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REGULAR ARTICLE

Volatility clustering and herding agents: does it matter what they observe?

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Abstract Recent agent-based models have demonstrated that agents' herding behavior causes volatility clustering in stock markets. We examine economies where agents herd on others, yet they have limited sets of information on other agents to imitate. In particular, we conduct experiments on economies with agents with different levels of information sharing where agents can imitate: (1) the strategies of others but with an error, (2) the strategies of only a fraction of agents, or (3) the strategies of others, but update their parameters only by a proportion. In each experiment we change the likelihood that agents make errors to copy the strategy of others, the fraction of agents to herd, or the proportion of the parameter that agents update, in order to examine the effect of the different degrees of information sharing on volatility clustering. We show that volatility clustering tends to disappear when agents have limited information on the strategies of others, and agents need to imitate the strategy details of others in order to generate the clustered volatility.

Keywords Agent-based · Learning · Volatility clustering · Herding

JEL Classification G12 · G14 · D83

1 Introduction

Volatility clustering is an important empirical feature of stock markets.[1] Many agent-based models have successfully replicated the persistence of return volatility and

[1] For example, clustered volatility is documented by Engle (1982) and Pagan (1996).

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provided theoretical explanations for it.[2] One popular theoretical explanation is that agents' herding behavior is related to this phenomenon, but agents in those agent-based herding models are assumed to herd on others by looking at detailed information on other agents that may not be observable in reality. For example, a series of spin-type models assume that agents can immediately observe whether the nearest neighbors bought or sold an asset and the exact information on the market-wide order flow.[3,4] However, in reality (for example, in Asia-Pacific stock exchanges), although the immediate reporting of trade details is generally required for both on- and off-market trades, delayed reporting is allowed for some off-market trades, e.g., in the Australian Stock Exchange, Hong Kong Exchanges and Clearing, and the Singapore Exchange.[5] Thus, the exact information on the net order flows or even on the nearest neighbors' actions is not often available immediately in those markets.

We conjecture that agents' ability to observe and imitate the strategy details of others is related to volatility clustering. We conduct three experiments independently with different levels of information sharing. In our first economy, agents can imitate the strategies of others but they make errors when copying the strategies of others. Our second economy describes a market where agents can imitate the strategies of only a fraction of the agents. In our third economy, agents can imitate the strategies of others, but update their parameters only by a proportion. In each experiment we change the probability of errors to copy the strategy of others, the fraction of agents to herd, or the proportion of the parameter that agents update, in order to examine the effect of the different degrees of information sharing on volatility clustering. We show that volatility clustering tends to disappear as agents have smaller information sets on others to imitate. Thus, we conclude that agents need to imitate the strategy details of others so as to generate clustered volatility. Since stock investors in reality cannot perfectly observe the actions of others, our result implies that other forms of social interactions, e.g., interactions via market sentiment indices (Lux 2009)[6], influences from the news media in setting the stage for market moves and in instigating the moves themselves (Shiller 2001), and/or some other behaviors of agents (like order-splitting behavior, e.g., Yamamoto and LeBaron (2010)), would also be related to generate clustered volatility.[7]

[2] For example, Lux (1998), Lux and Marchesi (1999), and Gaunersdorfer and Hommes (2005) explain volatility clustering as an endogenous phenomenon caused by the interaction between fundamentalists and technical analysts. Bornholdt (2001), Chowdhury and Stauffer (1999), and Kaizoji et al. (2002) also replicate clustered volatility in spin-type herding models, while LeBaron and Yamamoto (2007, 2008) generate it in their herding model. Yamamoto and LeBaron (2010) show that agents' order-splitting behavior causes persistence of volatility.

[3] Examples of the spin models include those by Bornholdt (2001), Chowdhury and Stauffer (1999), and Kaizoji et al. (2002).

[4] The market-wide order flow is the sum of the signed trading volume in the market. A buy (sell) order is counted as positive (negative). In the spin-type models, agents can trade one unit at a time. Thus, a buy (sell) order is counted as $+1$ (-1).

[5] See Comerton-Forde and Rydge (2006) for details of post-trade transparency in Asia-Pacific exchanges.

[6] Lux (2009) analyzes survey data on the business climate index for the German economy to show that respondents' assessments of the economic outlook tend to change through social interactions.

[7] Yamamoto and LeBaron (2010) generate volatility clustering when agents split their large orders into small pieces and execute them piece by piece.

Herding plays an important role in real-world decision making. Pingle and Day (1996) conduct an experimental study on imitative behavior. They show that when people make economic decisions they tend to economize on their decision costs, such as time, energy, or other valuable resources, by following the decisions of others. An experimental work by Offerman and Sonnemans (1998) shows that individuals learn from imitating successful others as well as from their own experience. Apesteguia et al. (2007) also give support to imitative behavior at the individual level, in terms of both choice and perception. They also show that individuals are more likely to imitate successful actions as the payoff differences among agents become larger. As Offerman and Sonnemans (1998) mention, such experimental evidence suggests that it is a promising way to model agents' behavior in an environment where they learn from successful others. Thus, we assume that our agents herd on successful others and analyze how crucial such herding behavior is in order to generate an empirical feature in stock markets, i.e., volatility clustering. Moreover, the previous experimental works imply that herding is prevalent when the environment becomes more complex or largely unknown. Financial markets should be an environment in which we examine the impact of herding, because they are quite complicated.

