Economic Modelling 68 (2018) 74–81

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/econmod

Herding, social network and volatility☆

Guocheng Wang[a], Yanyi Wang[b,*]

[a] Institute of Quantitative and Technical Economics, Chinese Academy of Social Sciences, Beijing 100732, PR China
[b] School of Finance, Renmin University of China, Beijing 100872, PR China

ARTICLE INFO

JEL classification:
G02
G10

Keywords:
Heterogeneous beliefs
Herding
Social networks
Guru
Adaptive beliefs system
Market volatility.

ABSTRACT

Investors' expectations are highly influenced by their surroundings' opinions, especially from those who are believed as gurus. These opinion leaders (i.e., gurus) may manipulate the information when the information is disseminated to their followers. It is unclear whether herding behaviors will still emerge in this situation and if so, how these behaviors would influence the market volatility. In this paper, we model agents who choose either to follow the gurus with different precisions of information, or to be a chartist based on evolutionary considerations. Numerical simulations show that increasing the quality of gurus' private information would lead to more intensive herding behavior of followers and produce a U-shaped effect on the market volatility. Besides, increasing the proportion of gurus in the market would lead to more intensive herding but would decrease the market volatility. Interestingly, the market environment also affects investors' choices. Investors are more willing to herd on gurus in boom times or in depression. This paper sheds light on how informed gurus affect investors' behavior and market volatility through direct communication.

1. Introduction

Individuals' investment decisions are inevitably influenced by others. In the financial market, uncentralized influences might lead to herding behaviors. Specifically, herding refers to the convergence in the behavior of investors, analysts and firms in their respective decisions. Such convergent behaviors could be caused by agents' observations of predecessors' actions (e.g. Scharfstein and Stein, 1990; Banerjee, 1992; Bikhchandani et al., 1992; Welch, 1992; Ellison and Fudenberg, 1993; Trueman, 1994; Schlag, 1998; Cipriani and Guarino, 2008), or the observations of the aggregate consequences of actions (e.g. the market price) (Grossman and Stiglitz, 1976; Lux, 1995; Avery and Zemsky, 1998; Smith and Srensen, 2000; Cipriani and Guarino, 2008; Dasgupta et al., 2011).

Previously, much theoretical research has explained agents herding through observational learning: investors infer the information from actions of previous investors and emulate these actions subsequently. For example, the seminal works by Banerjee (1992) and Bikhchandani et al. (1992) find that upon observing a sequential trading of others, people would simply imitate others' actions and disregard their own information. They suggest that people might overvalue the information represented in decisions made by others, even though their private information might suggest alternatives. The ignorance of their own information would exert a 'negative externality' on the rest of participants, and engender irrational decisions based on ill-defined fundamental value in the market (Banerjee, 1992).

Herding behavior could also simply build up through direct communication in a social network (Ellison and Fudenberg, 1995; Shiller, 1995). Much research has shown that people do benefit from the information advantage through networks in many activities, such as job search (Ioannides and Loury, 2004), stock recommendations (Cohen et al., 2010) and venture capital investments (Hochberg et al., 2007). At the same time, sharing the same information can also result in herding decisions with purblind consideration. In fact, recent empirical literature has demonstrated that individuals are highly influenced by their social peers and incline to take similar actions in a variety of finance-related decisions such as stock market participation (Hong et al., 2004; Brown et al., 2008), corporate finance policies making (Fracassi (Forth coming), 2016), portfolio choice (Hong et al., 2005; Ivkovi and Weisbenner, 2007; Heimer, 2016), investment

☆ We want to thank the Editor as well as two anonymous referees for their thoughtful comments that permitted to highly improve the manuscript. We are also extremely grateful to Aiqing Ling for his helpful comments and discussions. The financial support of National Basic Research Program of China (973 project No. 2012CB955802), National Natural Science Foundation of China (NSFC) (Grant No. 71471177) and of CASS-ESRC partnership project of China-UK governments (Grant No.: ES/N00762X/1) are gratefully acknowledged by the authors. We have benefitted from comments from two anonymous referees as well as from participants at the 21rd annual conference on Computing in Economics and Finance (CEF, 2015) and the 4th International Symposium in Computational Economics and Finance (ISCEF, 2016) and in particular from Ricardo M. Sousa, Shu-Heng Chen, Te Bao, Shunming Zhang.

* Corresponding author.
E-mail addresses: wanggc@aliyun.com (G. Wang), wangyanyi@ruc.edu.cn (Y. Wang).

http://dx.doi.org/10.1016/j.econmod.2017.04.018
Received 25 May 2016; Received in revised form 20 April 2017; Accepted 21 April 2017
Available online 05 May 2017
0264-9993/

returns (Ozsoylev et al., 2014), and welfare plan participation (Bertrand et al., 2000).

In the financial market, when price perfectly reflects most information, the distributed information from an informed agent seems to be more valuable, which will ignite people to trade in the same direction sightlessly. Herding by direct communication thus may have two opposite effects on market outcomes. On the one hand, if the informed agent conveys precise and authentic signals, the information would be impounded into the price more quickly, and the market would operate more efficiently. On the other hand, however, spreading unavailing information would lead to less informative price and greater market volatility (Bommel, 2003). From the followers' perspective, it is hard to distinguish whether this unavailing information comes from an intentional manipulation or an innocent mistake. This leaves space for the occasional manipulation by the informed ones to disseminate the information besides altruism in a network (Battaglini, 2004).

In the prior research, the possibility of information manipulation in direct communication has been overlooked to the understanding of herding behavior. Specifically, it is unclear whether the herding behavior will still be formed if the information through direct communication might be manipulated. If so, what factors would affect the intensity of herding behavior, and how market volatility will be altered accordingly? Our paper attempts to address these questions by extending the theoretical understanding of herding behavior with respect to information quality. Moreover, our paper also makes methodological contributions by applying a heterogeneous-agents asset pricing model in the study of market volatility. The advantage of using agent-based models is that they are capable of simulating a complex system where a number of agents interact through prescribed rules. This will handle a wide range of behaviors that cannot be explained by conventional equilibrium models (Farmer and Foley, 2009). This is particularly suitable for our research purposes. In our study, the heterogeneous agents model helps to simulate the complex interactions among different types of agents in their social networks and estimate the market outcomes.

