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Research Article

The Hesitation of Anxious Traders in an Agent-Based Model

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Anxiety prevails in financial markets. In accordance with psychological research, anxious traders' hesitant behavior differs from the frequently dissected herding and speculative behaviors. This paper examines the interactions between agent anxiety and price inertia in an artificial financial market. We incorporate an evolutionary mechanism to analyze the strategic benefit of the boundedly rational anxious agent. According to our simulation results, deviations in asset prices from their fundamentals increase with the behavioral hesitation of the anxious agent. The investment rigidity from the anxious agent's lack of confidence mitigates the possibility of price reversal. Moreover, the average strategic benefit of the anxious agent is close to zero. To ensure the reliability of our finding, we further include the irrationality of the anxious agent in our evolutionary setting. Such an endeavor again demonstrates that the strategic benefit of the fundamentalist agent is inferior to that of the anxious agent. Since the anxious agent is characterized by an intolerance for uncertainty, we also investigate the artificial market under various degrees of risk aversion. We perceive that it is less possible for price reversal to emerge when considering higher levels of hesitation. The behavioral hesitation of the anxious agent enables the agent to cleverly evade the risk raised by the speculator.

1. Introduction

Anxiety is a prevalent psychological phenomenon, resulting from physical illnesses, age, investing pressures, and so on. Physical illnesses have been documented to give rise to mental health problems. In relation to such an argument, what is most distinct is the anxiety referred to by Santomauro et al. [1] and Taquet et al. [2]. In addition to physical illnesses, age affects anxiety as well. To be specific, Brenes [3] and Dyck and Smither [4] have perceived that the elderly exhibits milder anxiety compared to the young. In a similar vein, Weiss Wiesel et al. [5] have found that anxiety attenuates on account of the increase in age. Furthermore, when agents participate in crucial and costly investments, they are also prone to anxiety (e.g., [6–8]). Furthermore, based on a survey involving 88,611 persons in Henan province, China, Li et al. [9] have indicated that 12.01% of persons aged 18 to 30 are affected by anxiety. Moreover, anxiety prevails among 12.5% of persons aged 30 to 40. Such a prevalence comes into being among 12.13% of those aged 40 to 50 and 9.52% of the elderly aged 60 to 100.

Research on anxiety can be traced back, at least, to Bellack and Lombardo [10], who classified anxiety into two categories, namely, objective anxiety and neurotic anxiety. To be precise, objective anxiety emanates from the response to realistic threats. In addition, the response to internal conflict without any underlying basis enables neurotic anxiety to take shape. When it comes to the origin of anxiety, Pereira et al. [11] deem that repeated exposure to negative events will certainly lead to anxiety. In a similar vein, Roberts [12] and Charles and Carstensen [13] clarify that adverse events can induce the emergence of anxiety.

The emergence of anxiety elicits a battery of agents' behavioral responses. In relation to this statement, the behavioral hesitation and decision rigidity of anxious agents are obvious. Such anxious agents are unable to adjust their decisions quickly and immediately, which is in a sharp contrast to herding and speculative agents (e.g., [14–16]). In more detail, Holaway et al. [17] provide evidence that agents will be unable to solve problems and cope with threatening situations when they embody severe anxiety. As a result, agents tend to engage in safety behaviors and are unwilling to change their decisions (e.g., [18, 19]).

Similarly, Lorian and Grisham [20] perceive that those suffering from anxiety are characterized by milder risk-taking behaviors than their nonanxious counterparts. Put differently, those suffering from anxiety are more risk-averse. Furthermore, Amstadter [21] verifies that anxiety can alleviate the attentional resources of agents, thereby increasing the difficulties faced by them in coming up with adaptive responses. Moreover, existing agent-based models of sentiment mainly draw attention to the formation of sentiment, the tone of sentiment, the contagion of sentiment, and the variation in sentiment (e.g., [22–27]). Such extant agent-based modeling research has not involved anxiety in modeling the agent's beliefs and behavior. Consequently, it is indispensable to interpret the impact of anxiety on belief and behavior.

Apart from what has been mentioned above, there are two commonly accepted viewpoints concerning the origin of anxiety. To be more specific, Carleton et al. [28] and Boelen and Reijntjes [29] suggest that anxiety by and large emanates from an intolerance for uncertainty and the distress tolerance of those suffering from it. To be precise, despite the probability of occurrence, the intolerance for uncertainty reflects a tendency of sufferers to regard the uncertainty as unacceptable [30]. Moreover, Laposa et al. [31] and Mitchell et al. [32] have emphasized that distress tolerance refers to the ability of those suffering from anxiety to resist negative sentiment. In compliance with such conceptual statements, the intolerance for uncertainty is positively correlated with anxiety, while anxiety is negatively correlated with distress tolerance.

Motivated by research in psychology and agent-based modeling, this paper proposes and develops an artificial market that is populated by both anxious and fundamentalist agents. In our model, anxious and fundamentalist agents have their beliefs regarding the expectations and variances for price. Furnished with agent beliefs, we follow Chen et al. [33] and Hommes [34] to determine the agents' demands using such beliefs and their risk aversion. In addition, inspired by Zhu et al. [35] and Chiarella and He [36], the price of an asset is derived from the excess demand in the agent-based artificial market.

Due to the uncertainty about the future returns of changing strategies, the anxious agents will tend to exhibit behavior that is characterized by searching for safety, so that it is difficult for them to make adjustments to their decisions. As a result, the anxious agent exhibits a delayed reaction or a underreaction to new information (e.g., [37–39].

However, such reactions to information indicate that the past price trend of the asset is maintained and further activates price continuation and inertia (e.g., [40, 41]). Therefore, in the spirit of Jegadeesh and Titman [42], we design momentum strength to digest the impact of the amount of anxiety on price inertia. We dissect interactions between anxiety and deviations in the asset price from its fundamentals. Comparisons are drawn between the respective performances of the anxious agent and the fundamentalist agent.

Research into the psychological aspects provides conflicting evidence as to whether the anxious agent is rational or irrational (e.g., [43, 44]. Therefore, in the agent evolutions of our agent-based market, the agent is assumed to be rational and evolve by referring to self-benefit. Such evolutions are performed using the mechanism provided by Hommes [34]. In addition, we further modify such a mechanism to echo the irrationality of the anxious agent. To be precise, the anxious agent evolves unless the relative benefit of the fundamentalist agent is higher than an upper bound. Otherwise, the anxious agent sticks to the existing strategy even if the fundamentalist agent has already exhibited superior performance.

This research contributes to the literature in three major ways. First, extant studies mainly draw attention to the impact of disposable panic from traders in the stock market (e.g., [45–47]). However, few papers have mainly concentrated on the influence of continuous panic and intrinsic anxiety from traders in the stock market. Hence, compared to such current endeavors in relation to panic, what we strive to settle will extend the boundary with regard to this line of research based on stochastic simulations using an agent-based model. Second, looking back at the existing studies on the artificial stock market, it is found that most of them enlist the fundamentalist agent and the chartist agent, for instance, as in Krichene and El-Aroui [48], Franke [49], Alfi et al. [50], and Alfarano et al. [51]. Based on the fact that anxiety already exists, we design the anxious agent and incorporate such an agent in the agent-based market. As a consequence, this paper is designed in such a way that it expands the class of agents in the field of agent-based modeling research.

Third, in recent years, the bulk of finance research has been continuously devoted to price inertia and reversal, such as the studies by Hung et al. [52], Luo et al. [53], Ali and Hirshleifer [54], and Atilgan et al. [55]. To be specific, they inspect price inertia and reversal in terms of investor attention, investor overconfidence, analyst coverage, investor underreaction, and so on. However, these studies have not exploited anxiety to explore the associated mystery of these two phenomena. Therefore, armed with stochastic simulations, we further dissect the effect of anxiety from the anxious agent in relation to price inertia and reversal. Our analysis also provides experimental explanations for the emergence of inertia and reversal in the real market (e.g., [56–58]). Actually, price inertia and reversal are vital indicators for identifying the market volatility (e.g., [59, 60]). When an asset gives rise to price inertia, the price is not prone to extreme volatility. By contrast, the volatility is apt to emerge when there is salient risk associated with price reversal.

Following this Introduction, which focuses on the paper's motivations and contributions, in the next section, we present a review of related agent-based modeling literature. In Section 3, the agent-based artificial market, which is populated by both fundamentalist and anxious agents, is established. In Sections 4 and 5, we perform simulations as well as digest anxious agents' rationality and irrationality. Moreover, robustness checks come into being in Section 6. In the final section, we provide our conclusions.

2. Literature Review

Existing agent-based models are by and large populated by the fundamentalist agent and the chartist agent. Armed with these two strands of agents, Hommes and Vroegop [61] posit that the trend chasing behavior of chartist agents destabilizes markets, resulting in unpredictable price bubbles and crises. Likewise, Hommes and Veld [62] and Hommes et al. [63] also perceive that the trend chasing behavior is a prominent booster of booms and busts in asset prices. Moreover, Hommes [64] provides evidence that price bubbles and crashes actually originate from shocks to the fundamental information. The behavioral switching between these two groups of agents magnifies such bubbles and crashes. Differing from these two types of agents, the anxious agents cannot adjust their investments in a timely manner. It is less possible for anxious agents to switch their behavioral modes. Consequently, in a similar vein, we also seek to determine whether anxious agents destabilize the market.

Anxious agents are generally unlikely to imitate the other agents on account of their behavioral hesitation and decision rigidity. Such properties are in a sharp contrast with herding behavior. Extant agent-based modeling research on herding behavior endeavors to probe its impact on the volatility, such as Lee and Lee [14], Di Guilmi et al. [65], and Yamamoto [16]. In actual fact, they have documented that herding behavior boosts the market volatility.

To be more specific, Lee and Lee [14] demonstrate that the herding behavior of irrational agents will promote high market volatility. However, when the market proportion of herding agents reaches 3%, such agents obtain considerably positive returns. Likewise, Di Guilmi et al. [65] also posit that the more intensive herding behavior increases drastic market volatility. In addition, Yamamoto [16] perceives that the volatility tends to disappear when agents have limited information to herd. Since anxious agents' behavioral hesitation differs quite significantly from herding behaviors, we endeavor to confirm whether anxious agents bring about a deterioration in market stability.

