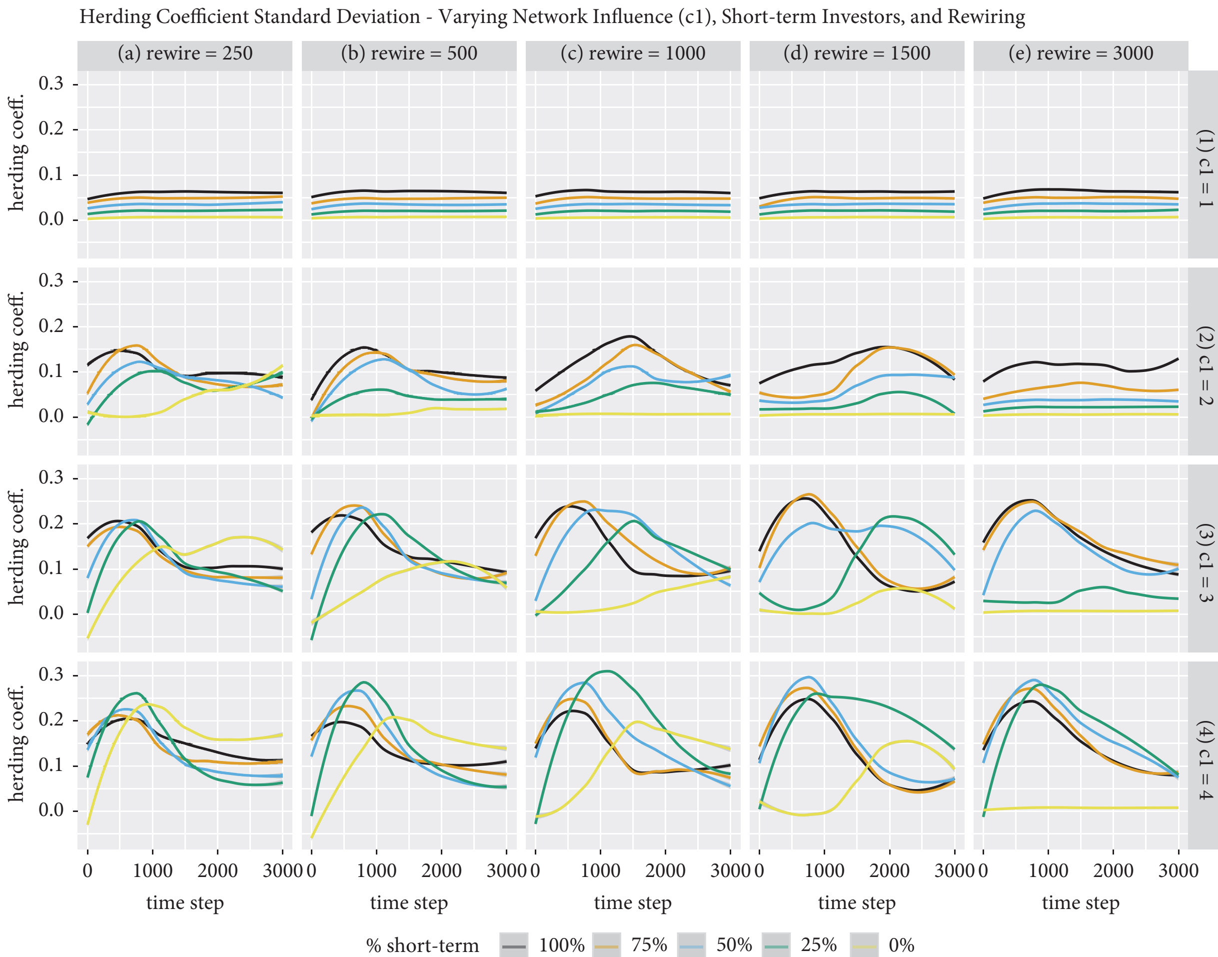

Figure 6: The evolution of the herding coefficient with rewiring. The lines come from applying a LOESS process to the standard deviation of the herding coefficient determined at each step from the runs of a specific experimental setting.

The short-term investors, in general, appear better equipped to match or exceed their benchmark. Crucially, the ability to match or exceed the market appears dependent on shorter intervals between reassessing and selecting advisers and the proportion of long-term investors. The implication from this observation is that without long-term investors to "feast" off, short-term investors struggle to outperform. They can correct this situation by rewiring their investor network, a process which may involve ignoring the advice from other investors. These results all provide strong support for the need to assess a market ecosystem.