Our model is outstretched from the seminal work by Brock and Hommes (1997, 1998), who introduce the adaptive belief systems, where agents can choose from a finite set of predictors of the future price of a risky asset based on performance measures (e.g. past realized profits). In their model, there are two types of agents: fundamentalists and chartists. Investors switch between these two predictors based on the past realized profits. Under this setting, they identify how an increase in the 'intensity of choice' (i.e. the sensitivity to the difference in profits between these two predictors) can lead to market instability. This work thus provides a good framework to model evolutionary heterogeneous agents in financial market (He et al., 2009; Ke and Shi, 2009; Westerhoff and Wieland, 2010; Di Guilmi et al., 2014; Zhang et al., 2016; Zheng et al., 2017). In particular, it is suitable to elaborate how the strategies of agents with limited rationality could cause anomalies in the market. In a recent work by Lof (2015), for example, he assumes that multiple agents could have different investment horizons. In his work, there are three types of agents: the long-horizon investors who are called fundamentalists, and the short-term investors including rational speculators and contrarian speculators. He shows that this heterogeneity in investment horizon can produce far more excess volatility than a standard present value model. Especially, he mentions that a large fraction of contrarian speculators contributed to the irrational bubble in 1990s stock market. Different from Lofs' work, our model emphasizes the connections among agents beliefs and how agents communications eventually affect market volatility. We assume three type of agents: gurus, informed speculators and chartists. Gurus are those who have private information in the networks. Other investors choose to be informed speculators, who just simply follow the gurus, or chartists, who chase the trend in the market. To some extent, the gurus and informed speculators are both fundamentalists despite the fact that they have different information sources. Specifically, gurus collect the information and form their expectations by themselves, while informed speculators follow the information given by gurus. This setting outlines a framework for how communications in a social network could shape investors beliefs and affect the market volatility.

We found that the quality of gurus' own information was a core factor that determined whether they would manipulate the information in the direct communication. Interestingly, an increase in the quality of private information would generate a U-shaped effect on market volatility. Specifically, when the private information was highly precise, it would attract more investors to follow gurus and trade on the informative information. This reduced the variance and increased the market efficiency. Meanwhile, gurus were more likely to send opposite information to followers in order to make profits from their precise private information. Even though followers knew that the probability of manipulation was high, they would still follow gurus if the past realized profits were sufficiently high. This led to the deviation from the fundamental value and increased the market volatility. These results provide support to regulate informed trading of insiders and their relatives to ensure the market stability.

In addition, we also investigated other parameters of interest, such as the proportion of gurus, the intensity of choice and the fundamental values in our model, providing a rich set of testable implications. For example, we showed that an increase in the proportion of gurus would lead to more followers and lower the market volatility. When the market has more gurus, the price would be closer to the fundamental value, and followers would gain more if they go after gurus. In the meanwhile, high quality private information will also elicit higher incentives for gurus to manipulate information. The effects of increasing proportion of gurus (i.e. lowering the market volatility) would be less discernible in a market where all the gurus are highly informed. Therefore, this indicated that more diversified views toward the market would decrease the market volatility, and the effects would be more apparent in markets with more poorly informed participants, such as in the emerging markets where individual investors dominate than in the developed market with more well-informed investors or institutional investors.

Our simulation results also showed that when the unconditional expectation of the fundamental value went to extreme (i.e. either high or low), the intensity of herding would be stronger. The intuition is that when the unconditional expectation of the fundamental value is high, for example, a negative signal carries more valuable information than in a normal time. This indicates that investors are more likely to take advantage of the valuable information and herd on others' opinions. The same pattern will hold when the unconditional expectation is low in a bear market. In the meanwhile, however, if we consider the effects of information quality, the aforementioned principle will also apply: the more informed gurus in the market, the more likely the information is manipulated for chasing their own utilities, and hence the market volatility will be higher. Therefore, herding in a bull market or a bear market would increase the volatility in a market with more sophisticated and well-informed investors, while decrease the volatility in a market with more poorly informed participants.

Our research is associated with some recent work on information communication on herding behaviors (Tedeschi et al., 2009; Tedeschi et al., 2012; Jouini and Napp, 2015). For example, Tedeschi et al. (2012) studied the herding effects induced by investors' imitations on gurus expectations. In their model, however, the imitation behavior is endogenously determined by a preferential attachment rule, and all agents are uninformed noisy traders. Therefore, the gurus are endogenously determined by the intensity of imitation. By assuming that gurus own private information with different levels of precision and that they have the opportunities to manipulate the information, our model establishes a more dynamic setting to illustrate how herding and market volatility are influenced by gurus' information.

Another work by Jouini and Napp (2015) also analyzed the impacts of gurus' influences on other investors' expectations in a single period trading model. Relatedly, their model considered the probable manipulation by gurus when they announced their beliefs. They suppose that followers can observe both the announcements made by gurus and gurus' portfolios. However, the information manipulation by gurus is driven by the differences in the risk tolerance between gurus and followers. In contrast, our model assumes that followers cannot observe the action of gurus but they can update their beliefs about gurus reputation for each trading period. Since we apply the agent-based model to simulate multi trading periods, we are able to draw more implications on market fluctuations that are unrevealed in the previous literature.

The flow of the paper is organized as following. We first introduce a heterogeneous asset pricing model with three agents in Section 2. Section 3 examines the impacts of different factors on agents' behaviors and market volatility. The final section offers conclusions and discussions.

2. The model

Following Brock and Hommes (1998), we consider a market with one risk-free asset and one risky asset. Let p_t denote the price per share of the risky asset at time t, y_t be dividend of the risky asset, where $y_t \in \{0, 1\}$. The risk-free rate is $R > 1$. We have

$$\mathbf{W}_{t+1} = RW_t + (\mathbf{p}_{t+1} + \mathbf{y}_{t+1} - Rp_t)z_t \tag{1}$$

for the dynamic wealth, where bold face type denotes random variables and z_t denotes the number of shares of the asset purchased at date t. Let E_t,V_t denote the conditional expectation and variance operator, based on a publically available information set consisting of past prices and dividends. Let E_{ht}, V_{ht} denote the belief of the type h about conditional expectation and conditional variance. Then, we obtain

$$E_{ht}(\mathbf{W}_{t+1}) = RW_t + E_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1} - Rp_t)z_{ht} \tag{2}$$

$$V_{ht}(\mathbf{W}_{t+1}) = V_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1} - Rp_t)z_{ht}^2 \tag{3}$$

Assume that each agent has a constant absolute risk aversion (CARA) utility function: $U(W_t) = \exp(-\alpha_h W_t)$, where $\alpha_h > 0$ is the risk aversion coefficient that allows for a difference according to the agent's type. By maximizing the expected utility of wealth, type h agent obtains the optimal demand on the risky asset:

$$z_{ht} = \frac{E_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1}) - Rp_t}{\alpha_h V_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1})} \tag{4}$$

Let z_{st} denote the supply of shares of the risky asset, n_{ht} be the fraction of investors type h at date t. In the equilibrium, market clearing implies

$$\sum_h n_{ht} \frac{E_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1}) - Rp_t}{\alpha_h V_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1})} = z_{st}. \tag{5}$$

Following Brock and Hommes (1998) and Hommes (2001), we assume a zero supply of outside risky shares, namely $z_{st} = 0$, without loss of generality. Hence, the market clearing price of risky asset is:

$$Rp_t = \frac{\sum_h n_{ht} \dfrac{E_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1})}{\alpha_h V_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1})}}{\sum_h \dfrac{n_{ht}}{\alpha_h V_{ht}(\mathbf{p}_{t+1} + \mathbf{y}_{t+1})}} \tag{6}$$

where N is the total number of all traders in the market.