Furthermore, agent-based models with fundamentalist and chartist agents have been implemented to dissect agents' speculative behaviors. Schmitt et al. [66], Ghonghadze and Lux [15], and Franke and Westerhoff [49] are recent examples. They provide by and large experimental evidence that the market is prone to extreme volatility due to chartist agents' speculative activities. When chartist agents screen out strong technical trading signals from past price trends, the extreme market volatility is maintained and lasts. On the contrary, the fundamentalist agent is a crucial stabilizer of the market. Our agent-based model is populated by fundamentalist and anxious agents. In this respect, under various proportions of fundamentalist agents, it is valuable to probe reversal risk and price deviations.

The modeling framework introduced by Brock and Hommes [67, 68] in two of their studies is the main basis of this paper when modeling heterogeneous agents. To be precise, agents in the model within such a framework are endowed with heterogeneous beliefs pertaining to the expectations and risk regarding the asset's price. In addition, trading strategies come into being in compliance with agents' beliefs. The implementation of a discrete choice model leads to the adaptation of agent beliefs and the interaction between agents. Furthermore, according to Brock and Hommes [67, 68], agents opt whether to alter their previous strategies in line with the accumulated strategic benefit. An agent in a crowd may switch to another crowd when her strategy does not ameliorate the welfare. Indeed, agents learn from their past experience and are thus evolutionary. In the same vein, the anxious agent evolves in line with the self-benefit of strategy in the rational circumstances of our model.

Genetic algorithms and genetic programming are two commonly used tools for agent evolutions and the optimization problem in agent-based models. Chen and Yeh [69, 70] adopt genetic programming to establish a novel framework for designing an artificial financial market. In such an artificial market, a pool of forecasting rules is implemented for agents to engage in social learning. The genetic programming is employed to evolve the pool in accordance with the accuracy of the forecasting rules. Moreover, agents will visit the pool in order to modify their strategies when they are characterized by dramatic incentives. The agents will resort to the pool when their strategies are drastically inferior to those of their counterparts. By performing experiments in this artificial market, these two studies verify the rational expectations hypothesis and document that it is difficult to predict asset prices. In the irrational scenario of our model, such a pool inspires us to design a mechanism for the anxious agent to evolve by referring to the relative strategic benefit of the fundamentalist agent. Moreover, Chen and Yeh [71] can be regarded as a classical attempt to apply genetic programming to financial market issues. Through a genetic programming approach, they demonstrate the concept of price unpredictability. In later applications of genetic programming, Chen and Liao [72] enlist such an approach to establish an artificial market and document that the causal relationship between the asset price and trading volume is an intrinsic characteristic of the market. Moreover, Chen et al. [73] dissect the emergence of sunspot events based on a similar method. They indicate that sunspot believers will never be eliminated from the market. However, in the long run, it is extremely difficult for sunspot believers to survive.

Arthur et al. [74] and Palmer et al. [75] are two cornerstones of agent-based models with genetic algorithms. These two papers build up the Santa Fe Institute artificial market in which price bubbles, crashes, and continued high trading volume emerge. In such an artificial market, the agents are able to evolve on their own. To be precise, they are machine-learning traders recruiting the classifier system to predict asset prices. Equipped with the genetic algorithm, agents evolve and discover new forecasting rules (LeBaron [76] and LeBaron et al. [77]) and further fine-tune the foregoing market. They dissect volatility persistence, leptokurtosis, and large price jumps in the market. Likewise, Chen and Huang [78] recruit an agent-based model with a genetic algorithm to examine the agents' ability to survive. Such an investigation demonstrates that the risk preference is essential to the agents' survivability. A genetic algorithm is also employed in our model. Differing from such extant studies, we follow Chen et al. [33] to implement genetic algorithm for model calibration. Based on such a method, the parameters are calibrated through a constrained optimization problem.

3. The Artificial Financial Market

In our agent-based model, two types of heterogeneous agents are involved, namely, fundamentalist agents and anxious agents. To be specific, we construct an artificial financial market from the perspective of agents' beliefs regarding the expectations and variances of the asset price. In addition, the agents' strategy (demand), the market's evolution, and the procedure used to determine the asset price are also presented.

3.1. Overview. Anxiety is a prevalent psychological phenomenon as indicated by Kessler et al. [79] and Wittchen and Hoyer [80]. Such anxiety mainly results from physical, mental, and social factors. Anxiety results in agents finding it difficult to come up with adaptive responses to the changes in reality. Anxious agents are unable to immediately and quickly make adjustments. It takes them quite a long time to form a decision.

In order to examine this issue, we develop an agent-based model that is populated by anxious and fundamentalist agents. The heterogeneous beliefs regarding the expectations and variances of the asset price are first established. Such beliefs will be recruited to derive the heterogeneous agents' demand as well as the aggregate demand. The asset price is determined by the aggregate excess demand.

Most importantly, the anxious agent is characterized by a lack of confidence, behavioral hesitation, and severe risk aversion. When designing the anxious agent, we incorporate decision rigidity into the agent's belief regarding the expectation for price. Put differently, the anxious agent only makes a decision when recognizing multiperiod and qualitatively similar forecast errors.

3.2. Design Concepts. Compared to herding and speculative agents, the anxious agent embodies behavioral hesitation and decision rigidity. Of particular note, the controversy as to whether anxious agents are rational or irrational needs to be jointly addressed by medical, psychological, and economic research. Consequently, the evolutions under rational and irrational circumstances are both employed in our model.

3.2.1. The Beliefs of the Anxious Agents. Anxious agents are afraid of altering their strategy since such an action will result in uncertainty regarding returns, and they give rise to a lack of confidence. Such agents begin to change unless numerous previous predictions are verified as being inaccurate. Otherwise, they tend to accept the observed losses and stick to the original belief. Hence, in designing the beliefs for anxious agents, we incorporate their forecast errors into their expectation for price. The burgeoning behavioral hesitation and decision rigidity will cause them to refer to more forecast errors. This concept is represented by equation (4).

3.2.2. The Decisions of the Anxious Agents. In decision making, anxious agents only adopt adjustments when they qualitatively discover the same forecast errors across various periods. More specifically, a perception of only positive forecast errors or only negative errors will cause anxious agents to alter their decisions. By contrast, the original decision is maintained when they have not continuously overpriced or underpriced the asset. Such a concept is reflected in equation (7).

3.2.3. The Evolutions within Rational and Irrational Scenarios. Within the rational circumstances of our artificial market, anxious agents evolve when past strategies have not ameliorated their welfare. Besides, in the scenario of irrationality, anxious agents only evolve when there are exceedingly drastic incentives. To be precise, when the relative strategic benefit of fundamentalist agents exceeds an upper bound, such anxious agents will opt to change. Indeed, even though fundamentalist agents obtain a higher strategic benefit, it is still possible that anxious agents will persistently maintain their inferior strategies. This concept is embedded in equation (11).

3.3. The Details. In this section, we present the computational procedure for agent beliefs and agent demands. The fundamentalist agents' beliefs depend on the mean-reversion of the asset price. In addition, the anxious agents' beliefs are based on their forecast errors. For both fundamentalist and anxious agents, their demands are derived from beliefs and their risk aversions. Our design of the evolutionary mechanism both in rational and irrational scenarios is also presented. We further show the determination of the asset price based on the excess demand. Apart from such computations, the formula for momentum strength and the pseudocode of simulations are presented.

3.3.1. Heterogeneous Agent Beliefs. The fundamentalist agents' beliefs regarding the expectations and variances of the asset's price are presented in equations (1) and (2). Similar designs can also be found in Chiarella et al. [81] and Amilon [82].

$$E_t^c\left(p_{j,t+1} \mid p_{j,t}^*, p_{j,t}\right) = p_{j,t}^* + m\left(p_{j,t} - p_{j,t}^*\right), \tag{1}$$

$$V_{j,t}^c = \eta^c \sum_{i=0}^{\tau^c} \left(1-\eta^c\right)^i \left[E_{t-1-i}^c\left(p_{j,t-i}\right) - p_{j,t-i}\right]^2, \tag{2}$$

where c denotes fundamentalist agents, $E_t(\cdot)$ is the conditional expectations operator, $p_{j,t}$ is the actual price of asset j

in period t, $j = 1, 2, \cdots, N$, $p^*_{j,t}$ is assumed to be the fundamental price, $0 \le m \le 1$ is a mean-reverting coefficient, $V^c_{j,t}$ is the fundamentalist agents' belief regarding the asset risk, $\tau^c = t - 1$, and $\mathbb{E}^c_{t-1-i}(p_{j,t-i}) - p_{j,t-i}$ is the forecast error of fundamentalist agents. The fundamental price emanates from the following random walk process:

$$p^*_{j,t} = p^*_{j,t-1} + \varepsilon_{j,t}, \tag{3}$$

where $\varepsilon_{j,t} \sim \mathcal{N}(0, \sigma^2_\varepsilon)$ is an i.i.d. normal random variable.

In what follows, we propose and design a type of novel agent, namely, the anxious agent. Based on the psychological research of Carleton et al. [28] and Boelen and Reijntjes [29], anxiety originates from the agents' intolerance for uncertainty and distress tolerance. As a result, anxious agents tend to embody safety behaviors and have difficulty coming up with adaptive responses to the reality in a timely manner. Such characteristics foster the emergence of delayed decisions and an unwillingness to adapt to change (e.g., [18, 19]). Hence, differing from fundamentalist agents, in each period t, these anxious agents further refer to their past forecast errors in order to form their expectations for price in an attempt to mitigate risk (e.g., [8, 83]). In light of such discussions, we thus design the beliefs of anxious agents as follows:

$$E^x_t\left(p_{j,t+1} \mid F^x_{j,t-1}, F^x_{j,t-2}, F^x_{j,t-3}, \ldots, F^x_{j,t-d}\right) = \begin{cases} p_{j,t} + \lambda \times \left|E^x_{t-1}(p_{j,t}) - p_{j,t}\right|, & \text{if } \forall F^x_{j,t-s} < 0, s = 1, 2, \ldots, d, \\ p_{j,t} - \lambda \times \left(E^x_{t-1}(p_{j,t}) - p_{j,t}\right), & \text{if } \forall F^x_{j,t-s} > 0, s = 1, 2, \ldots, d, \\ p_{j,t} + \dfrac{V^x_{j,t}}{V^x_{j,t-1}}\left(E^x_{t-1}(p_{j,t}) - p_{j,t-1}\right), & \text{if } \exists \operatorname{sign}\left(F^x_{j,t-k}\right) \neq \operatorname{sign}\left(F^x_{j,t-g}\right), k \neq g, \end{cases} \tag{4}$$

$$V^x_{j,t} = \eta^x \sum_{i=0}^{\tau^x} (1 - \eta^x)^i \left[E^x_{t-1-i}(p_{j,t-i}) - p_{j,t-i}\right]^2, \tag{5}$$

where $k, g \in s$, x implies anxious agents, $F^x_{j,t-s} = E^x_{t-s}(p_{j,t-s+1}) - p_{j,t-s+1}$ refers to anxious agents' forecast errors, $\mathbb{V}^x_{j,t}$ is the anxious agents' belief regarding the asset risk, $\lambda > 0$, and $\tau^x = t - 1$.