The outline of the paper is as follows. Section 2 presents the market structure. Section 3 gives the results of the computer experiments. Section 4 concludes.

2 Market structure

This section describes an artificial stock market that is based on a standard asset pricing model with two assets employed by Grossman and Stiglitz (1980). The market structure of our model is a Walrasian auction that is widely used in several papers on agent-based stock markets.[8] Our model extends the concept of the market structure with a component for herding among agents.

The market has N agents and two tradable assets: a risky stock and a risk-free bond. The risk-free bond pays a constant interest rate r_f. Agents observe the past price p_{t-1} and know the fundamental price p^f. They set their demands at time t according to:

$$s_t^i = \frac{E_t^i(p_{t+1} + d_{t+1}) - (1 + r_f)p_t}{\gamma \hat{\sigma}^2_{p+d,i,t}}, \tag{1}$$

where E_t^i denotes the best forecast of agent i at time t, and γ is a constant absolute risk-aversion coefficient. We assume that dividend d_t is constant over time, i.e., $d_t = \bar{d}$. Term $\hat{\sigma}^2_{p+d,i,t}$ is the forecast error by agent i at t. It is assumed to take the same value for all agents and to be constant over time, i.e., $\hat{\sigma}^2_{p+d,i,t} = \bar{\sigma}^2$. This implies that the uncertainty does not influence their trading strategies, and we focus on the agents'

[8] Among several papers, the agent-based stock markets with this type of market structure include those of Arthur et al. (1997), LeBaron et al. (1999), Brock and Hommes (1998), DeLong et al. (1990a), DeLong et al. (1990b), Routledge (1999), and Brock et al. (2005). Among several papers of this type, the examples for the foreign exchange markets include those of Kirman (1991) and Kirman and Teyssière (2002).

interactions through their expectation formations as the main generator of volatility clustering.

Equation (1) can be derived by solving a maximization problem with the assumption of CARA utility and a Gaussian distribution for dividend and stock prices as:

$$\max E_t^i \left(U(w_{t+1}^i) \right) = \max E_t^i \left(-\exp(-\gamma w_{t+1}^i) \right) \tag{2}$$

s.t.

$$w_{t+1}^i = s_t^i (p_{t+1} + d_{t+1}) + (1 + r_f)(w_t^i - p_t s_t^i) \tag{3}$$

Here, w is wealth. We assume that our agents simply use Eq. (1) as their rule of thumb.[9]

This assumption implies that in Eq. (1) agents have heterogeneous expectations only on the future asset price. Agents form their expectations on the future price based on the deviation from the fundamental price, their estimate on technical indicators, and a noise-induced component by:

$$E_t^i(p_{t+1}) = p_{t-1} \exp\left(g_1^i \log\left(\frac{p^f}{p_{t-1}} \right) + g_2^i \bar{r}_{L_i} + n_i \varepsilon_t \right), \tag{4}$$

where g_1^i, g_2^i, and n_i are the respective weights for the fundamentalist, chartist, and noise-induced components for agent i. Terms g_1^i and n_i are randomly drawn separately from a uniform distribution over intervals $\left[0, g_{1,\max}\right]$ and $[0, n_{\max}]$, respectively. g_2^i is assigned to agent i according to a normal distribution with zero mean and a constant variance σ_{g_2}. Term $\bar{r}_{L_i}$ is the technical indicator given by:

$$\bar{r}_{L_i} = \frac{1}{L_i} \sum_{j=1}^{L_i} \log\left(\frac{p_{t-j}}{p_{t-j-1}} \right), \tag{5}$$

where L_i is initially assigned to agent i, which is randomly drawn independently from a uniform distribution over an interval $[0, L_{\max}]$.

Equation (4) is motivated as follows. First, we combine the fundamental and technical trading components of our agents' forecasting to reflect the financial markets in reality. The survey studies of market participants by Lui and Mole (1998) and Menkhoff and Taylor (2007) show that most respondents use a combination of fundamental and technical analyses in their forecasting. Second, the parameter for the technical component g_2^i takes both positive and negative values, in order for the parameter to be consistent with the findings of the survey studies of market participants by Lui and Mole (1998). Agents are momentum traders when g_2^i is positive, while they are contrarians when the value is negative. The survey respondents use technical indicators to

[9] This is possible in an economy with boundedly rational agents. They do not know the distributions and have limited computational skill. As a result, they do not know how to solve the maximization problem. This assumption is motivated by Simon (1979) and supported by laboratory experiments by Kahneman and Tversky (1973).

forecast trends as well as to predict turning points of the current market trend. Third, we include a noise trading component in Eq. (4) as well. Stock investors in reality may base their forecasts not only on past prices, but also on other factors. For example, they may sell shares just to have cash in their hands regardless of the past price movements.