In a homogeneous world where all agents have rational expectations and same information set, the asset price is equivalent to the fundamental price:

$$p_t^* = \sum_{k=1}^{\infty} \frac{E_t(\mathbf{y}_{t+k})}{R^k} \tag{7}$$

where E_t is the expectation conditional on the information set $\Phi_t = \{p_t, p_{t-1}, p_{t-2}, \ldots; y_t, y_{t-1}, y_{t-2}, \ldots\}$. Assume that $\mathrm{Prob}[y_t = 1] = \bar{y}$, then $E_t(\tilde{y}_t) = \bar{y}$. The fundamental price is constant and determined by:

$$p^* = \sum_{k=1}^{\infty} \frac{\bar{y}}{R^k} = \frac{\bar{y}}{R-1} \tag{8}$$

Suppose $x_t = p_t - p_t^*$, the realized excess return over period t to period $t+1$ is:

$$\begin{aligned} R_{t+1}p_t &= p_{t+1} + y_{t+1} - Rp_t = x_{t+1} + p_{t+1}^* + y_{t+1} - Rx_t - Rp_t^* \\ &= x_{t+1} - Rx_t + p_{t+1}^* + y_{t+1} - E_t(p_{t+1}^* + y_{t+1}) \\ &\equiv x_{t+1} - Rx_t + \delta_{t+1} \end{aligned} \tag{9}$$

where $\delta_{t+1} = p_{t+1}^* + y_{t+1} - E_t(p_{t+1}^* + y_{t+1})$ is a martingale difference sequence with respect to Φ_t.

Suppose that the performance measure is

$$\pi_{ht} = R_{t+1}p_t z_{ht} = (x_{t+1} - Rx_t + \delta_{t+1})z_{ht} \tag{10}$$

We can introduce additional memory into performance measure, by taking a weighted average of realized profits, as follows:

$$U_{ht} = \pi_{ht} + \eta U_{h,t-1} \tag{11}$$

where $0 \le \eta \le 1$ represents the memory strength. The updated fractions n_{ht} is determined by the discrete choice probability:

$$n_{ht} = \frac{\exp[\beta U_{h,t-1}]}{\sum_h \exp[\beta U_{h,t-1}]} \tag{12}$$

where β is the intensity of choice parameter that measures how sensitively the investor reacts to the differences in the attractiveness of trading rules.

Now we consider the situation where there exist differences in agents' beliefs and information sets. Specifically, our model included three types of agents: 1) the gurus (type G), each of them owns different private information with different precisions; 2) the informed speculators (type I), each of them follows one particular guru and has access to the information conveyed by the guru, and 3) the chartists (type C), who do not have private information and merely chase the trend. Similar to Benabou and Laroque (1992), we further set up two types of gurus: the honest ones (type G_H), who always tell the truth to their followers, and the opportunistic ones (type G_O), who may manipulate the information to maximize their expected utilities.

At the beginning of time t, guru i has access to a private signal $s_{i,t} \in \{0, 1\}$ with precision ρ_i about future dividend of the risky asset, where $i \in \{1, 2, \ldots, N_G\}$ and N_G is the number of gurus in the market and $\rho_i = \mathrm{Prob}[s_{i,t} = y_t]$. Hence, the guru i's expected mean of future dividend would be:

$$E_{G_i,t}(\tilde{p}_{t+1} + \tilde{y}_{t+1}) = E_t(\tilde{p}_{t+1}^*) + \rho_i s_{i,t} + (1 - \rho_i)(1 - s_{i,t}). \tag{13}$$

Then, each guru sends a signal $s_{i,t}^*$ to her followers, who become the informed speculators $I_{i,j}$, where i denotes which guru to follow and $j \in \{1, 2, \ldots, N_i\}$ where N_i is the total number of guru i's followers. The signal $s_{i,t}^*$ depends on the guru's type $J_{i,t} \in \{H, O\}$, which evolves according to a Markov Process:

$$\begin{aligned} &\mathrm{Prob}[\mathbf{J}_{i,t+1} = H | J_{i,t} = H] = \phi_i, \\ &\mathrm{Prob}[\mathbf{J}_{i,t+1} = O | J_{i,t} = O] = \psi_i, \end{aligned} \tag{14}$$

where ϕ_i and ψ_i are in (0, 1) and $\phi_i + \psi_i > 1$ expressing persistence. Honest gurus, due to the reputation or regulation concerns, send exactly the same signal to the informed speculators, that is $s_{H,t}^* = s_{H,t}$. Opportunistic gurus would like to maximize instantaneous profits. So they will send the opposite signal to the followers if $\rho_i \ge 0.5$ and the same signal if $\rho_i < 0.5$. Gurus' types are not fixed, unbeknown to the public, and evolve according to a Markov process. For investors, learning of gurus' types remains incomplete in this setting and thus leaves a space for manipulation.

At the end of each trading period, signal $s_{i,t}^*$ will be revealed, and all the investors other than gurus will update their beliefs about gurus' type in the next period. Let $q_{i,t} = \text{Prob}[J_{i,t+1} = H|\mathcal{F}_t]$ be the guru i's reputation, where $\mathcal{F}_t$ contains all the public information at time t. So the updated reputation is

when $s_{i,t}^* = y_t$,

$$q_{i,t} = \begin{cases} q_{i,t-1}\rho_i\phi + \left(1-q_{i,t-1}\right)(1-\rho_i)(1-\psi) & \rho_i \geq 0.5 \\ q_{i,t-1}\phi + \left(1-q_{i,t-1}\right)(1-\psi) & \rho_i < 0.5 \end{cases} \tag{15}$$

when $s_{i,t}^* \neq y_t$

$$q_{i,t} = \begin{cases} q_{i,t-1}(1-\rho_i)\phi + \left(1-q_{i,t-1}\right)\rho_i(1-\psi) & \rho_i \geq 0.5 \\ q_{i,t-1}\phi + \left(1-q_{i,t-1}\right)(1-\psi) & \rho_i < 0.5 \end{cases} \tag{16}$$

We can see that, when $\rho_i < 0.5$, investors cannot differentiate between opportunistic gurus and honest gurus because all the gurus would send the exact same signal they own to their respective followers.