Figure 7 illustrates the evolution of the median number of links in the network. The rationale for assessing the number of links is that it provides evidence of whether investors, on average, are inclined to add or reduce the number of advisers, remembering that this process is highly dependent on their investment performance. More links are indicative of a denser network, with investors on average utilizing a higher number of advisers and having higher trust in their network information. The first general observation is that the number of links declines through time. A notable exception is when there are no short-term investors (see facet row 1 and 2). A decline in links occurs because investors cut and do not replace advisers because their aggregate level of trust in their advisers becomes negative and they are underperforming the market. The second observation is that the rate of decline becomes progressively faster the higher the proportion of short-term investors. This finding is in step with higher and more volatile prices associated with an increased percentage of short-term investors.

The question arising from Figure 7 is: which investor class is disregarding the information available from their neighbors and thereby, causing the collapse of the network? Why this occurs comes from an assessment of the distribution of out-degree of the investors that is the number of advisers an investor utilizes and the performance of the investor subclasses. The rationale for this analysis is that it will provide evidence for the conditions responsible for investors having a higher inclination, or otherwise, for seeking advice. Investors increase their number of advisers when they are outperforming the market and have positive trust in the network information and cut advisers when they have negative trust in their network information and underperform.

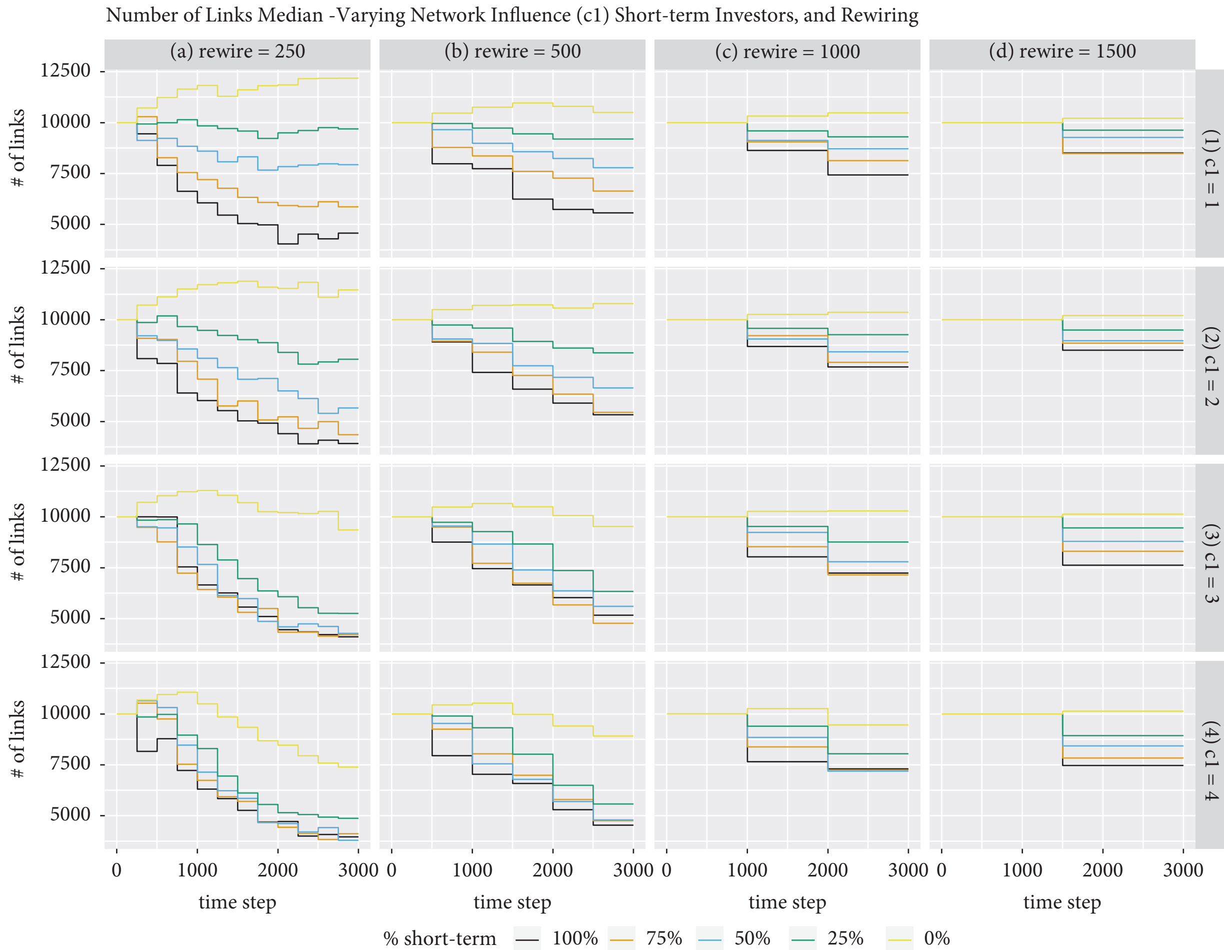

Figure 7: Temporal evolution of the variation in the median number of links maintained in the network after rewiring. Rewiring occurs at discrete steps; hence, the "jagged" appearance in the evolution of the metric. A higher frequency of rewiring is responsible for impairing the network.