The order size for agent i at time t, denoted x_t^i, is determined by the difference in the asset demands at t and $t-1$ as:

$$x_t^i = abs\left(s_t^i - s_{t-1}^i\right). \tag{6}$$

When the difference, $s_t^i - s_{t-1}^i$, is positive (negative), an agent i buys (sells) shares by x_t^i.

In our market we assume that there is one market maker and all the agents submit their requested demand to him. The market maker announces the equilibrium price by clearing the market as:

$$\sum_{i=1}^{N} s_t^i(p_t) = S, \tag{7}$$

where S is the fixed supply of shares, which is assumed to be zero in our market as in Brock and Hommes (1998). An agent here who wants to buy stock can always buy stock, whereas a seller can always sell stock in this market.

After the equilibrium price is realized, all the agents trade shares at p_t. As in Brock and Hommes (1998), agents update their realized excess profits at t by:

$$\text{profit}_t^i = s_{t-1}^i\left(p_t - \bar{d} - \left(1 + r_f\right)p_{t-1}\right) \quad i = 1, \ldots, N. \tag{8}$$

We examine volatility clustering in economies with and without herding separately. In an economy with herding agents, agent i updates parameters g_1^i, g_2^i, n_i, and L_i every 100 periods according to their trading performances in the past 100 periods. We conduct a genetic algorithm to update the parameters.[10] The trading performance for agent i over the past 100 periods is measured by accumulated realized excess profits as:

$$\text{fitness}_t^i = s_{t-1}^i\left(p_t - \bar{d} - \left(1 + r_f\right)p_{t-1}\right) + \omega\, \text{fitness}_{t-1}^i \tag{9}$$

where ω is a memory parameter measuring how much the past realized profits influence the current fitness.

We calculate the probabilities of the strategies being copied to the next generation by taking weighted averages of the fitnesses. However, since we assume that agents can remain in the market even if they have negative profits, we adjust the negative values to be non-negative so as to calculate the probabilities, by adding an absolute value of the lowest profit to all. Thus, all the fitnesses, denoted fitness$_i$ $i = 1, \ldots, N$,

[10] Mitchell (1996) and Muhlenbein and Schlierkamp-Voosen (1993) give an introduction to GA.

are expressed in positive values. The probabilities are given by:

$$P_i = \frac{\text{fitness}_i}{\sum_{i=1}^{N} \text{fitness}_i}. \tag{10}$$

Agents are more likely to imitate the parameters of others who have higher trading performances in the past 100 periods.

Agents update their four parameters independently according to the probability. Each parameter is replaced with the one drawn from the set of agents according to the probability. After this, the parameter is subjected to mutation with probability $p_m (= 0.04)$. Mutation replaces the parameter with a new parameter value drawn from an associated distribution of the parameters, and the new value replaces the old one. Once agents update their parameters, they clear their fitness values and the next trading round begins. All the agents update their parameters simultaneously.

In an economy without herding, all the parameters are initially assigned randomly from associated distributions and are constant over time.

We model our agents' learning and adaptation through the genetic algorithm. Among learning and adaptation mechanisms such as Bayesian learning and adaptive linear models, many agent-based models use the genetic algorithm to model learning and adaptation.[11] However, as discussed by LeBaron (2006), it is still not clear whether it is a good mechanism for replicating the learning and adaptation processes of stock investors in reality. However, this paper uses the genetic algorithm to model our agents' herding mechanism, because it captures some important characteristics of human behavior that are consistent with the findings of the laboratory experiments by Apesteguia et al. (2007) and Offerman and Sonnemans (1998). The genetic algorithm can demonstrate that individuals learn from successful others and are more likely to imitate successful strategies as the payoff differences become larger among agents.

3 Model experiments

We run simulations on economies with and without herding. We show that a herding economy can generate volatility clustering, but we cannot generate it when agents do not herd on others at all. We further conduct simulations on economies where agents have limited information to imitate the strategies of others. We show that volatility clustering tends to disappear as agents have less information on the strategies of others.

In our benchmark herding model, agents can exchange their opinions with all the agents in the market and perfectly imitate the strategies of other agents. Learning and adaptation in the benchmark model are based on a social learning mechanism through the genetic algorithm. A basic form of social learning allows the agents to observe the strategy details of others.[12] Previous agent-based models take different approaches to how much information on others agents can share. For example, Arthur et al. (1997)

[11] See, for example, Brenner (2006).

[12] Chen and Yeh's (2001) and Vriend (2000) explain more details of social learning.

assume no information sharing, while agents in Chen and Yeh's (2001) and LeBaron's (2001) research can share some information with others. However, previous empirical studies have not provided enough evidence on how much of the information of others stock investors actually observe and share. Thus, the correct model for information sharing is not identifiable, and how any agent-based herding model can be validated it is still a controversial issue. However, it is clear that some form of imitation takes place in reality.[13] Therefore, in addition to the simulation on our benchmark herding economy where agents are able to share strategy details with others, we conduct the following three experiments to examine herding economies with different levels of information sharing.