We assume that each investor belongs to a social group with one guru inside. This simplification helps to rule out the effects of other factors, such as the competition between gurus, which may also influence the behavior of gurus. One distinguished feature of our model is that Investors are able to choose whether they listen to their gurus' opinions. This decision depends on the past realized profits and the intensity of choice.

If investors decide to follow the guru i, they will receive a signal $s_{i,t}^*$. Then, their expectation about future variables would be:

$$E_{I_i,t}(\tilde{p}_{t+1} + \tilde{y}_{t+1}) = \begin{cases} E_t\left(\tilde{p}_{t+1}^*\right) + \rho_i + s_{i,t}^* - 2\rho_i s_{i,t}^* + (1-2\rho_i)\left(1-2s_{i,t}^*\right)q_{i,t} & \text{if} \quad \rho_i \geq 0.5 \\ E_t\left(\tilde{p}_{t+1}^*\right) + (2\rho_i - 1)s_{i,t}^* + (1-\rho_i) & \text{if} \quad \rho_i < 0.5 \end{cases} \tag{17}$$

Notice that when $\rho_i < 0.5$, guru's reputation $q_{i,t}$ will not influence informed speculators' expectation. That's because when the precision of guru's signal is very low, they will always tell the truth no matter whether they are honest or opportunistic. Thus, $s_{i,t}^* = s_{i,t}$, so we can rewrite the expectation as:

$$E_{I_i,t}(\tilde{p}_{t+1} + \tilde{y}_{t+1}) = \begin{cases} E_t\left(\tilde{p}_{t+1}^*\right) + \rho_i + s_{i,t}^* - 2\rho_i s_{i,t}^* + (1-2\rho_i)\left(1-2s_{i,t}^*\right)q_{i,t} & \text{if} \quad \rho_i \geq 0.5 \\ E_t\left(\tilde{p}_{t+1}^*\right) + \rho_i s_{i,t} + (1-\rho_i)(1-s_{i,t}) & \text{if} \quad \rho_i < 0.5 \end{cases} \tag{18}$$

Notice that the estimation of gurus reputation directly influences the expectation of future price, hence determines the demand of informed speculators and the final realized profits. And as we have mentioned, the realized profits would determine the choice in the next round. Therefore, we can see how gurus type would determine the fraction of informed speculators in the market.

For chartists, they follow the trend instead of listening to gurus. Since they do not have private information, their expectations would be:

$$E_{Ct}(\tilde{p}_{t+1} + \tilde{y}_{t+1}) = E_t(\tilde{p}_{t+1}^* + \tilde{y}_{t+1}) + \kappa x_{t-1} \tag{19}$$

where κ denotes the intensity of herding on the price. A positive κ implies chasing the trend while a negative one implies going against the trend.

According to Brock and Hommes (1998), suppose that

$$\mathbb{E}_{ht}[\mathbf{p}_{t+1} + y_{t+1}] = \mathbb{E}_t[\mathbf{p}_{t+1}^* + y_{t+1}] + f_{h,t}, \tag{20}$$

So from the above, we can derive that for each type

$$f_{G_i,t} = \rho_i s_{i,t} + (1-\rho_i)(1-s_{i,t}) - \bar{y} \tag{21}$$

$$f_{I_i,t} = \begin{cases} \rho_i + s_{i,t}^* - 2\rho_i s_{i,t}^* + (1-2\rho_i)\left(1-2s_{i,t}^*\right)q_{i,t} - \bar{y} & \text{if} \quad \rho_i \geq 0.5 \\ \rho_i s_{i,t} + (1-\rho_i)(1-s_{i,t}) - \bar{y} & \text{if} \quad \rho_i < 0.5 \end{cases} \tag{22}$$

$$f_{C,t} = \kappa x_{t-1} \tag{23}$$

Suppose there are N investors in the market, and each social group, noted by guru i, has potential i_N followers. For simplicity, we assume that there is no overlapping among these social groups. Hence, $N_G + \sum_i i_N = N$. At time t, the updated fractions of followers in group i is determined by

$$n_{i,t} = \exp\left[\beta\frac{(x_t - Rx_{t-1})(f_{I_i,t} - Rx_{t-1})}{\alpha_I\sigma^2}\right]Z_t^{-1} \tag{24}$$

where

$$Z_t = \exp\left[\beta\frac{(x_t - Rx_{t-1})(f_{I_i,t} - Rx_{t-1})}{\alpha_I\sigma^2}\right] + \exp\left[\beta\frac{(x_t - Rx_{t-1})(\kappa x_{t-2} - Rx_{t-1})}{\alpha_I\sigma^2}\right]. \tag{25}$$

Notice that the total number of investors who choose to follow the gurus would be $N_I = \sum_i i_N * n_{i,t}$ and we denote $n_I = \frac{N_I}{N}$ as the total fractions of gurus' followers, which measures the intensity of herding induced by direct communication.

Assume that $\alpha_h = \alpha$, $V_{ht} = V_t$, $\eta = 0$ and $\delta_t = 0$, we obtain the adaptive belief system:

$$x_t = \frac{\sum_{i\in G} f_{G_i,t} + \sum_{i\in I} i_N\left[n_{i,t-1}f_{I_i,t} + (1-n_{i,t-1})\kappa x_{t-1}\right]}{RN} \tag{26}$$

In the following section, by applying numerical simulations, we explore the effects of parameters of interest on the intensity of herding induced by direct communication and the associated market volatility.

3. Numerical simulations

Through numerical simulations, we explore how the distribution of signal precision ρ_i, the transition parameters in the Markov process of gurus type ϕ and ψ, the proportion of gurus in the market n_G, the fundamental value $\bar{y}$, the intensity of choice β and the intensity of herding on the price κ affect the intensity of herding induced by communication and the associated market volatility.

The numerical simulations are based on the deterministic system of Eqs. (24) and (26). The parameters and initial values are selected as follows[1]:

$R = 1.1$, $n_G = 0.02$, $\alpha\sigma^2 = 1$, $\beta = 3.5$, $\kappa = 1.2$, $\bar{y} = 0.5$, $\phi = 0.6$, $\psi = 0.6$.