From equation (4), we can see that when all the $\mathcal{F}^x_{j,t-s}$ are negative, the most recent forecast error will be regarded as a good signal for the asset holder. Hence, $\lambda \times |\mathbb{E}^x_{t-1}(p_{j,t}) - p_{j,t}|$ is employed when anxious agents construct their expectations for price. By contrast, if all the $\mathcal{F}^x_{j,t-s}$ are positive, the most recent forecast error turns to be a terrible signal for the asset holder. As a result, $-\lambda \times (\mathbb{E}^x_{t-1}(p_{j,t}) - p_{j,t})$ comes into the decision making of anxious agents. Within these two scenarios, major adjustments thus come into the anxious agents' minds. However, when anxious agents recognize that the signs of any two $\mathcal{F}^x_{j,t-s}$ are unequal, they are optimistic or pessimistic about the current situation. To be precise, a positive $\mathbb{E}^x_{t-1}(p_{j,t}) - p_{j,t-1}$ suggests optimism, whereas a negative $\mathbb{E}^x_{t-1}(p_{j,t}) - p_{j,t-1}$ indicates pessimism.

3.3.2. The Demand System.

In compliance with Chen et al. [33] and Hommes [34], we derive the demand of anxious and fundamentalist agents from the agent beliefs and risk tolerance. The demand of fundamentalist agents and anxious agents is defined using

$$q^{d,c}_{j,t} = \frac{\left[p^*_{j,t} + m\left(p_{j,t} - p^*_{j,t}\right)\right] - p_{j,t}}{\left\{\eta^c \sum_{i=0}^{\tau^c} (1 - \eta^c)^i \left[E^c_{t-1-i}\left(p_{j,t-i}\right) - p_{j,t-i}\right]^2\right\}} \times \frac{1}{\phi^c}, \tag{6}$$

$$q^{d,x}_{j,t} = \begin{cases} \dfrac{\lambda \times \left|\mathcal{F}^x_{j,t-1}\right|}{\left\{\eta^x \sum_{i=0}^{\tau^x} (1 - \eta^x)^i \left[\mathbb{E}^x_{t-1-i}\left(p_{j,t-i}\right) - p_{j,t-i}\right]^2\right\}} \times \dfrac{1}{\phi^x}, & \text{if } \forall \mathcal{F}^x_{j,t-s} < 0, s = 1, 2, \ldots, d \\ \dfrac{-\lambda \times \mathcal{F}^x_{j,t-1}}{\left\{\eta^x \sum_{i=0}^{\tau^x} (1 - \eta^x)^i \left[\mathbb{E}^x_{t-1-i}\left(p_{j,t-i}\right) - p_{j,t-i}\right]^2\right\}} \times \dfrac{1}{\phi^x}, & \text{if} \forall \mathcal{F}^x_{j,t-s} > 0, s = 1, 2, \ldots, d \\ q^{d,x}_{j,t-1}, & if\ \exists \operatorname{sign}\left(\mathcal{F}^x_{j,t-k}\right) \neq \operatorname{sign}\left(\mathcal{F}^x_{j,t-g}\right), k \neq g \end{cases}, \tag{7}$$

where $k, g \in s$, and $q^{d,c}_{j,t}$ denote the demand of fundamentalist agents, and $q^{d,x}_{j,t}$ is the demand of anxious agents.

From equation (7), when all the $\mathscr{F}^x_{j,t-s}$ are positive or negative, anxious agents are motivated by the identical information. As a result, they alter the demand. By contrast, unequal signs of any two $\mathscr{F}^x_{j,t-s}$ convey fuzzy and incomplete information. Consequently, anxious agents stick to their original demand. It is more possible for anxious agents to perceive unequal signs when d is higher. In a nutshell, anxious agents are more apt to maintain the original demand with progressively intense behavioral hesitation and decision rigidity.

Indeed, d measures the anxious agents' decision rigidity and behavioral hesitation. Although the information has been updated, there is a probability of approximately $(2^d - 2)/2^d$ for anxious agents to maintain their original demand/portfolios. Such agents need to refer to more forecast errors, and the hesitation is more obvious when d is larger. If d equals 1, the expectation for price of the anxious agent can be expressed as $\mathbb{E}^x_t(p_{j,t+1}) = p_{j,t} + \lambda \times \mathscr{F}^x_{j,t-1}$. That is, instead of multiperiod forecast errors, the anxious agent only refers to the single-period forecast error and does not embody behavioral hesitation in such a case. On the contrary, once d equals 2 or becomes more than 2, their beliefs are characterized by persistence, which can only be altered by multiperiod, long-term, and homogeneous information (e.g., [84, 85]).

Let Q^d_t be the aggregate demand in the market. It is the weighted average of the agents' demand using the proportion of anxious and fundamentalist agents in the market.

$$Q^d_t = \sum_{h=1}^{H} n^h_{j,t} \times \left[\frac{\mathbb{E}^h_t(p_{j,t+1}) - p_{j,t}}{\mathbb{V}^h_{j,t}} \times \frac{1}{\phi^h}\right], \quad (8)$$

where $h \in \{c, x\}$, $n^h_{j,t}$ denotes the market proportion of agents, ϕ^h is the risk aversion coefficient of agents, and the inverse reflects the risk tolerance. In line with Lorian and Grisham [20], compared to the fundamentalist agents, those suffering from anxiety give rise to more subtle risk-seeking behavior, thereby suggesting that their risk tolerance is weaker. Consequently, in this paper, we assume that $1/\phi^x < 1/\phi^c$ in Section 4 and explain it in Section 5.2.

3.3.3. The Evolutionary Mechanism. The evolutionary mechanism in this paper consists of two parts. First of all, agents evolve by assessing the self-benefit. To be more specific, when their strategies have not ameliorated their welfare, they will consider whether to switch their behavioral modes. Furthermore, they will also evolve in accordance with the relative benefit compared to their counterparts. Such a mechanism is described as well.

In the rational scenario, agents update their behaviors according to the benefit obtained from their strategies. Therefore, we follow Hommes [34, 86] to let the agents' market proportion evolve over time in the architecture based on

$$\theta^h_{j,t} = \left(\frac{p_{j,t} - p_{j,t-1}}{p_{j,t-1}}\right) \times q^{d,h}_{j,t-1} + \omega_\theta \theta^h_{j,t-1}. \quad (9)$$

where $h \in \{c, x\}$ and $\theta^h_{j,t}$ is the device used to acquire the agents' self-benefit. Armed with such a design, we calculate the market proportions of agents as follows:

$$n^h_{j,t} = \frac{\exp(\beta \times \theta^h_{j,t})}{\sum_{h=1}^{H} \exp(\beta \times \theta^h_{j,t})}, \quad (10)$$

where $n^h_{j,t}$ is the agents' market proportion, and β denotes the agents' sensitivities to their self-benefit.

As mentioned at the beginning of this section, agents can evolve in light of the self-benefit and the benefit compared with that of the other agents. The latter variety is referred to as the relative benefit in this paper. In the irrational scenario, irrational anxious agents are reluctant to imitate fundamentalist agents even though fundamentalist agents have outperformed them. To be more precise, agents adjust their strategies in the spirit of equation (11) in the irrational scenario.

$$n^x_{j,t} = \begin{cases} \dfrac{\exp(\beta \times \theta^x_{j,t-1})}{\exp(\beta \times \theta^x_{j,t-1}) + \exp(\beta \times \theta^c_{j,t})}, & \text{if} 0 \le (\theta^c_{j,t} - \theta^x_{j,t}) \le \overline{U}, \\ \dfrac{\exp(\beta \times \theta^x_{j,t})}{\exp(\beta \times \theta^x_{j,t}) + \exp(\beta \times \theta^c_{j,t})}, & \text{otherwise}, \end{cases} \quad (11)$$

where $\theta^c_{j,t} - \theta^x_{j,t}$ refers to the relative benefit of fundamentalist agents, implying the magnitude of the overperformance of such agents.

We take $\overline{U}$ to represent the upper bound of the anxious agents' bounded rationality. If $0 \le \theta^c_{j,t} - \theta^x_{j,t} \le \overline{U}$, the relative benefit is inferior to such a bound, and thus, anxious agents do not alter their original strategies. As a consequence, the population of anxious agents will be maintained as before. Consequently, a larger $\overline{U}$ suggests that anxious agents are increasingly reluctant to change their decisions even though they recognize the underperformance of their strategies. Such arguments indicate that the magnitudes of irrationality and anxiety are more dramatic due to a larger $\overline{U}$. Therefore, this bound actually draws attention to the bounded rationality of anxious agents.