In the first economy, agents can imitate the strategies of others, i.e., parameters (g_1^i, g_2^i, n_i, and L_i), but with an error. The error is randomly drawn from an associated distribution of the parameters. We modify the selection rule in accordance with the fitness-based probability by Eq. (10). Agents select a new parameter every 100 periods according to:

$$\begin{aligned} a\,new\,parameter = \theta * (&a\,parameter\,selected\,based\,on\ (10)) \\ &+ (1-\theta) * (a\,parameter\,drawn\,from\,an\,associated\,distribution) \end{aligned} \tag{11}$$

where θ is the weight determining the value of the new parameter. A smaller θ means that agents observe a parameter of others with a larger error. Thus, a smaller θ reflects less ability by agents to observe the information of other agents.

In the second economy, agents can imitate the strategies of only a fraction λ of agents. Agents individually and randomly select a fraction λ of agents from all the agents. Once each agent picks a fraction of the agents, he updates the parameters according to the fitness-based probability in Eq. (10), which is calculated from the past performances of the selected agents. Each agent selects a different set of agents every time he updates the parameters. The second economy reflects a situation where stock investors in reality may exchange their information with others but only with their colleagues or friends and not with all of the investors in the market.

In our third economy, agents can imitate the strategies of others, but we assume that agents update their parameters only by a proportion δ by imitating the strategies of others and inherit their own parameters by a proportion $1-\delta$, that is:

$$\begin{aligned} a\,new\,parameter = \delta * (&a\,parameter\,selected\,based\,on\ (10)) \\ &+ (1-\delta) * (a\ current\,parameter) \end{aligned} \tag{12}$$

where δ lies between 0 and 1. As δ becomes smaller, agents become more willing to continue to use their current parameters in the future so that the level of information sharing with others becomes lower. This set-up reflects some situations in which real investors may have a form of habit persistence in their own strategies so that they

[13] See, for example, Pingle and Day (1996), Apesteguia et al. (2007), and Offerman and Sonnemans (1998).

Table 1 Parameters

Number of agents: N	100
Risk-free interest rate: r_f	0.1
Fundamental value: p_f	1,000
A constant absolute risk-aversion coefficient: γ	0.5
Conditional variance: $\bar{\sigma}^2$	10,000
Dividend: $\bar{d}$	100
Memory parameter: ω	0.5
Max. value of a parameter for the fundamental component: $g_{1,\max}$	0.25
Std of a paremeter for the chartist component: σ_{g_2}	2.5
Max value of a parameter for noise component: $n_{\max}$	1
Time horizon in the chartist component: $L_{\max}$	100

prefer to keep using them for a while. Alternatively, they may be averse to taking the risk that the strategies of the others they imitate may not be profitable in the future.

Agents trade 15,000 periods in each simulation. Thus, in an economy with herding agents, since agents update their parameters every 100 trading periods, agents herd on others 150 times. We use artificial data from the last 10,000 periods for our analyses. The parameter values are set as in Table 1.[14] They are chosen as the levels where volatility clustering is not generated without herding. This is done in order to compare the results from economies with and without herding, and to highlight the positive impact of herding on generating the clustered volatility.

We conduct Engle's ARCH test (Engle 1982) and estimate the GARCH (1, 1) model to investigate volatility clustering.[15] To estimate the GARCH model, we define r_t as the rate of return on a risky asset from time $t-1$ to t, which is given by:

$$r_t = \ln(p_t) - \ln(p_{t-1}). \tag{13}$$

Let F_{t-1} be the past information set observed by the agents at time $t-1$. The conditionally expected return and variance are respectively $m_t = E(r_t|F_{t-1})$ and $\sigma_t^2 = Var(r_t|F_{t-1})$. Let r_t be expressed with unconditional expected return C, and ε_t

[14] We performed robustness checks on the parameters used in our simulations. In particular, we simulated our economies with difference sizes of agents, i.e., 50 and 150. We varied $\bar{\sigma}^2$, the conditional variance, from 7,500 to 25,000 from the original value of 10,000. We changed ω, the memory parameter, from 0.25 to 0.9 from the original value of 0.5. We adjusted $g_{1,\max}(n_{\max})$, the maximum value of a parameter for the fundamental (noise) component from 0.15 to 0.4 (from 0.5 to 1.1) from the original value of 0.25 (1). We also varied σ_{g_2}, the standard deviation of the parameter for the chartist component, from 1 to 5 from the original value of 2.5. We changed $L_{\max}$, the maximum time horizon in the chartist component, from 50 to 250 from the original value of 100. Finally, the mutation probability was adjusted from 0.01 to 0.12 from the original value of 0.04. In all these cases we find that our results do not change significantly. The outputs are summarized in Table 6 in the Appendix.