We first analyzed how gurus' information quality, the transition of gurus types and the proportion in the market affect investors' choices and market volatility. The decisions of whether to follow the gurus depend on two factors: the guru's capability, which is the precision of the obtained inside information, and the gurus' reputation, which determines how influential the gurus signal to the followers is. Normally, people are more likely to follow a guru with both highly precise information and good reputation. However, as we have mentioned before, when gurus own accurate private information, they can make more profits by manipulating the information rather than conveying the authentic information. Fig. 1 displays the box plots of (a) x_t and (b) $n_{I,t}$ under different distributions of private signal ρ_i. We can see that when the precision of gurus' signal is very low, the market volatility would be extremely high. When gurus obtain more precise information, the market volatility drops sharply and the intensity of herding induced by direct communication increases significantly. However, when the quality of information continues to improve, the market becomes less stable.

Result 1. The increase in the precision of gurus' private information displays a U-shape effect on the market volatility.

Normatively, when gurus have highly informative information, more investors would follow them and trade on the information. This reduces the variance and increases the market efficiency. However, when there is a certain amount of opportunistic gurus in the market,

[1] Except the parameter values of n_G, ϕ and ψ, the rest values are taken from Brock and Hommes (1998).

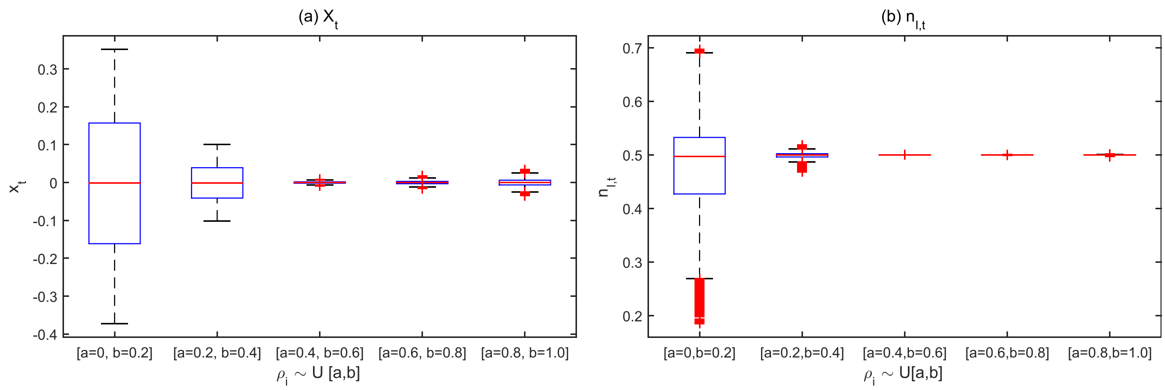

Fig. 1. The box plots of (a) x_t and (b) $n_{I,t}$ under different distributions of private signal ρ_i.

they would take advantage of their private information for their own benefits and send opposite information to misguide the followers. Interestingly, our results showed that herding would still be formed even though followers knew that the probability of receiving manipulated information was high. This unsound decision seemed to be caused by the psychological momentum of realized high profits in the past if investors did follow gurus. This sweet spot momentum not only effectively explains the high market volatility when trading obviously deviates from the fundamental value, but also provides a strong necessity to regulate insider trading for the sake of market stability.

As analyzed above, the incentive to manipulate the information would lead to a positive relationship between the intensity of herding and market volatility. In our model, the gurus types directly determine their incentives to manipulate the information. The gurus type are represented by two key parameters, ϕ and ψ, which are determined by the transition of the Markov process. A higher ϕ means a higher probability of being honest gurus in the consecutive trading periods, whereas a higher ψ implies a higher probability of being opportunistic gurus. Fig. 2(a) plots the volatility of x_t with different ϕ and ψ. From these results, we can see that, first, the market volatility would be lower when ϕ equals to ψ than if they are different. This is intriguing because normally we would suppose that the volatility is lower when ϕ is high because the limiting distribution of honest gurus is higher. However, because investors are likely to believe in the gurus when ϕ is high, any manipulation or wrong signals would make price significantly deviate from the fundamental value. This implies that if investors are neutral to the advice from guru, it will help to stabilize the market. Second, gurus types interact with information quality in determining the market volatility. In particular, the results showed that the changes in ϕ and ψ have marginal effects on the market volatility when the precision of private information is low. This is because there is no incentive for gurus to manipulate poor information so that ψ and ϕ would not affect investors' behavior.

Result 2. The market volatility would be lower when limiting distributions of honest gurus and opportunistic gurus are equal.

The last parameter of interest about gurus is the proportion of gurus in the market. Numerical simulation showed that an increase in the proportion of gurus would induce a stronger herding among investors to follow gurus advice and thus would reduce the market volatility. These results are displayed in Fig. 2(b). When there are more gurus in the market, the price would better reflect the fundamental value, so it is optimal for followers to herd on gurus information. However, at the same time, since gurus with high quality of private information are incentivized to manipulate the information, the effects of increasing proportion of gurus are also modulated by gurus information quality. In order words, the effects would be less pronounced in the market where the majority of gurus are highly informed and the ensuing likelihood of information manipulation is high. From the regulation perspective, this implies that diversified views across the market should be advocated so that the market volatility could be decreased especially when the proportion of gurus in the market is already high. Put into practice, our results could explain why herding behaviors are easily formed in the emerging markets than in the developed markets. Simply, emerging markets are fulfilled with nave participants whose behaviors are more easily steered by gurus if they are in large quantity. On the other hand, high proportion of gurus might still under power to instigate herding behaviors in the developed markets because of the sophisticate of these investors.

Result 3. The increasing proportion of gurus in the market would positively influence the extent of herding and negatively influence the market volatility. These effects are more salient in the market with more poorly informed gurus than in the market with well-informed ones.

From the perspective of other investors, their behaviors are mostly influenced by two parameters: the reaction sensitivity to two strategies' utilities β and the intensity of herding on the price κ. Fig. 3 plots the means of n_I with varied β and κ under different distributions of private signal ρ_i. As we can see, when investors are more sensitive to the differences in utilities between two strategies, they are reluctant to follow the gurus especially when information precision is low. This is intuitive because investors would be more active to change their strategies when β is high. Hence, if gurus circulate less informative signals, investors wouldn't listen to them and might rely on their internal signals for decisions.

Result 4. When investors are highly sensitive to the utilities differences between two strategies, they are less willing to follow the guru with poor information precision.

Furthermore, we found that when investors herd intensively on the price (which means the absolute value of κ is high regardless of its direction), fewer investors would follow the gurus with imprecise information. The rationale is similar to the situation when β is high and gurus' signal precision is low. Specifically, when gurus' information is less valuable, investors are more likely to be trend followers. Therefore, increasing either β or κ would improve the utilities of chartists. However, this would increase the market volatility since fewer people trade on the fundamental value of assets. Thus, to some extent, even if gurus are all honest, poor information will disappoint investors and transmit them the trend followers, leading to a more volatile market eventually.

Result 5. When gurus' information is poorly informative, herding on the price would be more intensive and the market will be more volatile.