3.3.4. Price Determination. Having established the systems for the agents' beliefs, the agents' demand, and the agents' evolution, we now follow Zhu et al. [35], Chiarella and He [36], and Chen and Yeh [70] to determine the actual price based on the excess demand. In the agent-based market, the actual price of the asset is determined using the following equation:

Initialization. Set the initial fundamental price, initial actual price, initial proportions of agents, and parameters for simulations.
(0) **Begin Algorithm.**
(1) **For** *each period* t, **do**
Procedure 1:
(a) Let the fundamentalist agents observe the current fundamental ($p^*_{j,t}$) and actual prices ($p_{j,t}$), as well as all available historical prices ($p^{\mathcal{H}}_{j,t}$). They thus form their beliefs regarding the expectation ($\mathbb{E}^c_t$) and variance ($\mathbb{V}^c_t$) of price based on $p^*_{j,t}$, $p_{j,t}$, and $p^{\mathcal{H}}_{j,t}$.
(b) The fundamentalist agents' demands ($q^{d,c}_{j,t}$) take shape in line with $\mathbb{E}^c_t$, $\mathbb{V}^c_t$, $p_{j,t}$, and their risk tolerances ($1/\phi^c$).
Procedure 2:
(a) Let the anxious agents discern the $p_{j,t}$ and $p^{\mathcal{H}}_{j,t}$, thereby calculating all their forecast errors ($\mathcal{F}^x_{j,t}$). Their beliefs with respect to the expectation ($\mathbb{E}^x_t$) and variance ($\mathbb{V}^x_t$) of price come into being according to $p_{j,t}$ and $\mathcal{F}^x_{j,t}$.
(b) **If** $\forall \mathcal{F}^x_{j,t} > 0$ or $\forall \mathcal{F}^x_{j,t} < 0$, **then**
the anxious agents' demands (($q^{d,x}_{j,t}$)) emerge in light of $\mathcal{F}^x_{j,t}$, $\mathbb{V}^x_t$, and their risk tolerances ($1/\phi^x$).
Elseif the signs of any two $\mathcal{F}^x_{j,t}$ are unequal, **then**
$q^{d,x}_{j,t}$ is maintained as before.
End Elseif.
End if.
Procedure 3:
(a) The fundamentalist and anxious agents calculate their strategic benefits, say, $\theta^c_{j,t}$ and $\theta^x_{j,t}$.
(b) The market proportions of fundamentalist agents evolve over time using the *discrete choice model* with the device of strategic benefits.
(c) **If** *anxious agents are rational*, **then**
anxious agents' proportions evolve using the *discrete choice model* with the device of strategic benefits.
Elseif *anxious agents are irrational*, **then**
anxious agents' proportions evolve when ($\theta^c_{j,t} - \theta^x_{j,t}$) is higher than an upper bound.
End Elseif.
End if.
End for.
(2) **For** *each period* $t+1$, **do**
The aggregate excess demand and $p_{j,t}$ are implemented to determine $p_{j,t+1}$ through a hyperbolic tangential function.
End for.
(3) **End Algorithm.**

ALGORITHM 1: The agent-based model with anxious and fundamentalist agents.

$$p_{j,t} = p_{j,t-1} \times \left\{ 1 + \gamma \times \left[\frac{\exp\left(\delta\left(Q^d_{t-1} - Q^s_{t-1}\right)\right) - \exp\left(-\delta\left(Q^d_{t-1} - Q^s_{t-1}\right)\right)}{\exp\left(\delta\left(Q^d_{t-1} - Q^s_{t-1}\right)\right) + \exp\left(-\delta\left(Q^d_{t-1} - Q^s_{t-1}\right)\right)} \right] \right\}, \quad (12)$$

where $\delta > 0$ denotes the sensitivity of the actual price to the excess demand, Q^s_t is the aggregate supply and a standard normal i.i.d. random variable, and $0 < \gamma \leq 1$ determines the upper and lower bounds of the price adjustments.

In equation (12), let $\mathbb{T}$ be $\exp(\delta(Q^d_{t-1} - Q^s_{t-1})) - \exp(-\delta(Q^d_{t-1} - Q^s_{t-1}))/\exp(\delta(Q^d_{t-1} - Q^s_{t-1})) + \exp(-\delta(Q^d_{t-1} - Q^s_{t-1}))$. In actual fact, $\mathbb{T}$ is a hyperbolic tangential function. Hence, when the excess demand tends to positive infinity, the limit of this function is 1. On the contrary, the limit reaches −1, given that the excess demand is inclined toward negative infinity.

3.3.5. Momentum Strength. Since the anxious agents are characterized by behavioral hesitation, it is possible that they will exhibit delayed reactions to new information (e.g., [37, 38]), thereby giving rise to price inertia. Hence, in the spirit of Jegadeesh and Titman [42], equation (13) is what is used to calculate the momentum strength and examine the price inertia of the asset. A similar such test can be seen in Lin et al. [87].

$$MS_{j,t} \equiv \begin{cases} p^g_{j,[t-d+1,t-1]} + p^g_{j,t}, & \text{if } p^g_{j,[t-d+1,t-1]} > 0, p^g_{j,t} > 0 \\ -\left(p^g_{j,[t-d+1,t-1]} + p^g_{j,t}\right), & \text{if } p^g_{j,[t-d+1,t-1]} < 0, p^g_{j,t} < 0 \\ p^g_{j,t} - p^g_{j,[t-d+1,t-1]}, & \text{if } p^g_{j,[t-d+1,t-1]} > 0, p^g_{j,t} < 0, \\ p^g_{j,[t-d+1,t-1]} - p^g_{j,t}, & \text{if } p^g_{j,[t-d+1,t-1]} < 0, p^g_{j,t} > 0 \end{cases} \quad (13)$$

where $p^g_{j,[t-d+1,t-1]}$ denotes the price growth rate during the period covering $[t-d+1, t-1]$, d is the indicator revealing the decision rigidity and behavioral hesitation, and $p^g_{j,t}$ denotes the price growth rate in period t.

3.3.6. The Pseudocode of Simulations. In what follows, we present the pseudocode for simulations of our agent-based model. Algorithm 1 shows the details. The parameters used in the simulations appear in Appendix A.

4. Baseline Simulations

We first examine how the asset price deviates from the fundamental information in a market populated by anxious and fundamentalist agents. Moreover, we continue to dissect the price inertia of the asset through momentum strength. The experiments that consider the evolutionary mechanism

Table 1: Simulations without evolutions. Note: This table reports deviations from fundamentals (differences between the asset price and the fundamental price) and momentum strengths considering various proportions of the anxious agent. The market proportions of the anxious agents lie between 0.5 and 0.9. The indicator of behavioral hesitation (denoted by d) is between 1 and 5. When d equals 1, the expectation for price of the anxious agent can be written as $\mathbb{E}_t^x(p_{j,t+1}) = p_{j,t} + \lambda \times \mathcal{F}_{j,t-1}^x$. Hence, the anxious agent does not embody hesitation since the agent only relies on the single-period forecast error in such a case. However, hesitation begins to emerge if d is 2 or over 2 since the agent refers to multiperiod forecast errors. In Panel A, we calculate the mean and the t-statistic of the mean for deviations from the fundamentals. To be precise, in our statistical inferences, we perform a one-sample t-test in each simulation window. After acquiring the t-statistic for each window, we then compute the average of the t-statistics across windows. Such a procedure used to infer the statistical significance can also be found in Gatti and Grazzini [88] and García-Magariño et al. [89]. As for the momentum strength of the asset, we show the results in Panel B. Note that a positive momentum strength denotes price inertia, whereas a negative momentum strength stands for price reversal.

d	0.5	0.6	0.7	0.8	0.9	0.5	0.6	0.7	0.8	0.9
Panel A: deviations from fundamentals			Deviations					t-Statistics		
1	−1.028	−0.859	−0.597	−0.340	−0.128	−3.334	−3.119	−2.599	−1.935	−1.018
2	−1.139	−0.991	−0.756	−0.446	−0.249	−3.628	−3.511	−3.221	−2.505	−2.052
3	−1.180	−1.014	−0.792	−0.491	−0.340	−3.758	−3.577	−3.345	−2.763	−2.687
4	−1.195	−1.045	−0.812	−0.542	−0.480	−3.804	−3.691	−3.437	−3.047	−3.657
5	−1.210	−1.074	−0.830	−0.547	−0.690	−3.848	−3.809	−3.527	−3.069	−4.706
Panel B: momentum strength			Strength					t-Statistics		
1	−0.263	−0.248	−0.248	−0.241	−0.174	−3.906	−4.206	−5.063	−6.375	−6.773
2	−0.253	−0.227	−0.190	−0.159	−0.111	−4.099	−4.182	−4.061	−4.260	−4.324
3	−0.131	−0.145	−0.155	−0.168	−0.141	−1.729	−2.210	−2.824	−4.006	−5.170
4	−0.259	−0.220	−0.195	−0.161	−0.096	−3.342	−3.276	−3.525	−3.801	−3.356
5	−0.087	−0.093	−0.116	−0.133	−0.081	−1.101	−1.389	−2.103	−3.152	−2.847

provided by Hommes [34, 86] are also conducted. Apart from momentum strength, we further examine the evolution of the anxious agent and the benefit of the anxious agent's strategy and draw comparisons between the anxious and fundamentalist agents.

4.1. Momentum Strength and Deviations from Fundamentals. This section examines the deviations in the asset price from the fundamental information when considering various market proportions of the anxious agent. Under such a setting, we also dissect the price inertia of the asset using momentum strength. Table 1 presents the results of the experiments regarding the deviations from the fundamental information and momentum strength.

In accordance with the agent-based model in Section 3, the anxious agent does not give rise to behavioral hesitation when d equals 1. After d approaches 2 or is over 2, the anxious agent begins to hesitate when making decisions. Hence, from Panel A of Table 1, the presence of the anxious agent is related to deviations from the fundamental information, and all the absolute t-statistics are higher than 2 or even 3 both before and after the appearance of behavioral hesitation (denoted by d). In addition, the absolute values of deviations are exacerbated with the increasing behavioral hesitation of the anxious agent. Furthermore, in Panel B, the artificial market is characterized by price reversal since the negative momentum strength is significant (most of the absolute t-statistics are over 2). The absolute values of negative momentum strength decrease with increasing hesitation. For example, in considering equal proportions of the agents, the negative momentum strength is −0.263 for no hesitation ($d = 1$), while it becomes −0.253 when the anxious agent is characterized by hesitation ($d = 2$). In addition, the absolute value of negative momentum strength continues to decline and becomes −0.087 when d equals 5. Hence, anxiety to a certain extent affects the negative momentum strength.

4.2. Simulations with Evolutionary Proportions. In Section 4.1, we have investigated the deviations from the fundamental information and price inertia without evolutions. In this section, the mechanism regarding the agents' evolution provided by Hommes [34, 86] is involved. Such a mechanism enables the agents to decide whether or not to change their strategies by means of assessing the benefits of previous strategies. Hence, this mechanism also influences the market proportions of the agents, thereby implying that the market proportion is time-varying. In addition, anxious agents change their strategies once they perceive that the previous investment did not benefit them. Consequently, the anxious agent is indeed assumed to be rational in this section.