Figure 8 shows the dynamics of the median out-degree of the various investor classes. The dynamics appear to strongly parallel those that were evident when assessing the pricing dynamic. The central dynamic is that when long-term investors are forced to compete in an environment rich with short-term investors, they suffer poor performance. This outcome, in turn, leads to an accelerated loss of trust and a more significant decline in the number of advisers they maintain. A critical condition for this process, as seen in facet rows 2ii through 4ii, is that the level of network influence must be higher than 1, a setting that has proven to generate excess price volatility. Otherwise, long-term investors are capable of outperforming under the right conditions, namely when there is a higher proportion of long-term investors. Under these conditions, long-term investors are less inclined to reduce advisers and are even inclined on average to add them.

Alternatively, short-term investors appear generally less inclined to disregard advisers, with the composition of the investor population being less influential. An important observation is that when there is a less volatile environment, that is, when the network influence variable equals 1, short-term investors generally do not perform as well and tend to reduce their adviser numbers (see facet a1i). This finding compounds the evidence that the behavior of the market and the ability of certain classes of investors to outperform is highly conditional on the composition of the investor ecosystem and inclinations that influence their investment decisions.

It is also vital to understand how the rewiring process creates perpetual Oracles, that is, advisers who retain a disproportionate number of followers. Figure 9 explores this aspect by illustrating the median and the upper and lower range for the number of followers for each investor, which are the investors in-links, and represents how many people are seeking advice from a given investor. The expectation is due to the processes involved with investors seeking Oracles the distribution will be highly skewed. However, it is imperative to understand to what extent the distribution is skewed, because investors only search for Oracles under certain circumstances, as defined in Table 2, and may not retain their faith in their Oracles.