Finally, we investigated how the fundamental value $\bar{y}$ affects investors' behavior. Fig. 4 displays the market volatilities and the means of informed speculators' proportions with different $\bar{y}$. We found that on average investors would like to follow gurus when $\bar{y}$ is either high or low. However, whether this would increase or decrease the market volatility is again dependent on the precision of gurus

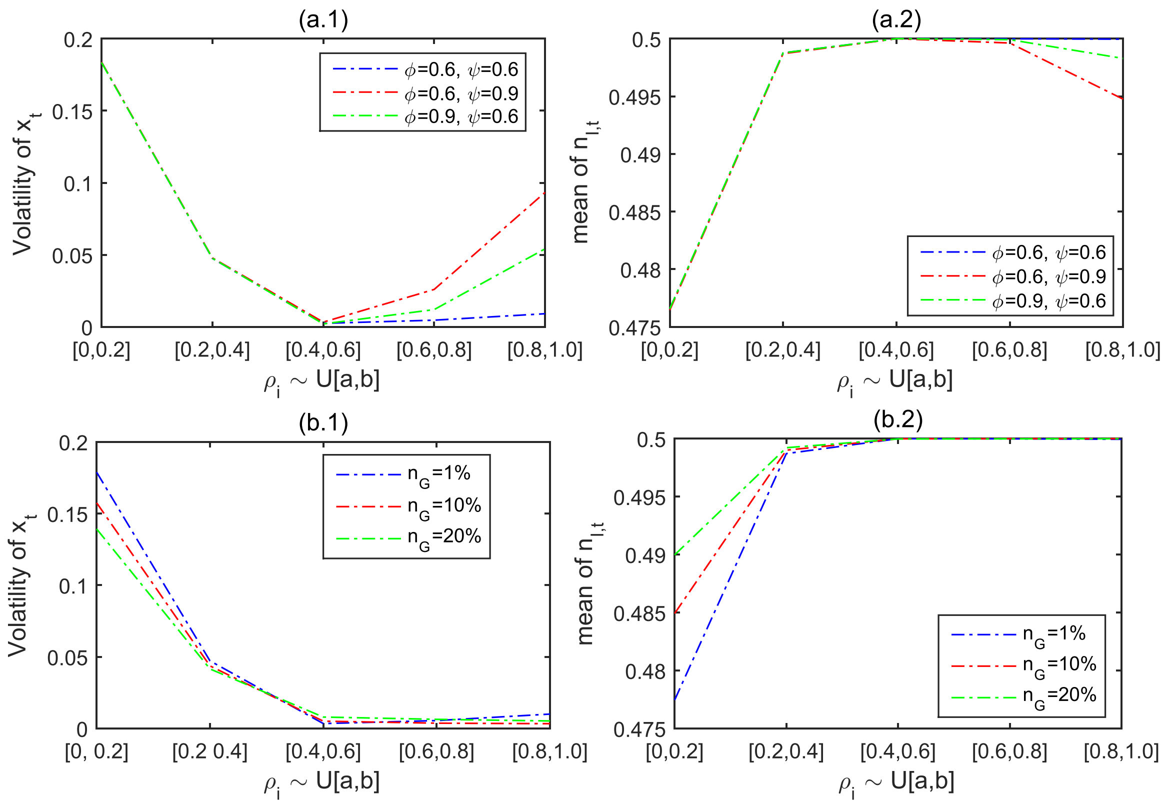

Fig. 2. The volatility of x_t and mean of $n_{I,t}$ under different distributions of private signal ρ_i with varied (a) ϕ and ψ and (b) n_G.

information. As seen in Fig. 4(c.1) and (c.2), when the signal precision is high, market is more volatile when $\bar{y}$ deviates from 0.5, whereas the market would be more stable if the precision is low. This is because the manipulation of information only exists when $\rho_i > 0.5$, which would cause higher deviations from the fundamental value. The implications we can draw from these results are thought-provoking. When all the participants have a high (low) expectation of the fundamental value, for example, in a bull (bear) market, more investors would like to take advice from gurus. This is in accordance with Clements, Hurn and Shi (2017)'s empirical findings. If the gurus were highly informative,

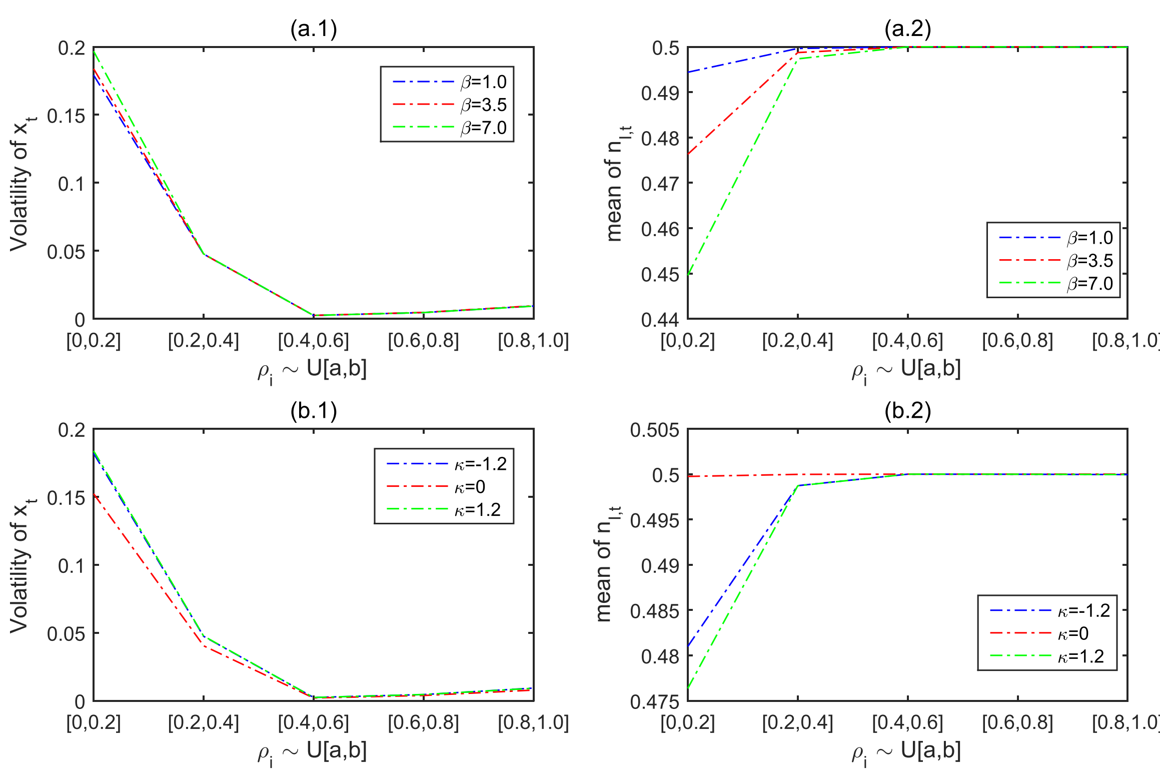

Fig. 3. The volatility of x_t and mean of $n_{I,t}$ under different distributions of private signal ρ_i with varied (a) intensity of choice β and (b) intensity of herding on the price κ.