In Table 2, as indicated by Panel A, deviations from the fundamental information are still relevant to the magnitudes regarding the behavioral hesitation of the anxious agent even if we enlist the evolution of the anxious agent. In Panel B, we find that the market proportions of the anxious agent are significantly different from 0.5 (the absolute t-statistics are over 3). In addition, despite behavioral hesitations, the market proportions of the anxious agent change at around 0.54. Although the benefit of the anxious agent's strategy changes around zero as suggested by Panel C, the anxious agent still obtains a better benefit than the fundamentalist agent. More specifically, in Panel D, the differences in benefits (anxious minus fundamentalist) are significantly

Table 2: Simulations with evolutionary proportions. Note: This table presents deviations from the fundamental information, market proportions of anxious agents, the benefit of the anxious agent's strategy, the difference in benefits between the anxious and fundamentalist agents, and the momentum strengths. The indicator of behavioral hesitation (denoted by d) ranges from 1 to 5. When d equals 1, the expectation for price of the anxious agent can be written as $\mathbb{E}_t^x(p_{j,t+1}) = p_{j,t} + \lambda \times \mathcal{F}_{j,t-1}^x$. Hence, the anxious agent does not embody hesitation since the agent only relies on the single-period forecast error in such a case. However, hesitation begins to emerge if d is 2 or over 2 since the agent refers to multiperiod forecast errors. For the sake of inferring statistical significance, we perform a one-sample t-test in every simulation window. Furnished with such exercises, the averages of the t-statistics across windows are obtained. Gatti and Grazzini [88] and García-Magariño et al. [89] also employ the same inference procedure.

d	Mean	t (mean)
Panel A: deviations from fundamentals		
1	−0.805	−2.866
2	−0.870	−3.058
3	−0.911	−3.191
4	−0.913	−3.194
5	−0.915	−3.210
Panel B: proportions of anxious agents		
1	0.544	4.189
2	0.541	3.915
3	0.540	3.744
4	0.541	3.866
5	0.541	3.818
Panel C: anxious agents' benefit		
1	0.00305	4.364
2	0.00015	0.202
3	−0.00004	−0.045
4	−0.00021	−0.259
5	−0.00032	−0.384
Panel D: anxious agents' benefit minus fundamentalist agents' benefit		
1	0.092	6.174
2	0.086	5.638
3	0.081	5.311
4	0.085	5.526
5	0.083	5.443
Panel E: momentum strength		
1	−0.314	−5.273
2	−0.221	−3.703
3	−0.195	−2.772
4	−0.230	−3.260
5	−0.141	−1.934

positive since the absolute t-statistics are greater than 5 or 6. Such outcomes indicate that the anxious agent is at least free of losses.

Moreover, in Panel E, with regard to the evolution of the anxious agent, we can perceive that the absolute values of negative momentum strengths are approximately attenuated by the increasing hesitation (denoted by d). For instance, the negative momentum strength is −0.314 for $d = 1$, but it becomes −0.141 when d is 5. Such results suggest that the behavioral hesitation of the anxious agent and resulting delayed transactions can alleviate the possibility of price reversal.

5. Dissections on Rationality and Irrationality

Indeed, the research on psychology has not reached a consensus on whether the anxious agent is rational or irrational. For instance, Addis and Bernard [44] and Himle et al. [90] have perceived that an increase in anxiety will lead to a deterioration in rational cognitive capability and thus give rise to boundedly rational behaviors. By contrast, since anxiety is a result of the agent's intolerance for uncertainty, the unwillingness of anxious agents to alter decisions and the salient risk aversion are just driven by their rationality (e.g., [43, 91, 92]).

By going back to the discussion in Section 3, the original evolutionary mechanism proposed by Hommes [34, 86] is based on the self-benefit of the agent. The anxious agent changes strategy when the previous strategy does not benefit, thereby suggesting that the agent is rational. In addition to incorporating such an evolutionary mechanism, we fine-tune it by allowing the agent to rely on the relative benefit in decision making. In other words, the anxious agent will not take any action when the relative benefit is inferior to an upper bound even if they find that the fundamentalist agent outperforms. Hence, the anxious agent is regarded as irrational. Furthermore, as we indicated in Section 3, the magnitude of the risk aversion of the anxious agent is generally greater than that of the fundamentalist agent. Consequently, in the upcoming experiments, we consider various degrees of risk aversion for the anxious agent. Armed with such experimental designs, we continue to dissect our artificial financial market.

5.1. The Upper Bound of Irrationality and the Nonherding Agent. Herding agents are apt to change their behaviors and exhibit irrationality (e.g., [14, 65]). Compared to such agents, anxious agents give rise to behavioral hesitation and decision rigidity. Hence, it is less possible for them to make a difference to decisions. In the evolutionary mechanism of the irrational scenario, the agents update their strategies by referring to the relative benefit compared to the strategies of the other agent. Since anxious agents are constrained by their anxiety, they are characterized by a lack of confidence and behavioral hesitation. Even though anxious agents perceive that their benefits are inferior to those of fundamentalist agents, they will stick to the extant strategy unless the relative benefit exceeds an upper bound. A higher upper bound corresponds to more severe anxiety and irrationality. It is, therefore, quite possible that such a psychology of the anxious agent will contribute to deviations from fundamentals and the emergence of price inertia. Therefore, in Table 3, the anatomy of the artificial market under various upper bounds comes into play.

From Table 3, when concerning the irrationality of the anxious agent, deviations from fundamentals are still related to the degrees of behavioral hesitation from the anxious agent. Despite upper bounds of irrationality, deviations are positively correlated with the degrees of behavioral hesitation. Moreover, just as we perceive in the original evolutionary mechanism provided by Hommes [34, 86], the anxious agents' market proportions are significantly different from 0.5 (the absolute t-statistics are at least greater than 3 across all panels).

As for agent benefits, the anxious agents encounter significantly positive benefits (the absolute t-statistics are over 4) when they do not exhibit behavioral hesitation ($d = 1$). If such agents are characterized by hesitation (d is greater than 1), the benefit turns to be insignificant and close to zero (absolute t-statistics are lower than 1). However, the anxious agent still outperforms the fundamentalist agent since most of the absolute t-statistics for the difference in their benefits are higher than 5 across all panels. Such outcomes again indicate that anxious agents will not be inferior to fundamentalist agents even if they are characterized by irrationality.

The momentum strengths are all negative regardless of the magnitudes of the behavioral hesitations (indicated by d). However, with a higher d, the absolute values of negative momentum strengths are lower. To be precise, when d equals 1 in Panel A, the negative momentum strengths are close to −0.3. Such negative momentum strengths, respectively, vary around −0.17 and −0.12 when d is 3 and 5. To sum up, in considering the irrationality of the anxious agent, such experiments imply that the anxious agent's hesitation can mitigate the possibility of price reversal in financial markets.

5.2. Various Degrees of Risk Aversion. In considering the various degrees of risk aversion of the anxious agent, this section continues to check our findings regarding the benefits of agents' strategies and momentum strengths already discussed. The results of such experiments are presented in Table 4.

In Table 4, as implied by Panel A, we can find that most of the absolute t-statistics for the positive difference in benefits are higher than 4 or even 5 despite different degrees of risk aversion and behavioral hesitation. In addition, the behavioral hesitation of anxious agents has not exerted a positive impact on their strategic outperformance. Such a result can be shifted unless they engage in active transactions after perceiving long-term information on forecast errors. To be specific, when the risk aversion coefficient of the anxious agent is 0.1, their investments thus become active, and significant outperformance increases with the behavioral hesitation (the absolute t-statistics are over 3 or 4).

Regardless of the degrees of hesitation and risk aversion in Panel B, most of the momentum strengths are significantly negative (the absolute t-statistics are mainly over 2 or 3). However, the negative momentum strengths are mitigated as the behavioral hesitation is stronger. For instance, when the risk aversion coefficient is 0.1, the negative momentum strength is −0.349 when d is 1, whereas the negative strength is −0.165 if d is 2. Moreover, in considering more severe hesitation (d equals 4 or 5), such a process results in positive momentum strengths. These outcomes again demonstrate that the behavioral hesitation of the anxious agent alleviates the possibility of price reversal.

5.3. Summary of Results. Having already conducted a battery of experiments in this and the previous section, we continue to summarize the existing results. In experiments without the evolutions in Table 1, the *market proportion* of the anxious agent will be related to the deviations from the fundamental information. In addition, the magnitudes of the negative momentum strengths decrease after the appearance of behavioral hesitation. The *behavioral hesitation* of the anxious agent can reduce the possibility of price reversal. Moreover, such observations are more evident after including the agent evolutions in the experiments in Table 2. These results persist even though we consider the irrationality of the anxious agent in the evolutions as presented in Table 3.

Since agent evolutions rely on the benefit of the agent's strategy, we dissect and compare the benefits between the two types of agents. In evolutions without considering the upper bound of irrationality, the anxious agent's benefits are close to zero in Table 2. However, such benefits are not inferior to those of the fundamentalist agent. These findings are maintained when we include the upper bound of irrationality in the agent evolutions in Table 3. Hence, these results suggest that the anxious agent will at least not encounter losses in the artificial market developed in this paper.

Table 3: Simulations for the upper bound of irrationality. Note: In this table, by focusing on the upper bound of irrationality in agent evolutions, we dissect deviations from the fundamental information, market proportions of anxious agents, the benefit of the anxious agents' strategy, the difference in the benefit between the anxious and fundamentalist agents, and the momentum strength. The magnitudes of the lack of confidence and behavioral hesitation (denoted by d) are 1, 3, and 5, respectively. When d equals 1, the expectation for price of the anxious agent can be written as $\mathbb{E}_t^x(p_{j,t+1}) = p_{j,t} + \lambda \times \mathcal{F}_{j,t-1}^x$. Hence, the anxious agent does not embody hesitation since the agent only relies on the single-period forecast error in such a case. However, hesitation begins to emerge if d is 2 or over 2 since the agent refers to multiperiod forecast errors. The upper bounds are 0.01, 0.05, 0.1, 0.2, and 0.5, respectively. In order to ensure the accuracy of statistical inference, we thus follow Gatti and Grazzini [88] and García-Magariño et al. [1, 8]] to perform a one-sample t-test for each simulation window. Equipped with such endeavors, we proceed to calculate the averages of the t-statistics across windows.