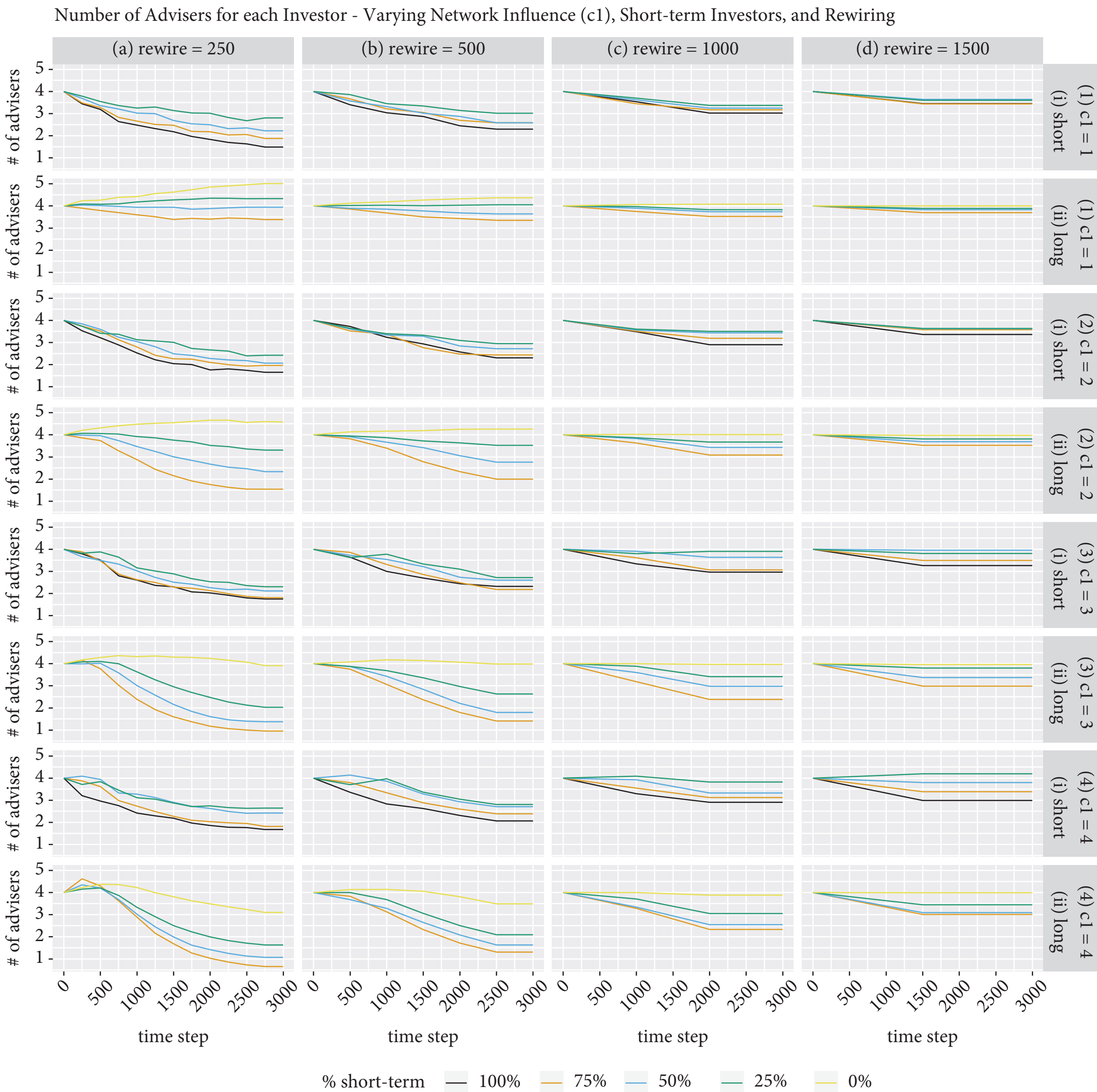

Figure 8: The development of the median number of advisers the investor population maintains. The investor subclasses split the facets and along with the other settings highlight the different behavior of the two classes, with the lines representing the median.

The immediate impression from Figure 9 is, as expected, evidence of a highly skewed distribution. More critically, meaningful differences across the various settings appear. From facet column a, the first difference of note appears with the skewness increasing as the proportion of short-term investors decreases. The other point from facet column a is that when comparing facet a4 to the others, it appears that the upper range peaks before declining in the latter portion of the simulation. Noting the similar extreme price characteristic for facet a4 and the ability of investors to rewire on a more regular basis, this suggests that investors tend to lose faith in taking advice from other investors.

The next question relates to how to classify the evolved network topology. Given the rewiring process, namely, the ability to select Oracles, it was expected that the model would evolve into a scale-free network. This finding would be consistent with Tedeschi et al. [31]. Alternatively, the network may be unable to maintain its structure; that is, it will match a random network with little structure as the volatility of the market will result in investors losing faith in the information coming from their network. The difference in the two processes would see the scale-free network maintain an intermediate level of clustering and a highly skewed in-degree as investors connect to Oracles, while the random network would have a low level of clustering as investors either do not connect or Oracles consistently change. From Figures 7 through 9, plus an analysis of the clustering and closeness coefficients (not provided) implies that the proportion of