[15] The test procedure subtracts the average return from the actual return series and saves the residuals. We then regress the squared residuals on a constant and p lags. The asymptotic test statistic is $M * R^2$, where M is the number of squared residuals included in the regression and R^2 is the sample multiple correlation coefficient. It is asymptotically chi-square distributed with p degrees of freedom under the null hypothesis.

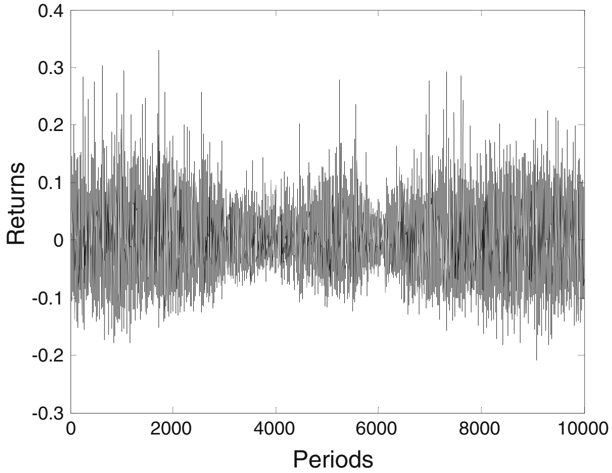

Fig. 1 Returns in a herding economy

be an uncorrelated, white-noise disturbance term, such that:

$$r_t = C + \varepsilon_t. \tag{14}$$

The GARCH (1, 1) model for the conditional variance of the innovations with the leverage term is:

$$\sigma_t^2 = K + \text{GARCH} * \sigma_{t-1}^2 + \text{ARCH} * \varepsilon_{t-1}^2, \tag{15}$$

where K, GARCH, and ARCH are parameters to be estimated with the constraints that $\text{GARCH} + \text{ARCH} < 1$, $K > 0$ and $\text{GARCH},\ \text{ARCH} \geq 0$.

Figures 1 and 2 display the snapshots of the return series in one of the runs for the herding and non-herding economies, respectively. The changes in returns look clustered in a herding economy, while they are not in a non-herding economy.

Figure 3 illustrates the average autocorrelation functions of absolute returns over 20 runs with 100 lags for the herding and non-herding economies, respectively. The autocorrelations are strictly positive even with long lags in a herding economy. They are larger in very short lags, and around 0.05 with other lags. The strictly positive autocorrelations would give visual evidence of volatility clustering in a herding economy. In a non-herding economy, although we see slightly positive autocorrelations with very short lags, they are usually around 0, suggesting that there would be no evidence of volatility clustering in a non-herding economy.

Table 2 summarizes the test results of volatility clustering. The numbers reported are the means of the test statistics over 20 runs. The numbers in brackets are the fractions of runs rejecting the null hypotheses at the 99% confidence level.[16] The numbers

[16] The null hypothesis in the ARCH test is "no ARCH" effect, while that in the GARCH-(1, 1) model is that the parameter value is zero.

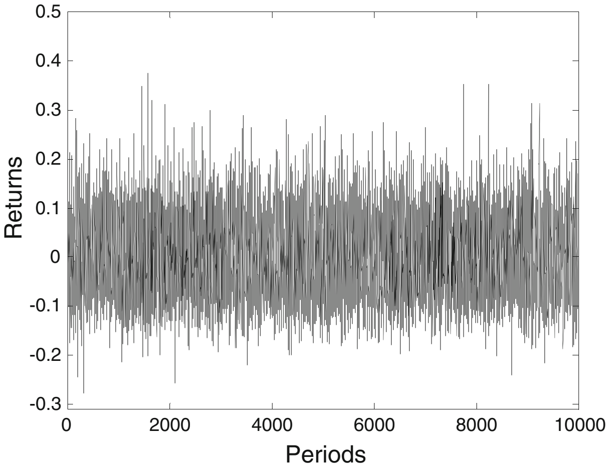

Fig. 2 Returns in a non-herding economy

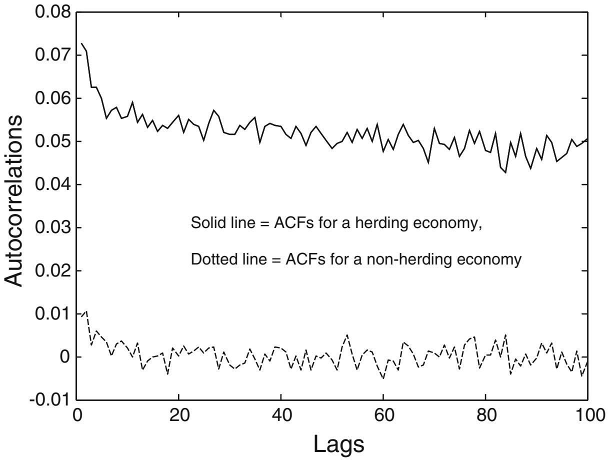

Fig. 3 Autocorrelation functions of absolute returns in herding and non-herding economies

in parentheses are the standard errors of the estimates over the 20 runs. Table 2 also introduces the GARCH and ARCH parameter estimates in the GARCH (1, 1) model. The first column shows the results for a daily series of the S&P500 composite index from January 1, 1964 to January 12, 2009.[17] The ARCH test statistic (226.6) suggests that we reject the "no ARCH null" at the 99% confidence level, while the estimates of the GARCH and ARCH parameters are significant at the 99% confidence level with the values of 0.926 and 0.066, respectively, suggesting the existence of volatility clustering in the actual data. The second column shows strong support for the

[17] We use this index from Datastream. The sample size is 11,748.