	Deviations		Anxious agents' proportions		Anxious agents' benefit		Anxious agents' benefit minus fundamentalist agents' benefit		Momentum strength	
U	Mean	t (mean)	Mean	t (mean)	Mean	t (mean)	Mean	t (mean)	Mean	t (mean)
Panel A: d = 1										
0.01	−0.836	−2.921	0.542	3.957	0.003	4.236	0.087	5.662	−0.305	−4.939
0.05	−0.849	−2.965	0.542	3.977	0.003	4.214	0.087	5.639	−0.303	−4.910
0.1	−0.852	−2.994	0.543	4.015	0.003	4.278	0.088	5.687	−0.305	−4.947
0.2	−0.846	−2.964	0.543	4.061	0.003	4.305	0.089	5.775	−0.311	−5.046
0.5	−0.853	−2.986	0.542	3.992	0.003	4.234	0.087	5.637	−0.301	−4.869
Panel B: d = 3										
0.01	−0.931	−3.214	0.541	3.842	$-5.45E-05$	−0.055	0.084	5.496	−0.179	−2.502
0.05	−0.945	−3.240	0.540	3.769	$-2.28E-05$	−0.017	0.081	5.289	−0.177	−2.475
0.1	−0.939	−3.236	0.541	3.853	$-1.76E-05$	−0.012	0.083	5.410	−0.182	−2.561
0.2	−0.947	−3.247	0.540	3.765	$-2.67E-05$	−0.023	0.080	5.238	−0.172	−2.408
0.5	−0.935	−3.205	0.540	3.813	$-1.92E-05$	−0.014	0.082	5.317	−0.172	−2.398
Panel C: d = 5										
0.01	−0.952	−3.275	0.540	3.741	−0.0003	−0.372	0.081	5.303	−0.122	−1.653
0.05	−0.979	−3.353	0.540	3.760	−0.0003	−0.378	0.081	5.263	−0.120	−1.619
0.1	−0.953	−3.265	0.540	3.776	−0.0003	−0.345	0.081	5.260	−0.127	−1.722
0.2	−0.960	−3.282	0.540	3.812	−0.0003	−0.370	0.082	5.311	−0.112	−1.514
0.5	−0.955	−3.280	0.541	3.860	−0.0003	−0.375	0.083	5.398	−0.119	−1.621

Table 4: Simulations with various degrees of risk aversion. Note: The agents' benefits and momentum strengths for various degrees of risk aversion in agent evolutions are presented in this table. The indicator of hesitation (represented by d) lies between 1 and 5. When d equals 1, the expectation for price of the anxious agent can be expressed as $\mathbb{E}_t^x(p_{j,t+1}) = p_{j,t} + \lambda \times \mathcal{F}_{j,t-1}^x$. Hence, the anxious agent does not embody hesitation since the agent only relies on the single-period forecast error in such a case. However, hesitation begins to emerge if d is 2 or over 2 since the agent refers to multiperiod forecast errors. The risk aversion (RA) of the anxious agent lies between 0.1 and 5. In the pursuit of accuracy regarding statistical inference, we follow Gatti and Grazzini [88] and García-Magariño et al. [89] to perform a one-sample t-test for each window. This procedure enables us to calculate the averages of the t-statistics across windows. The upper bound of the evolutionary mechanism is 0.1.

	Mean					t (mean)				
	RA = 0.1	RA = 0.5	RA = 1	RA = 2	RA = 5	RA = 0.1	RA = 0.5	RA = 1	RA = 2	RA = 5
Panel A: anxious agents' benefit minus fundamentalist agents' benefit										
$d = 1$	0.124	0.085	0.086	0.086	0.086	4.791	4.935	5.410	5.574	5.733
$d = 2$	0.133	0.077	0.083	0.083	0.086	3.581	4.627	5.330	5.461	5.688
$d = 3$	0.498	0.074	0.083	0.084	0.086	3.974	4.443	5.309	5.483	5.725
$d = 4$	2.200	0.066	0.080	0.084	0.085	3.852	3.880	5.080	5.487	5.626
$d = 5$	2.376	0.063	0.082	0.083	0.086	3.464	3.687	5.159	5.405	5.700
Panel B: momentum strength										
$d = 1$	−0.349	−0.269	−0.292	−0.300	−0.304	−5.177	−4.182	−4.647	−4.852	−4.959
$d = 2$	−0.165	−0.223	−0.222	−0.224	−0.214	−1.857	−3.723	−3.660	−3.682	−3.531
$d = 3$	−0.102	−0.142	−0.155	−0.186	−0.193	−0.974	−1.979	−2.160	−2.571	−2.680
$d = 4$	0.034	−0.220	−0.264	−0.249	−0.232	0.134	−2.933	−3.671	−3.454	−3.233
$d = 5$	0.002	−0.132	−0.102	−0.127	−0.161	0.039	−1.673	−1.362	−1.718	−2.207

6. Robustness Checks

We check the robustness of this paper in three ways. First of all, the agent-based model is validated by confirming whether it reproduces stylized facts. Second, the long short-term memory neural network is enlisted for agents to learn. Furnished with such a technique, we compare the difference in strategic benefit between the fundamentalist and anxious agents. Third, key parameters of the agent-based model are calibrated using data from a real financial market. We further check whether the model still reproduces stylized facts after key parameters are calibrated.

6.1. Reproductions of Stylized Facts. In our baseline simulations, the model parameters follow Zhu et al. [35] and Amilon [82]. To be precise, our procedure for determining the asset price and modeling the fundamental price is the same as in Zhu et al. [35]. In addition, Amilon [82] performs empirical analysis for the S&P 500 index, and we follow such a study to set parameters for agent beliefs. From our previous results, we have clarified the influence of anxiety on deviations in asset prices from their fundamentals and price reversal. Hence, we continue to validate the model following Arifovic et al. [93], Fagiolo et al. [94], and Chen et al. [33]. More specifically, we confirm whether the model reproduces well-known fat-tailed returns and the absence of autocorrelation among the returns from real markets. Table 5 presents the outcomes of fat-tailed returns. The results regarding the autocorrelation of returns come into being in Figures 1 and 2.

In Table 5, we show the skewness and kurtosis of returns both in rational and irrational scenarios. The simulations are performed using the parameters from Zhu et al. [35] and Amilon [82]. The kurtosis exceeds 19 regardless of rationality and irrationality, suggesting that the returns from our artificial market are leptokurtic and fat-tailed. Such findings are similar to those of Arifovic et al. [93], Brandouy et al. [95], and Cont [96]. Accordingly, it is obvious that our agent-based model well reproduces fat-tailed returns. In addition, the returns from the model give rise to a long right tail since the skewness is positive and higher than 3.

As depicted by Figure 1, the autocorrelation of returns is evidently negative at the beginning but quickly becomes very close to zero. Such a perception is persistent across all degrees of behavioral hesitation and decision rigidity (denoted by d). Armed with the parameters from Zhu et al. [35] and Amilon [82], the agent-based model in this paper reproduces the absent autocorrelation of returns.

Figure 2 depicts the same findings as in Figure 1. To be specific, the autocorrelation of returns is negative at the beginning. However, it is prevalently close to zero when the lag is lengthened. Such a pattern emerges despite the magnitude of behavioral hesitation and decision rigidity (indicated by d). Therefore, our agent-based model is again validated using the absent autocorrelation of returns in the irrational scenario.

Table 5: Skewness and kurtosis of returns. Note: This table reports the outcomes of reproducing fat-tailed returns using the parameters from Zhu et al. [35] and Amilon [82]. The skewness and kurtosis of returns are calculated, respectively, in rational and irrational scenarios. d suggests the degree of behavioral hesitation and decision rigidity of the anxious agent.

d	Skewness	Kurtosis
Panel A: the rational scenario		
1	3.201	19.120
2	3.223	19.277
3	3.246	19.453
4	3.207	19.188
5	3.230	19.347
Panel B: the irrational scenario		
1	3.223	19.303
2	3.213	19.237
3	3.197	19.116
4	3.200	19.129
5	3.210	19.164

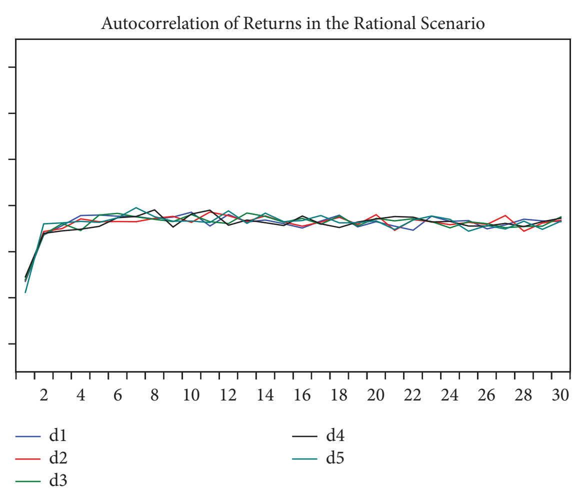

Figure 1: Autocorrelation of returns in the rational scenario. This figure plots the autocorrelation of returns in the rational scenario. In the simulations, we use the parameters from Zhu et al. [35] and Amilon [82]. d is the strength regarding the behavioral hesitation and decision rigidity of the anxious agent. The length of the lag extends from 1 to 30.

6.2. Alternative Learning Mechanism. The long short-term memory (LSTM) neural network has been extensively employed in time-series forecasting, for example, in Zhang et al. [97], Ghimire et al. [98], Nguyen and Bae [99, 101], and Somu et al. [101]. (In Appendix B, we present the theory of the LSTM in detail.) The LSTM neural network is a type of recurrent neural network (RNN). It is a loopback framework armed with interconnected neurons in which information is shared between time steps. It also performs well in tackling long-term information.

Specifically, the LSTM network is treated as a route for fundamentalist agents to learn and obtain the expectation for price. In our original results, the strategy of the fundamentalist agent underperforms that of the anxious agent.

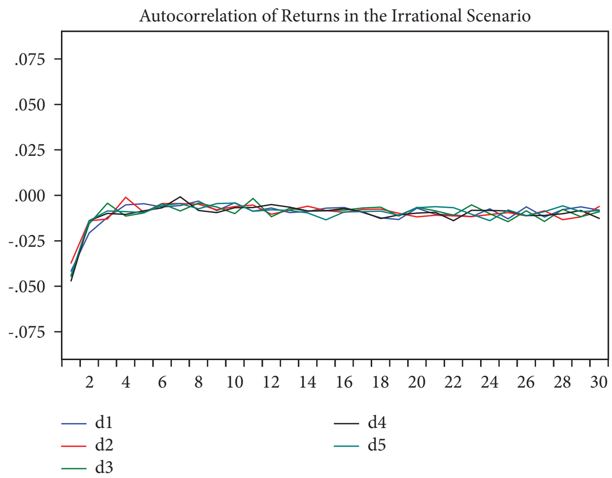

Figure 2: Autocorrelation of returns in the irrational scenario. The autocorrelation of returns in the irrational scenario is shown in this figure. The parameters from Zhu et al. [35] and Amilon [82] are implemented in the simulations. d is the strength regarding the behavioral hesitation and decision rigidity of the anxious agent. The length of the lag ranges from 1 to 30.