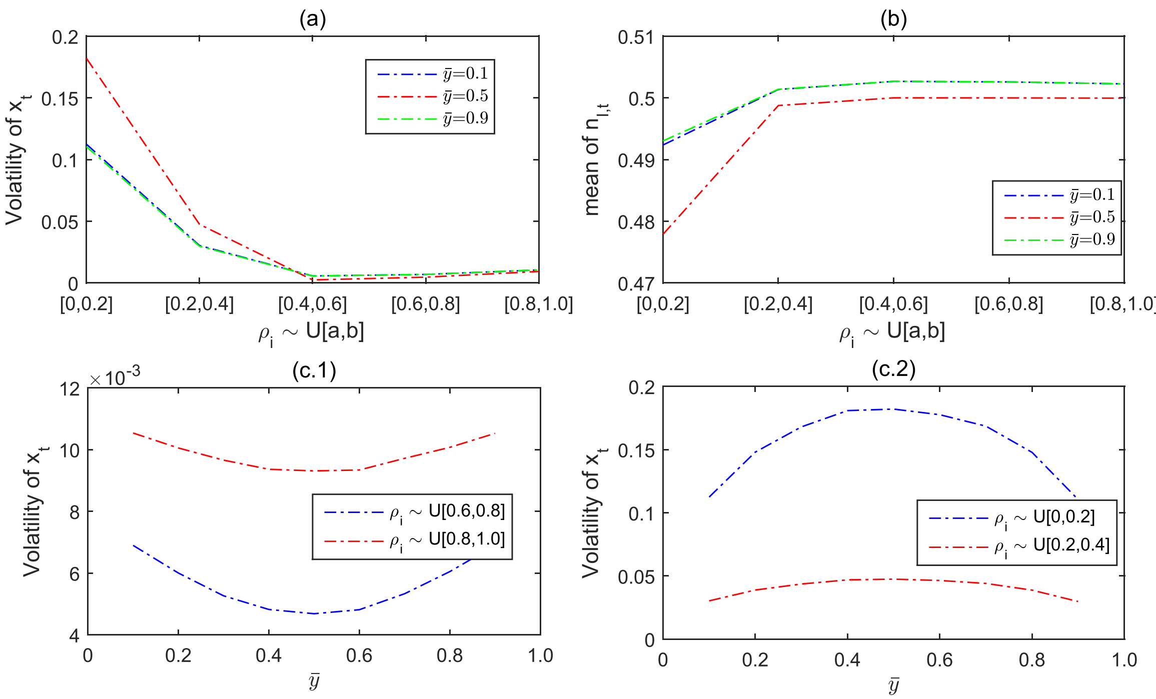

Fig. 4. The volatility of x_t and mean of $n_{I,t}$ under different distributions of private signal ρ_i with varied $\bar{y}$.

intensive herding on gurus would result in higher volatility, and make the market more fluctuant. However, if gurus were poorly informed, the market volatility would decrease due to intensive herding on gurus in bull (bear) market.

Result 6. The intensity of herding is stronger when the fundamental value is either high or low, and the market volatility would increase (decrease) if gurus' information were precise (imprecise).

4. Conclusion

This paper applied an adapted heterogeneous agents model (Brock and Hommes, 1997, 1998) to investigate the herding behavior induced by direct communication with gurus. We model the strategic interactions between gurus and their followers. Different from previous research, we consider the possibility of information manipulation by gurus and focus on its impacts on market volatility due to followers herding behavior. The findings indicate that agents' choices and market volatility are largely affected by the precision of gurus' information, the types of gurus, the amounts of gurus, the reaction sensitivity, the herding intensity and the level of fundamental value. In general, the precision of gurus information has a U-shape effect on market volatility. In addition, when there are more gurus in the market and if the proportion of honest gurus and opportunistic gurus is balanced, the market volatility would decrease. Increasing of either reaction sensitivity or herding intensity on the price would lead to higher market volatility when gurus own poor information. Finally, when the expectation of fundamental value is either high or low, the market volatility would increase if information is revealing and decrease if the information value is poor.

The paper provides insights into the disputes on herding behavior and market volatility. We find that intensive herding induced by direct communication can both increase and decrease market volatility under different situations. The direction of the effect depends on the quality of gurus private information. Increasing the precision of private information would lead to more intensive herding on gurus and more trading based on this information, which will close the price to the fundamental value. However, at the same time, high precision would incentivize the gurus to manipulate the information. In this case, because they already attract large groups of investors to follow their advice, manipulation of information would make trading deviate from the fundamental price, and cause high market volatility. The double edge effects of information quality should be attended by the regulation bodies on regulating gurus behaviors.

There are several further theoretical extensions that seem worth pursuing. First, during the trading periods, the variation in wealth may affect the investors' preferences and strategies, and lead to changes in prices. Some recent studies have elaborated the impact of wealth or endowments on risk perception (e.g., Sousa, 2010, 2015a). For example, Sousa (2015a) shows that a fall in the wealth-to-income ratio would predict a higher risk premium in the future. This is because the decrease in asset wealth would increase investors risk exposure to labor income, and therefore, investors would demand a higher risk premium in stocks. An intriguing future direction would be to integrate investors' wealthiness to the formation of herding behaviors. Second, the assumption of constant absolute risk aversion (CARA) utility function in our model may not always be valid. In effect, it assumes that agents' absolute risk aversion is constant regardless of any situational factors. This assumption could be violated. For example, the empirical research by Sousa (2015b) shows that risk aversion could be time-varying and counter-cyclical. Using the U.S. macroeconomic data, Sousa finds that the risky asset share significantly changes with the wealth shocks in the same direction. This result is robust after considering the price effect. Therefore, to further analyze investors' herding behavior, future work should take into account factors that would moderate risk preferences such as loss aversion, ambiguity aversion, habit-formation or wealth-dependent preferences.