Table 2 Test results for volatility clustering

	Description	S&P500	Herding	No herding
ARCH test	ARCH(1)	226.6	39.94	1.87
			[1]	[0.15]
GARCH (1, 1) model	GARCH	0.926	0.986	0.449
			(0.003)	(0.353)
			[1]	[0.45]
	ARCH	0.066	0.013	0.011
			(0.003)	(0.009)
			[1]	[0.15]

The numbers reported are the means of the test statistics over 20 runs. The numbers in *brackets* are the fractions of runs rejecting the null hypotheses at the 99% confidence level. The numbers in *parentheses* are the standard errors of estimates over the 20 runs

Table 3 Test results for volatility clustering

	Description	$\theta = 1$	$\theta = 0.9$	$\theta = 0.5$	$\theta = 0$
ARCH test	ARCH(1)	39.94	3.91	1.80	2.50
		[1]	[0.25]	[0]	[0.15]
GARCH (1, 1) model	GARCH	0.986	0.73	0.47	0.58
		(0.003)	(0.40)	(0.43)	(0.41)
		[1]	[0.75]	[0.5]	[0.6]
	ARCH	0.013	0.010	0.011	0.011
		(0.003)	(0.010)	(0.008)	(0.009)
		[1]	[0.75]	[0.3]	[0.4]

Agents in this economy can imitate the strategies of others, but with an error represented by θ. A smaller θ means that agents observe a parameter of others with a larger error. The numbers reported are the means of the test statistics over 20 runs. The numbers in *brackets* are the fractions of runs rejecting the null hypotheses at the 99% confidence level. The numbers in *parentheses* are the standard errors of estimates over the 20 runs

clustered volatility in a herding economy. We reject the null for all 20 runs in the ARCH test, and the GARCH and ARCH parameter estimates are significant in all the simulations with much smaller standard errors. These results are consistent with those of the previous agent-based literature in the sense that the herding behavior of agents is critical for generating volatility clustering. The third column describes the results from the non-herding economy. It states that there is no evidence of volatility clustering when agents do not imitate each other, because the "no ARCH" null hypothesis is rejected only for 15% of 20 simulations at the 99% confidence level. The GARCH (ARCH) parameter estimate is not significant in 55% (85%) of 20 runs.

We next restrict the amount of information agents have on the strategies of other agents. We examine the above-mentioned three economies separately. In the first economy, agents can imitate all the parameters (g_1^i, g_2^i, n_i, and L_i) but with errors given by Eq. (11). Table 3 summarizes the results.

Table 4 Test results for volatility clustering

	Description	$\lambda = 1$	$\lambda = 0.9$	$\lambda = 0.5$	$\lambda = 0.1$
ARCH test	ARCH(1)	39.94	3.73	3.11	5.94
		[1]	[0.15]	[0.15]	[0.25]
GARCH (1, 1) model	GARCH	0.986	0.74	0.70	0.79
		(0.003)	(0.32)	(0.39)	(0.34)
		[1]	[0.7]	[0.7]	[0.75]
	ARCH	0.013	0.012	0.009	0.010
		(0.003)	(0.009)	(0.009)	(0.010)
		[1]	[0.55]	[0.65]	[0.75]

Agents in this economy can imitate the strategies of only a fraction λ of agents. Agents individually and randomly select a fraction λ of agents from all the agents. The numbers reported are the means of the test statistics over 20 runs. The numbers in *brackets* are the fractions of runs rejecting the null hypotheses at the 99% confidence level. The numbers in *parentheses* are the standard errors of estimates over the 20 runs

The results in Table 3 suggest that the herding effect on volatility clustering tends to disappear as agents have less information on others. The economy with $\theta = 1$ is the herding economy where agents can herd on others without any error. This is the economy whose results are those labeled "Herding" in Table 2, and we repeat the results in the first column in Table 3. We do not have any evidence on volatility clustering even when the agents imitate the parameters with only small errors ($\theta = 0.9$). For any value of θ less than 1, we reject the "no ARCH" null only in 25% or fewer than 25% of 20 simulations. The GARCH parameter estimates suggest much less persistence of volatility than the GARCH parameter estimate in a herding economy without any error (0.986) or in the S&P 500 (0.926 in Table 2). With $\theta = 0$, we do not generate the clustered volatility as well. When θ is zero, agents only receive a noise for updating their parameters and they do not herd on others.[18]