Hence, in retrieving the belief of the anxious agent, we use the original method and do not resort to the LSTM. Armed with such an experimental design, we can observe whether the LSTM helps the fundamentalist agent improve the strategy. The neural network is trained with the deep learning toolbox of MATLAB.

Such agents train their own LSTM in accordance with the agent-based studies of Kieu et al. [101], Fraunholz et al. [102], Dehghanpour et al. [103], Salle [104], Yıldızoğlu et al. [106], and Sgroi and Zizzo [107, 108]. The simulation with the LSTM is comprised of 104 periods. (104 periods echo 104 trading weeks for two years in real financial markets.) We select 50% of the data for the period as the original training set in the spirit of Tang et al. [109] and Baek and Kim [110]. In addition, we follow Liu et al. [111], Gao et al. [112], Xia et al. [113], and Tian et al. [114] to perform sliding-window training for the LSTM network.

During the training procedure, the output is the expected asset price. The inputs of the fundamentalist agents' network are all available historical fundamental prices and historical price deviations. With regard to the parameters for training, the initial learning rate is 0.005 with a drop factor of 0.2 in compliance with Ghimire et al. [98]. In addition, the batch size is 10, and there are 200 epochs following Zhang et al. [97] and Fischer and Krauss [115]. The optimization method is adaptive moment estimation (Adam) in light of Nguyen and Bae [99] and Ghimire et al. [116].

Furnished with the trained network, fundamentalist agents incorporate information into the network. Before including such data in the trained network, agents standardize the data using the mean and standard deviation of the training sample employed in the training procedure. After acquiring the prediction from the network, the agents destandardize the prediction using the same mean and standard deviation.

To be precise, fundamentalist agents incorporate the fundamental price and price deviation into the network. The belief of such agents is derived from them in the original agent-based model. Such executions enable their expectations for price at time $t+1$ to take shape. Such a simulation with the embedded LSTM network is repeated 30 times. We probe the difference in strategic benefit between fundamentalist and anxious agents within such a market. Table 6 presents the results of the experiment.

Table 2 reports positive differences in the strategic benefits between anxious and fundamentalist agents. (In Table 2, the evolutionary proportion of the anxious agent varies around 0.5. Such results are mainly compared with the results of Table 6 with proportions of 0.5 and 0.6.) According to Table 6, the anxious agent is no longer superior to the fundamentalist agent since most of the differences in strategic benefit are negative. Such a finding prevails regardless of the anxious agent's proportions and the magnitude of behavioral hesitation. In short, furnished with the deep learning belief, the fundamentalist agent successfully ameliorates the strategic benefit.

6.3. Calibration with the Genetic Algorithm. Tesfatsion [117], Dieci and He [118], and Fabretti [119] have suggested calibrating key parameters of the agent-based model when the model is used to study the real market. Consequently, in this section, the parameters of price determination and the fundamental price will be calibrated using the data for the S&P 500 index. (We obtain the data from http://www.investing.com, which is one of the top three websites for financial markets.) Bertschinger and Mozzhorin [120], Lux [121], and Franke [122] also apply the stock market index to calibrate their parameters.

In the spirit of Moya et al. [123] and Recchioni et al. [124], the constrained optimization problem proceeds from equations (14) to (16). To solve such a constrained optimization problem, we follow Chen et al. [33] to enlist the genetic algorithm. In accordance with Soh and Yang [125] and Davis [126], the population size is 50, the size of tournament selection is 4, and the crossover is intermediate. The mutation rate is adaptive in compliance with Marsili Libelli and Alba [127]. We execute the genetic algorithm using the global optimization toolbox of MATLAB.

$$\omega^* = \left(\gamma^*, \delta^*, \sigma_\varepsilon^*\right) = \arg\min_{\omega\in\Omega} f(\omega), \tag{14}$$

Table 6: Agents' strategic benefit in considering the LSTM. Note: In this table, we report the difference in strategic benefit between anxious agents and fundamentalist agents and related t-statistics. More specifically, the anxious agent maintains the original route to obtain the expectation for price, while the fundamentalist agent applies the long short-term memory (LSTM) neural network to acquire the expectation for price. The market proportion of the anxious agent lies between 0.5 and 0.9. d denotes the magnitude of behavioral hesitation and decision rigidity. It extends from 1 to 5.

d	0.5	0.6	0.7	0.8	0.9
Panel A: anxious agents' benefit minus fundamentalist agents' benefit					
1	−0.566	−0.659	−0.370	−0.488	−0.687
2	−0.472	−0.516	−0.526	−1.041	−0.639
3	−0.688	−0.680	−0.469	−0.538	−0.323
4	−0.322	−0.580	−0.603	−0.674	−0.871
5	−0.703	−0.938	−1.062	−0.480	−0.390
Panel B: t-statistics					
1	−0.922	−1.600	−0.800	−1.324	−1.120
2	−1.401	−1.417	−1.565	−1.804	−0.755
3	−1.407	−1.690	−1.386	−1.401	−0.961
4	−1.540	−1.366	−1.538	−1.060	−1.594
5	−1.727	−1.249	−1.705	−0.895	−1.294

where

$$f(\omega) = \frac{1}{\mathcal{K}}\left[\sum_{k=1}^{\mathcal{K}}\sum_{t=1}^{T}\left(\frac{p_t^m - p_t^a}{p_t^a}\right)^2\right]_k, \quad (15)$$

subject to

$$\begin{cases} 0 < \gamma^* \leq 1, \\ \delta^* > 0, \\ \sigma_\varepsilon^* > 0, \end{cases} \quad (16)$$

where Ω denotes the parameter space, ω^* denotes the optimal parameter vector, $\mathcal{K}$ suggests the number of simulations, p_t^m is the price emerging from the agent-based model, p_t^a is the price from the real market, and T is the length of the sample period. Such an objective function has two merits. First of all, the positive and negative values of $p_t^m - p_t^a$ will not offset each other. Second, we divide the $p_t^m - p_t^a$ by p_t^a so that the outcome will not be disturbed by the scale of the data. In Table 7, we report the calibrated parameters of the model in both rational and irrational circumstances.

Armed with the calibrated parameters from Table 7, we then seek to figure out whether our model reproduces fat-tailed returns and the absent autocorrelation of returns. In Table 8, we calculate the skewness and kurtosis of returns from our model in both rational and irrational scenarios. We depict the autocorrelation of returns for these two scenarios in Figures 3 and 4. It is notable that the model is validated when fat-tailed returns and the absence of autocorrelation among the returns are reproduced.

From Table 8, as demonstrated by Panel A, we assert that returns from our agent-based model are characterized by a long right tail since the skewness is persistently positive (the skewness exceeds 2). In addition, it is evident that returns are leptokurtic and fat-tailed since the kurtosis goes beyond 11 or even 12. Such similar outcomes take shape in Panel B. In a nutshell, our agent-based model with the anxious agent reproduces the fat-tailed returns in the real market quite well.

Furnished with Figure 3, the autocorrelation is negative at the beginning and soon turns to be very close to zero. Consequently, it is obvious that the autocorrelation of returns is absent in our agent-based model when considering rationality. After calibrating key parameters, the model is still validated in the rational scenario using the absence of autocorrelation among the returns.

Likewise, in the irrational scenario, Figure 4 exhibits negative autocorrelation at the beginning. However, we have not observed evident autocorrelation of returns when the lengths of the lags mushroom since the autocorrelation is approximately zero. Despite the theoretical parameters or calibrated parameters, our agent-based model is validated through fat-tailed returns and the absence of autocorrelation in the returns in both the rational and irrational scenarios.

In Table 9, price deviations are significantly positive and burgeoned with behavioral hesitation (the absolute t-statistics exceed 10). Notably, price deviations with no hesitation ($d = 1$) are different from those with severe hesitation ($d = 5$). Such discoveries appear in both the rational and irrational scenarios. In addition, absolute values of negative momentum strengths increase with behavioral hesitation when considering rationality and irrationality. Compared to the fundamentalist agent, the anxious agent is characterized by more severe pessimism (e.g., [128, 129]).

The original experiments in Sections 4 and 5 suggest that the asset price is below the fundamental price in the market. However, the anxious agent does not quickly make adjustments on account of the behavioral hesitation. The anxious agent expects that the asset price will tend not to increase to the fundamental price. As a consequence, such pessimism on the part of the anxious agent slows down the change in the asset price to return to the fundamental price. Hence, the behavioral hesitation of the anxious agent alleviates the possibility of price reversal.

After the calibration based on the S&P 500 in Table 9, the asset price is higher than the fundamental price in the market due to positive price deviations. In such a market, the

Table 7: Calibrated parameters of the model. Note: In this table, the calibrated parameters of the model are presented, including γ and δ in price determination, as well as σ in modeling the fundamental price. d denotes the magnitude of the behavioral hesitation and decision rigidity of the anxious agent.

d	γ	δ	σ
Panel A: the rational scenario			
1	0.932	7.629	4.943
2	0.949	6.843	9.123
3	0.944	6.846	9.066
4	0.946	6.881	9.750
5	0.949	7.218	9.776
Panel B: the irrational scenario			
d	γ	δ	σ
1	0.986	6.413	8.959
2	0.949	6.843	9.123
3	0.945	6.863	7.558
4	0.947	6.650	14.604
5	0.915	7.726	12.878

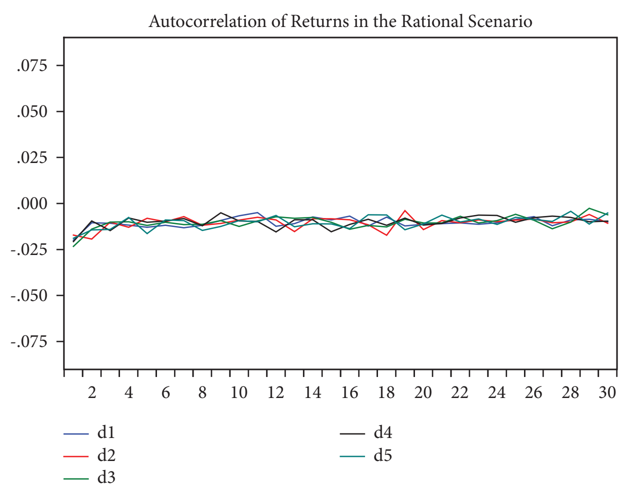

Figure 3: Autocorrelation of returns in the rational scenario. This figure shows the autocorrelation of returns in the rational scenario. The parameters of price determination and the fundamental price used in simulations are calibrated. d represents the magnitude of behavioral hesitation and decision rigidity, which ranges from 1 to 5. The lengths of the lags range from 1 to 30.