References

Avery, C., Zemsky, P., 1998. Multidimensional uncertainty and herd behavior in financial markets. Am. Econ. Rev. 88 (4), 724–748.
Banerjee, A.V., 1992. A simple model of herd behavior. Q. J. Econ. 107 (3), 797–817.
Battaglini, M., 2004. Policy advice with imperfectly informed experts. Adv. Theor. Econ. 4 (1), 1–32.
Benabou, R., Laroque, G., 1992. Using privileged information to manipulate markets: insiders, gurus, and credibility. Q. J. Econ. 107 (3), 921–958.
Bertrand, M., Luttmer, E.F., Mullainathan, S., 2000. Network effects and welfare cultures. Q. J. Econ. 115 (3), 1019–1055.
Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and

cultural change as informational cascades. J. Political Econ. 100 (5), 992–1026.
Bommel, J.V., 2003. Rumors. J. Financ. 58 (4), 1499–1520.
Brock, W.A., Hommes, C.H., 1997. A rational route to randomness. Econ.: J. Econ. Soc. 65 (5), 1059–1095.
Brock, W.A., Hommes, C.H., 1998. Heterogeneous beliefs and routes to chaos in a simple asset pricing model. J. Econ. Dyn. Control 22 (8), 1235–1274.
Brown, J.R., Ivkovi, Z., Smith, P.A., Weisbenner, S., 2008. Neighbors matter: causal community effects and stock market participation. J. Financ. 63 (3), 1509–1531.
Cipriani, M., Guarino, A., 2008. Herd behavior and contagion in financial markets. B.E. J. Theor. Econ. 8 (1), 1–54.
Clements, A., Hurn, S., Shi, S., 2017. An empirical investigation of herding in the US stock market. Econ. Model., (Forth coming)https://doi.org/10.1016/j.econmod.2016.12.015.
Cohen, L., Frazzini, A., Malloy, C., 2010. Sellside school ties. J. Financ. 65 (4), 1409–1437.
Dasgupta, A., Prat, A., Verardo, M., 2011. The price impact of institutional herding. Rev. Financ. Stud. 24 (3), 892–925.
Di Guilmi, C., He, X.Z., Li, K., 2014. Herding, trend chasing and market volatility. J. Econ. Dyn. Control 48, 349–373.
Ellison, G., Fudenberg, D., 1993. Rules of thumb for social learning. J. Political Econ. 101 (4), 612–643.
Ellison, G., Fudenberg, D., 1995. Word-of-mouth communication and social learning. Q. J. Econ. 110 (1), 93–125.
Farmer, J.D., Foley, D., 2009. The economy needs agent-based modelling. Nature 460 (7256), 685–686.
Fracassi, C., 2016. Corporate finance policies and social networks. Manag. Sci., (Forth coming)http://dx.doi.org/10.1287/mnsc.2016.2433.
Grossman, S.J., Stiglitz, J.E., 1976. Information and competitive price systems. Am. Econ. Rev. 66 (2), 246–253.
He, X.Z., Li, K., Wei, J., Zheng, M., 2009. Market stability switches in a continuous-time financial market with heterogeneous beliefs. Econ. Model. 26 (6), 1432–1442.
Heimer, R.Z., 2016. Peer pressure: social interaction and the disposition effect. Rev. Financ. Stud. 29 (11), 3177–3209.
Hochberg, Y.V., Ljungqvist, A., Lu, Y., 2007. Whom you know matters: venture capital networks and investment performance. J. Financ. 62 (1), 251–301.
Hommes, C.H., 2001. Financial markets as nonlinear adaptive evolutionary systems. Quant. Financ. 1 (1), 149–167.
Hong, H., Kubik, J.D., Stein, J.C., 2004. Social interaction and stock-market participation. J. Financ. 59 (1), 137–163.
Hong, H., Kubik, J.D., Stein, J.C., 2005. Thy neighbor's portfolio: word of mouth effects in the holdings and trades of money managers. J. Financ. 60 (6), 2801–2824.
Ioannides, Y.M., Datcher Loury, L., 2004. Job information networks, neighborhood effects, and inequality. J. Econ. Lit. 42 (4), 1056–1093.
Ivkovi, Z., Weisbenner, S., 2007. Information diffusion effects in individual investors' common stock purchases: covet thy neighbors' investment choices. Rev. Financ. Stud. 20 (4), 1327–1357.
Jouini, E., Napp, C., 2015. Gurus and belief manipulation. Econ. Model. 49, 11–18.
Ke, X., Shi, K., 2009. Stability and bifurcation in a simple heterogeneous asset pricing model. Econ. Model. 26 (3), 680–688.
Lof, M., 2015. Rational speculators, contrarians, and excess volatility. Manag. Sci. 61 (8), 1889–1901.
Lux, T., 1995. Herd behaviour, bubbles and crashes. Econ. J. 105, 881–896.
Ozsoylev, H.N., Walden, J., Yavuz, M.D., Bildik, R., 2014. Investor networks in the stock market. Rev. Financ. Stud. 27 (5), 1323–1366.
Scharfstein, D.S., Stein, J.C., 1990. Herd behavior and investment. Am. Econ. Rev. 80 (3), 465–479.
Schlag, K.H., 1998. Why imitate, and if so, how?: a boundedly rational approach to multi-armed bandits. J. Econ. Theory 78 (1), 130–156.
Smith, L., Srensen, P., 2000. Pathological outcomes of observational learning. Econometrica 68 (2), 371–398.
Sousa, R.M., 2010. Consumption, (dis)aggregate wealth and asset returns. J. Empir. Financ. 17 (4), 606–622.
Sousa, R.M., 2015a. Linking wealth and labour income with stock returns and government bond yields. Eur. J. Financ. 21 (10/11), 806–825.
Sousa, R.M., 2015b. What is the impact of wealth shocks on asset allocation? Quant. Financ. 15 (3), 493–508.
Tedeschi, G., Iori, G., Gallegati, M., 2009. The role of communication and imitation in limit order markets. Eur. Phys. J. B 71 (4), 489.
Tedeschi, G., Iori, G., Gallegati, M., 2012. Herding effects in order driven markets: the rise and fall of gurus. J. Econ. Behav. Organ. 81 (1), 82–96.
Trueman, B., 1994. Analyst forecasts and herding behavior. Rev. Financ. Stud. 7 (1), 97–124.
Welch, I., 1992. Sequential sales, learning, and cascades. J. Financ. 47 (2), 695–732.
Westerhoff, F., Wieland, C., 2010. A behavioral cobweb-like commodity market model with heterogeneous speculators. Econ. Model. 27 (5), 1136–1143.
Zhang, H., Huang, Y., Yao, H., 2016. Heterogeneous expectation, beliefs evolution and house price volatility. Econ. Model. 53, 409–418.
Zheng, M., Wang, H., Wang, C., Wang, S., 2017. Speculative behavior in a housing market: boom and bust. Econ. Model. 61, 50–64.