Table 4 summarizes the results in the second economy where agents randomly select a fraction λ of agents and imitate the strategies of the selected agents. When λ is 1, all the agents simultaneously update their parameter by exchanging the strategies of all the agents in the market, which is the herding economy in Table 2 and the results are given in the first column in Table 4. The results in Table 4 show that when λ becomes less than 1, the volatility becomes much less persistent than in reality. We do not reject the null hypothesis in the ARCH test in 75% or more than 75% of 20 simulations. The GARCH parameter estimates are much lower than in reality (0.926 in the S&P

[18] In Table 3 the GARCH coefficient is larger with $\theta = 0$ than with $\theta = 0.5$, meaning that volatility would have more persistent periods with $\theta = 0$ than $\theta = 0.5$. Actually as in Fig. 2, when $\theta = 0$, the volatility looks persistent, although it is not clustered at all. When $\theta = 0.5$, agents start imitating the strategies of others, although the imitative learning effect is not large enough to generate clustered periods of volatility. But it is large enough to destruct the persistence of the price changes as with $\theta = 0$. When $\theta = 0.9$ or more, the larger GARCH coefficient would be generated from the clustered periods of volatility. However, the standard errors of estimates over 20 runs are quite large for all cases, i.e., $\theta = 0.9, 0.5$, and 0.1. Thus, the mean can be larger or smaller if we try 20 different runs.

Table 5 Test results for volatility clustering

	Description	$\delta = 1$	$\delta = 0.9$	$\delta = 0.5$	$\delta = 0$
ARCH test	ARCH(1)	39.94	8.89	3.94	2.66
		[1]	[0.45]	[0.1]	[0.15]
GARCH (1, 1) model	GARCH	0.986	0.896	0.76	0.64
		(0.003)	(0.25)	(0.32)	(0.41)
		[1]	[0.9]	[0.7]	[0.6]
	ARCH	0.013	0.009	0.011	0.011
		(0.003)	(0.007)	(0.01)	(0.009)
		[1]	[0.9]	[0.65]	[0.45]

Agents in this economy can imitate the strategies of others, but update their parameters only by a proportion δ. The numbers reported are the means of the test statistics over 20 runs. The numbers in *brackets* are the fractions of runs rejecting the null hypotheses at the 99% confidence level. The numbers in *parentheses* are the standard errors of estimates over the 20 runs

500) when λ is less than 1. When agents collect less information on other agents, the volatility clustering tends to disappear.[19]

In the third economy agents herd on others but update their parameters by taking weighted averages of their current parameters and the parameters of others according to Eq. (12). Table 5 gives the results, suggesting that volatility clustering tends to disappear as agents have less information on the strategies of others.[20] For example, when $\delta = 0.9$, 90% of the new parameter is taken from the strategy of others and the rest comes from their current parameter. In a case of $\delta = 0.9$, we still observe some evidence of volatility clustering, although the evidence is weaker than in the herding economy where agents only use information on other agents for updating their strategies (when $\delta = 1$). We reject the "no ARCH" null in 45% of 20 simulations, while the estimate of the GARCH parameter is still significantly close to reality (0.89). However, as δ becomes smaller, our model does not generate the clustered volatility. As agents are more willing to inherit their own parameters, i.e., a smaller δ, they share less information with others. Our results suggest that the level of information sharing matters for generating volatility clustering.

Figures 4–6 explore some relations between our results and the dynamics of the forecast parameters with different degrees of δ. We plot time series on the cross-sectional standard deviations of a forecast parameter g_2^i. As in Fig. 4, when agents perfectly share their information with others, i.e., $\delta = 1$, the value shows wide fluctuations, leading to convergence for some periods and divergence for other periods. As they are more willing to inherit their own parameter, i.e., $\delta = 0.5$ in Fig. 5 or 0.1 in

[19] As in Table 4, volatility is less persistent with $\lambda = 0.9$ or 0.5 than $\lambda = 0.1$. As in the case of $\lambda = 0$ in Fig. 2, the volatility would be persistent when λ is very small, like 0.1. As λ becomes bigger, like 0.5 or 0.9, more agents start changing their strategies. However, the imitation effect is not large enough to generate persistent periods of large or small price changes. Nevertheless, the standard errors of estimates over 20 runs are quite large for all cases, i.e., $\lambda = 0.9$, 0.5, and 0.1. Thus, the mean estimates can be larger or smaller if we try 20 different runs.

[20] The economy with $\delta = 1$ is the herding economy in Table 2, so the results are repeated in the first column in Table 5.