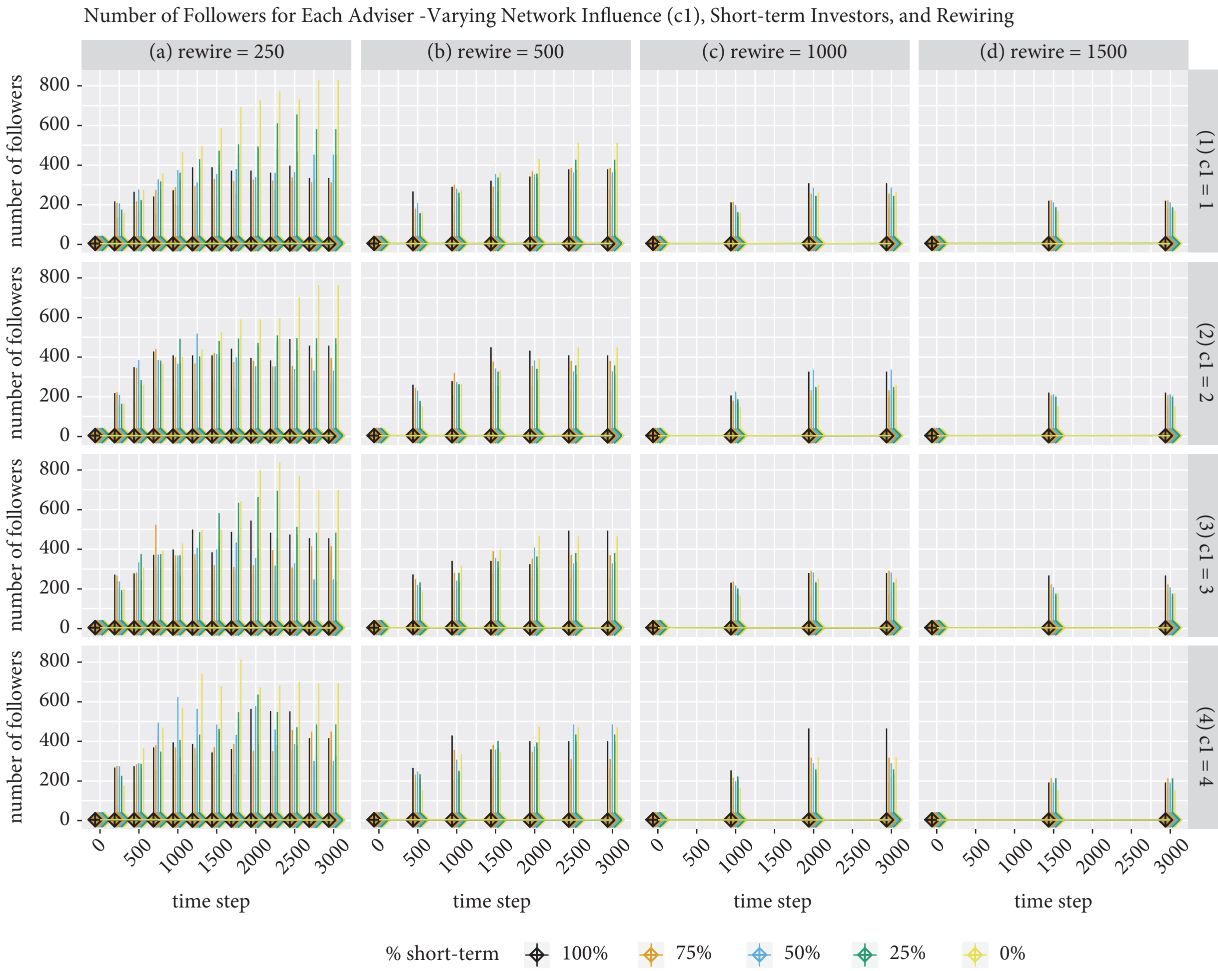

FIGURE 9: The dynamics for changes in the range of followers per adviser. The lines represent the range while the circles represent the median, noting that the data collection occurs after each rewiring process.

short-term investors in the ecosystem meaningfully affects the topology. That is, the investor network ranges between a scale-free network when there is a lower proportion of short-term investors (and therefore less volatility), to a random network when there is a higher proportion of short-term investors (and hence more volatility). The result implies that in a more volatile market Oracles themselves have trouble maintaining their status, and investors tend to disregard the actions of other investors and focus on public and private information.

(3) The Hunt for Oracles. The previous sections identified the factors that influenced the behavior of the system and how that affected the various investor classes. The findings made it very clear that investors need to be aware of the environment they are engaged in because the system behaves in significantly different ways. Investors need to be particularly mindful of whether short- or long-term investors hold sway in the market and whether investors are predisposed to seek advice from other investors. This section uncovers the attributes of the more successful investors, thus identifying the secrets of investment Oracles.

Figure 10 presents the median portfolio value of the investors and the range of the various portfolio values at each rewiring stage. Therefore, the graph does not capture any wealth that may accumulate and then disappear within a rewiring interval, which would occur as asset bubbles can come and go within a rewiring interval. The most striking result occurs in facet aii4, where the relevant parameters see an asset bubble appear, with the instigation of the boom brought forward by the network rewiring process. What is striking is the extreme skewness in the wealth distribution when the ecosystem is comprised entirely of long-term investors. The extreme result occurs because a given investor starts the positive feedback loop, most likely because the investor has a relatively low threshold, and as more investors follow that investor's action the bubble inflates, and long-term investors build higher and sustainable trust in the original Oracle. The investor is then the first to leave the buying herd while the other long-term investors slowly adjust and start selling well after the original Oracle, thus providing the Oracle ample opportunity to sell at the top of the market. Therefore, the original Oracle achieves the perfect combination of buying low and selling high. This relationship