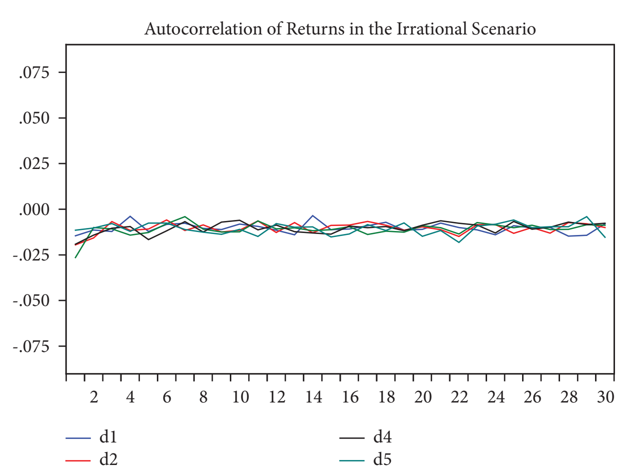

Figure 4: Autocorrelation of returns in the irrational scenario. In this figure, we plot the autocorrelation of returns when considering irrationality. The parameters of price determination and the fundamental price used in the simulations are calibrated. The behavioral hesitation and decision rigidity of the anxious agent are represented by d, which extends from 1 to 5. The lengths of the lags range from 1 to 30.

Table 8: Skewness and kurtosis of returns after calibration. Note: We present the skewness and kurtosis of returns in this table. Panels A and B, respectively, show outcomes for the rational and irrational circumstances. d denotes the strength in regard to the behavioral hesitation and decision rigidity of the anxious agent.

d	Skewness	Kurtosis
Panel A: the rational scenario		
1	2.011	11.907
2	2.176	12.891
3	2.191	12.940
4	2.186	12.933
5	2.096	12.433
Panel B: the irrational scenario		
d	Skewness	Kurtosis
1	2.244	13.268
2	2.165	12.808
3	2.170	12.844
4	2.227	13.088
5	2.035	12.039

Table 9: Price deviations and momentum strengths after calibration. Note: This table reports the price deviations and momentum strengths after the model parameters are calibrated. In light of Recchioni et al. [124], the initial asset price and initial fundamental price in the calibration are equal to the first weekly observation of the S&P500 in 2021. We calculate the deviations in asset prices from their fundamentals and momentum strengths for both the rational and irrational scenarios. The magnitude of behavioral hesitation and decision rigidity of the anxious agent is denoted by d. When d equals 1, the anxious agent does not embody hesitation. The anxious agent begins to exhibit hesitation when d equals 2 or is even higher than 2. The upper bounds for the irrational circumstances are 0.1, 0.2, and 0.5, respectively.

	Deviations		Momentum strength	
d	Mean	t (mean)	Mean	t (mean)
Panel A: evolutions in the rational scenario				
1	1937.722	13.149	−0.002	−0.084
2	1909.506	13.899	−0.002	−0.147
3	1949.298	14.519	−0.003	−0.165
4	1959.178	14.331	−0.002	−0.125
5	2011.462	13.725	−0.003	−0.181
Panel B: evolutions in the irrational scenario ($\overline{U} = 0.1$)				
1	1887.498	14.488	−0.001	−0.085
2	1940.968	14.247	−0.002	−0.109
3	1934.550	14.409	−0.002	−0.121
4	1898.376	14.271	−0.002	−0.132
5	1975.848	13.646	−0.004	−0.198
Panel C: evolutions in the irrational scenario ($\overline{U} = 0.2$)				
1	1873.440	14.463	−0.001	−0.086
2	1909.521	14.353	−0.002	−0.131
3	1929.630	14.477	−0.002	−0.145
4	1874.889	14.088	−0.002	−0.156
5	1982.344	13.170	−0.003	−0.187
Panel D: evolutions in the irrational scenario ($\overline{U} = 0.5$)				
1	1833.252	14.117	−0.001	−0.077
2	1902.283	13.427	−0.001	−0.092
3	1922.032	14.708	−0.002	−0.140
4	1908.596	14.426	−0.002	−0.162
5	1943.689	12.876	−0.003	−0.179

absolute values of the negative momentum strengths mushroom with the behavioral hesitation (denoted by d). Such a finding suggests that the progressive anxiety will increase the possibility of price reversal. When the asset price goes beyond the fundamental price, there is a higher likelihood that the asset price will attenuate due to the more drastic lack of confidence of the anxious agent (a higher d).

Table 10: Parameters of the agent-based model. Note: This table reports the parameters used in this paper. These parameters are chosen in accordance with Zhu et al. [35] and Amilon [82].

Parameters	Values
$p^*_{t=0}$	10
$p_{t=0}$	10
σ_ε	0.01
Q^s_t	$\mathcal{N}(0, 1)$
γ	0.8
δ	2
ω_θ	0.04
β	1.5
m	0.06
λ	0.06
ϕ^c	1
ϕ^x	2
η^c	0.4
η^x	0.4

7. Conclusions

This paper proposes and develops an artificial market, which is populated by anxious agents and fundamentalist agents. In accordance with the psychological research of Clapp et al. [18] and Lorian and Grisham [20], we take the lack of confidence and behavioral hesitation into account when designing the anxious agent's belief in the expectation regarding the asset's price. We analyze the relationship between anxiety, the evolutionary mechanisms, and price deviations through computational experiments. Furthermore, the effect of anxiety on price inertia is also investigated. In addition to these dissections, we strive to confirm whether there is a significant difference in the strategic benefit between the rational fundamentalist agent and the irrational anxious agent.

From our experimental outcomes, we perceive that the deviations from the fundamental price are related to the behavioral hesitation of the anxious agent (denoted by d). The mean of the deviations increases with the hesitation of anxious agents in the market. In light of Jegadeesh and Titman [42], we design momentum strength to analyze the interactions among anxiety, price inertia, and price reversal. Our experiments indicate that the behavioral hesitation of the anxious agent is positively correlated with momentum strength.

Moreover, the evolutionary mechanism of Hommes [34] is employed in our agent-based model. Under the circumstance of agent evolution, the absolute values of the negative momentum strengths are attenuated with an increasing d. Since anxious agents lack confidence, they need continuous and multiperiod positive (negative) information to alter their beliefs and adjust their trading strategies. Such results imply that it is less possible for price reversal to emerge when the anxious agent embodies more severe hesitation.

According to the definition of a strategic benefit provided by Hommes [34, 86], we find that the average benefit of the anxious agent's strategy is close to zero. Since deviations from fundamentals prevail in the market, and the fundamentalist agent's beliefs are based on fundamentals, the average benefit of the fundamentalist agent is negative. In Section 5.1, irrationality is implemented in the anxious traders' evolutionary mechanism. Likewise, we still discover that fundamentalist traders cannot obtain significant benefits. Such findings from the simulations also echo the strategic benefit, which can be observed in the real market.

In a nutshell, the fundamentalist agent cannot outperform in a market in which there are deviations from the fundamental price. The anxious agent engages in delayed transactions as a result of a lack of confidence. Such decisions enable the agents to be immune to losses. From this perspective, the strategy of the anxious agent may be a wise one. We believe that it would be valuable to incorporate the overconfident speculator into such an anxiety agent-based model in future research.

Appendix

A. Simulation Design and Parameters of the Model

We follow Chiarella et al. [81] to design our simulations for the artificial financial market developed in this paper. To this end, a simulation is comprised of 52 periods. In addition, these 52 periods correspond to 52 trading weeks of a year in the real financial market. Such a simulation is repeated 100 times. Before performing simulations for the artificial market, it is necessary to define several parameters used in the model. In Table 10, we report the parameters following Zhu et al. [35] and Amilon [82].

B. The Long Short-Term Memory Neural Network

Furnished with the design of memory cells, Hochreiter and Schmidhuber [130] construct a long short-term neural network (LSTM). The involvement of self-connected memory cells enables the LSTM to tackle long-term information. Within each memory cell, there are three gates to maintain and control the cell state, encompassing the forget gate, input gate, and output gate. These three gates serve as information filters. We describe such a neural network model in more detail as follows.

First of all, the forget gate determines which information should be removed from the cell state at time t-1. The activation value of the forget gate at time t is obtained through the following equation:

$$f_t = \text{sigmoid}\left(W_{f,x}x_t + W_{f,h}h_{t-1} + B_f\right), \tag{B.1}$$

where x_t is the input at time t, h_{t-1} is the output from the cell at t-1, $W_{f,x}$ and $W_{f,h}$ are weight matrices, B_f is the bias vector, and $\text{sigmoid}(z) = (1+e^{-z})^{-1}$ with a range between 0 and 1.

Second, the model screens out which information is to be added to the cell state at time t. Such a task is accomplished using the following two procedures:

$$\begin{aligned} &\tilde{c}_t \\ &i_t = \text{sigmoid}\left(w_{i,x} x_t + w_{i,h} h_{t-1} + b_i\right), \end{aligned} \tag{B.2}$$

where $\tilde{c}_t$ is the candidate value of the cell state, i_t denotes the input gate, $W_{\tilde{c},x}$, $W_{\tilde{c},h}$, $W_{i,x}$, and $W_{i,h}$ are weight matrices, $B_{\tilde{c}}$ and B_i are bias vectors, and $\tanh(z) = (e^z - e^{-z})/(e^z + e^{-z})$.

Third, the cell state at time t is updated through the following equation:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \tag{B.3}$$

where $\odot$ denotes element-wise multiplication.

Finally, the output of the memory cell at time t is derived from the following equations:

$$\begin{aligned} &o_t \\ &h_t = o_t \odot \tanh(c_t). \end{aligned} \tag{B.4}$$

Here, $W_{o,x}$ and $W_{o,h}$ are weight matrices, B_o is a bias vector, o_t is the output gate, and h_t is the output of the cell state, c_t.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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