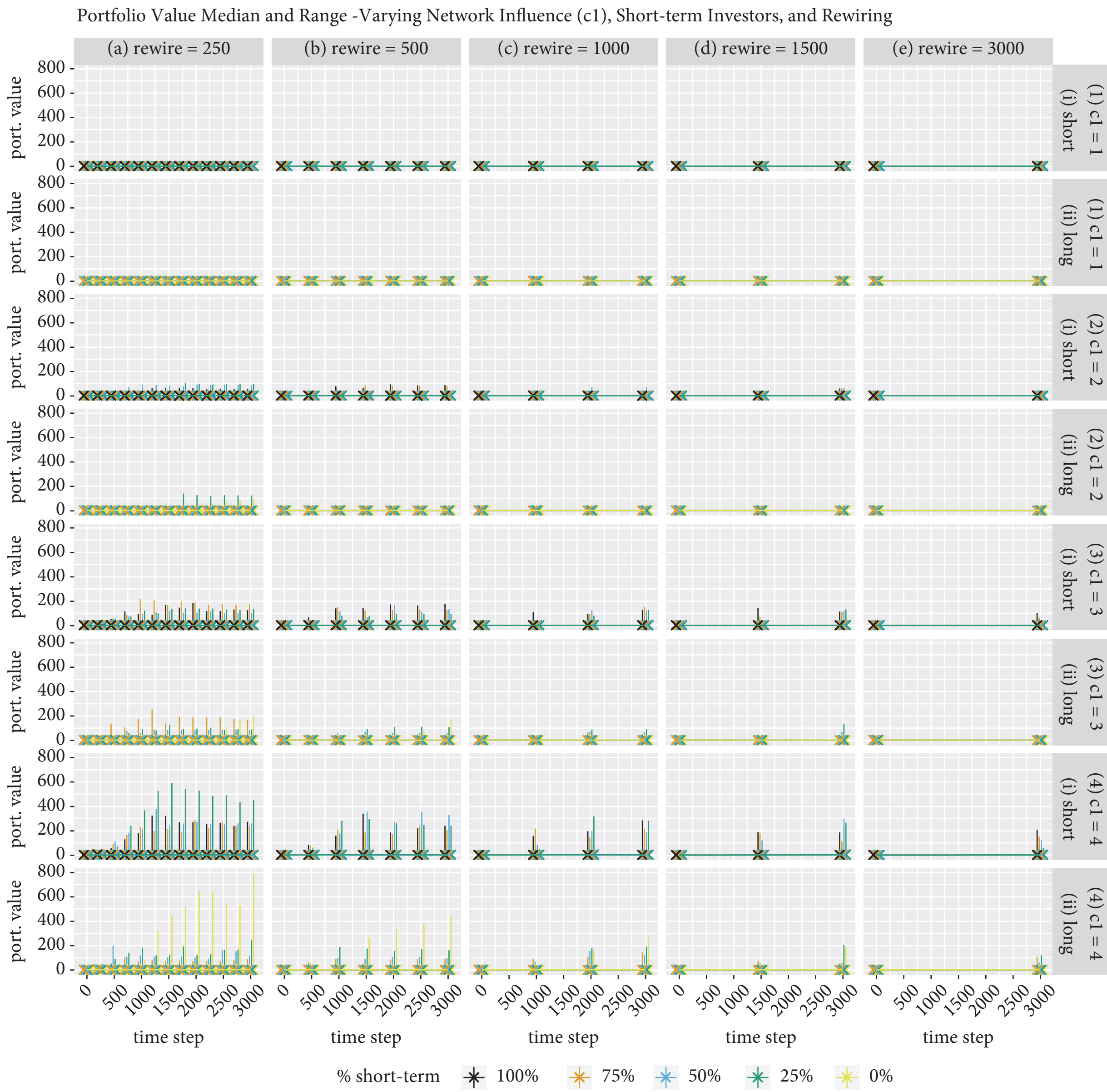

FIGURE 10: The dynamics of wealth creation. The plot summarizes the distribution of wealth (the agent's portfolio value), per the y-axis, labelled port. value. The vertical lines represent the range of wealth, while the stars represent the median. The range updating occurs after each rewiring step.

is most pronounced with shorter rewiring intervals but does hold with longer intervals.

The previously identified situation of short-term investors gaining wealth at the expense of long-term investors is also evident. Again, in the lower facet rows, the outperformance of at least one short-term investor over the highest performing long-term investor is clear. The gap also increases as the percentage of short-term investor decreases, which is indicative of the advantage short-term investors have in being able to adjust more quickly to the market. The final point of note is that material inequality only occurs when the network influence variable is greater than 2. Under this scenario, it is again short-term investors interacting with a more substantial proportion of long-term investors that produces the outcome.

A principal component analysis (PCA) was conducted on the agent level data to identify the primary influence on wealth creation. The first component showed the significant effect of the dynamics of the network, with the rewire setting making the highest contribution to explaining wealth variation. This result was anticipated given the finding that by allowing agents to rewire affects the dynamics of the market. This dynamic was seen in Figure 4, where decreasing the rewiring interval increased the activity of the system, ceteris paribus. The second component identified the investment decision-making process of the investors, especially their

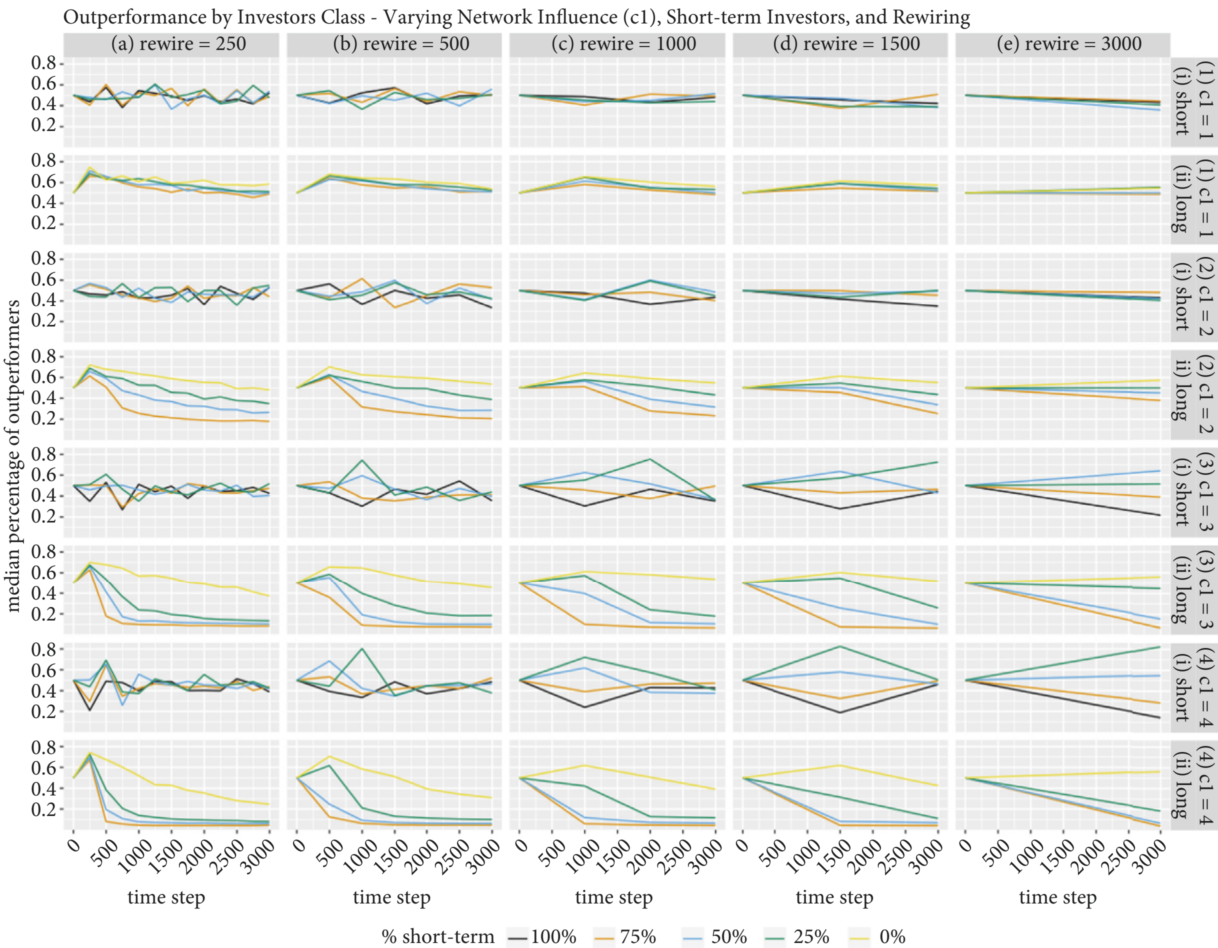

Figure 11: Proportion of outperformers within each investor subclass. Facets now differentiate for the rewiring and c_1 variables and the investor subclasses. The lines represent the temporal evolution of the proportion of outperformers for the various combination of short- and long-term investors. Short-term investors appear to exhibit superior performance.

decision threshold (with a lower threshold being beneficial) and the structure of the population, thereby confirming the previously inferred importance of the investment horizon of investors and the composition of the ecosystem.

4. Discussion

This paper combined research from a variety of fields including agent-based artificial stock markets ([13, 22, 37]), behavioral finance ([11, 49, 50]), evolving social networks ([31, 51]), and empirical research into investor networks ([25, 26, 52]) and financial markets ([17, 53]). By successfully combining these fields the paper delivers meaningful insights into the dynamics responsible for enhanced volatility in financial markets, divergent wealth accumulation by investors, and the detrimental effects of short-term behavior. In addressing these topics, the model added to the developing research of how investor network may evolve, and the effects that the network's evolution has on the behavior of the market. Regarding the detrimental consequence of short-termism, the model demonstrated how short-term traders benefit by exploiting long-term investors, who take longer to adjust to the changing market conditions. However, this trait is only relevant when investors disregard their other information sources and blindly follow the herd, an environment that generates higher volatility. Under such conditions, investors should be more reactive, a result consistent with LeBaron [13]. In contrast, when markets do not experience excessive price movements, short-term investors trade excessively in the futile attempt to find nonexistent profits, a result in line with the work of Barber and Odean [11].

The benefit of pursuing a greater understanding of how a social network, of any description, evolves was demonstrated through the model identifying the conditions under which the investors tended to form and maintain a network of intermediate connectedness. Understanding this process was vital based on the empirical results suggesting that an investor network of intermediate connectedness produces higher volatility ([25, 26]) and scale-free topologies are associated with fragile markets ([28, 54]). An agent-based modeling approach was appropriate for this purpose because it can simulate the effects of heterogeneous interacting agents within a CAS, thereby uncovering the mechanisms responsible for not only scale-free networks but also extreme market behavior [55]. More specifically this paper uncovered the process by which a benign environment becomes volatile as investors rewire their adviser network. Critically, rewiring at more regular intervals accelerates the arrival of the elevated volatility. The findings also suggest that a higher prevalence of short-term investors, which ceteris paribus produces higher volatility, was responsible for the network becoming relatively unstable as long-term investors disengaged from their advisers.

While this paper provides meaningful insights, it should be considered an interim step in the pursuit of gaining a greater understanding of investors and how their social interaction affects financial markets. To enhance the model's usefulness, the model should look to enhance the decision-making process of the investors, reduce the general level of abstractions, and improve the use of empirical data to inform and calibrate the model. Regarding the investors, a possible enhancement would be to allow the investors to learn (a significant benefit of ABMs [56]) and therefore recognize the conditions that feed the positive feedback loop and adjust their investment approach. Concerning the abstractions, the processes by which investors identify and follow Oracles and modify trust levels are areas of realistic improvements. While allowing investors to search the entire population to identify the leading investors is feasible given the availability of past performance data over more extended periods, the search could be adjusted to allow some agents to obtain time-sensitive trading and investment data. Regarding quantifying investor trust, Gruber [57] and Sirri & Tufano [58] established that the flow into and out of mutual funds is highly dependent on manager performance; thus, flows provide an ex-post proxy of trust. Additionally, the recommendations of stock analysts have been found to influence stock prices positively [59], thereby providing possible insight into what is required for investors to build (and lose) trust in their Oracles.

Efforts to better inform the model with real-world network and trading behavior data are essential. While there has been promising work in the area (see [26, 52]), capturing sufficiently detailed data in a time-sensitive manner remains a challenging pursuit. A crucial issue relates to the confidentiality requirements of investors. Therefore, advances in this area of research will only come from specific companies undertaking assessments of their share registry or making that data available [52]. The benefit of conducting this analysis is that firms would gain a greater appreciation of who their owners are (especially short-term versus long-term investors), thereby improving their ability to interpret signals from the market. Alternatively, share registry services and custodians maintain the necessary shareholder data but accessing this data is extremely difficult due to privacy issues and the need for investors to protect their intellectual property.

5. Conclusion

By leveraging the advantages of agent-based modeling, this paper produces important insights into how investors can prosper and identifies tell-tale signs that policymakers should consider if they aim to reduce market volatility. For investors, they must be vigilant to the environment in which they find themselves, and if there is an overabundance of short-term investors, they can either try and remain just ahead of the market, something many have tried and failed, or, as proposed by the likes of Warren Buffett, find a sustainable investment strategy and stick to it. This finding correlates with Lo's [9] Adaptive Market Hypothesis, which suggests that subgroups of investors can survive and prosper in the market and, more important, can influence the market, even though their strategy is not optimal over the long-term. Without the implementation of a bottom-up modeling process, this insight could not be achieved.

For policymakers, the principal consideration is the appearance of a negative externality in that it may be optimal for any one investor to rewire an information network. However, when the entire population does so, it leads to a homogeneous investment approach appearing, with predictable excessive price movements resulting. Critically, the relevance of the investor network is not consistent, as the results indicated that, in more volatile environments, investors tended to disregard following their advisers. The rise of passive investing in the real world is a comparable phenomenon to these implications; that is, in the aftermath of the Global Financial Crisis (GFC), investors lost faith in active management and were prepared to sacrifice upside gains for the benefit of lower risk and matching the market. It is also apparent that researcher focuses their efforts on understanding how investors form and evolve their information needs, a process that is reliant on simulation to provide the initial insights.

The last conclusion to be drawn from this paper is the pressing need to access detailed empirical data. However, data alone will not provide all the necessary answers as it is essential to identify why data forms in a given way, which in turn allows practitioners to determine if and why a step-change will occur and what effects it may produce and assess whether the economy is moving toward a dangerous state. Therefore, researchers utilizing ABMs must continue to balance the need to integrate more data while also demonstrating their primary advantage of being capable of considering a richer set of specifications, which allows for the assessment of complex phenomena [60]. A practical solution is for those using ABMs to accelerate the process of incorporating data into their modeling process and deliver outputs that can be verified against stylized facts, thereby providing more holistic solutions.

Appendix

See Figure 11.

Data Availability

The CSV file and R scripts used to support the findings of this study are available from the corresponding author upon request. Additionally, the model, with the experiments preloaded, can be found at http://tidy.ws/28jdyT.

Disclosure

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Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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