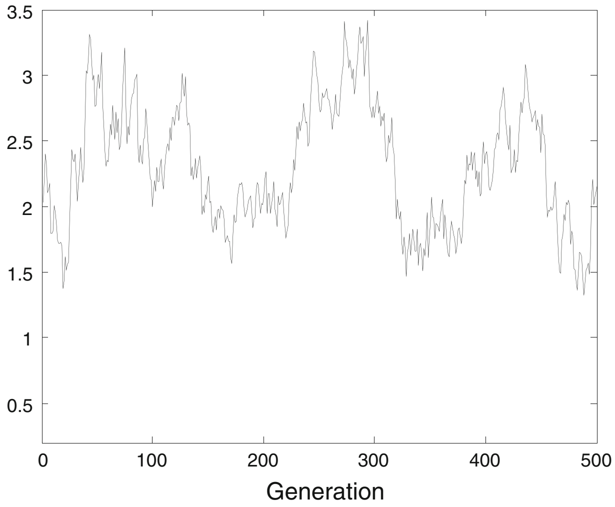

Fig. 4 Time series on the cross-sectional standard deviation of a forecast parameter g_2^i ($\delta = 1$)

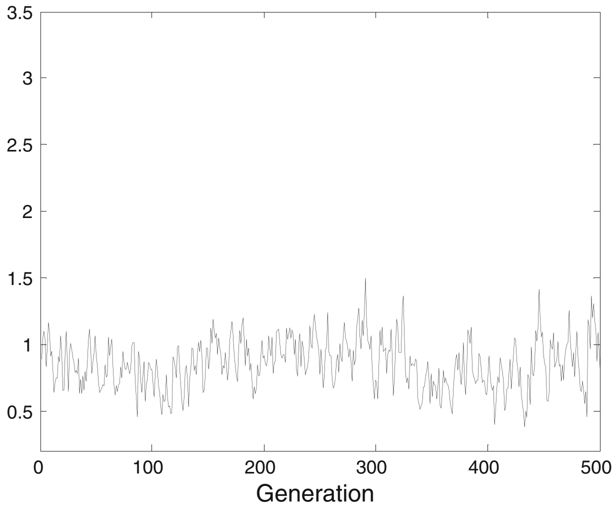

Fig. 5 Time series on the cross-sectional variance of a forecast parameter g_2^i ($\delta = 0.5$)

Fig. 6, the parameter value settles down over time. The results suggest that the population dynamics in forecast parameters differs with respect to the level of information sharing, and the dynamics of the forecast parameter is connected with the time series property of return volatility.

4 Conclusion

This paper investigates volatility clustering in different types of herding economies. We have shown that agents' imitative behavior is important for replicating this phe-

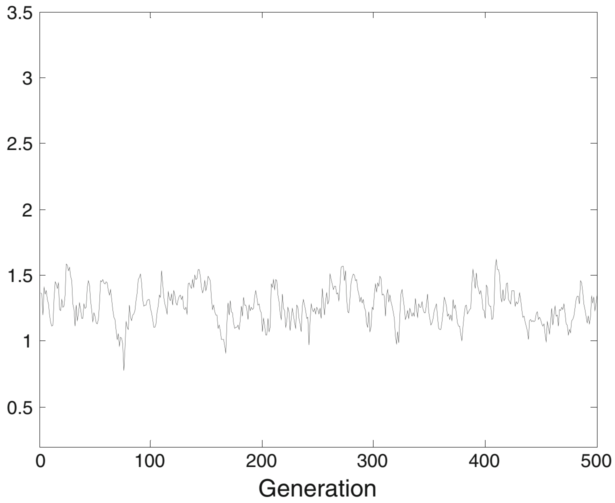

Fig. 6 Time series on the cross-sectional variance of a forecast parameter g_2^i ($\delta = 0.1$)

nomenon, as previous agent-based models suggest. However, when agents have limited information on the strategies of others, we have found much weaker evidence of clustered volatility. Agents in reality may not be able to observe the details of others' strategies. Even if they can, they may not imitate all of the information all of the time. This implies that other forms of social interactions, e.g., interactions via market sentiment indices (Lux 2009), influences from the news media (Shiller 2001), and/or some other factors—for example, investors' order-splitting, e.g., Yamamoto and LeBaron (2010), would also be related to volatility clustering.

Finally, we conclude our discussion with policy implications for regulation and supervision to hedge funds in light of the results in this paper. On April 2, 2009, the G20 members issued an official statement titled "Global plan for recovery and reform".[21] It includes an agreement, "Strengthening financial supervision and regulation", on regulating hedge funds to stabilize financial markets. In accordance with this statement, we expect that member countries will strengthen their regulation and supervision. Recently, the US congress has been contemplating a variety of rules to govern hedge funds. The congress has been arguing about whether hedge funds are subject to periodic examination, and the regulator asks questions about their investment and business practices (Washington Post, March 14, 2009).[22] On the one hand, if hedge funds provide more information on their trading strategies to the public, our results indicate that the volatility clustering will be more pronounced since agents can share more information each other. It implies that we will possibly observe more pronounced periods of large price fluctuation. Our paper suggests that such information disclosure may lead to more instability in financial markets.

[21] For more details see http://www.londonsummit.gov.uk/en/.

[22] For more details, see the Restoring American Financial Stability Act of 2010, which was passed at the Senate on May 20, 2010.

On the other hand, the hedge fund regulations may stabilize the market. Hedge funds are institutions that make large profits from their trading strategies constructed based on their private information. If hedge funds disclose their investment strategies and their performance, they will lose their competitiveness and may not be able to survive in the financial markets. If the hedge funds are driven out of the market, investors will have less useful information to share. Thus, in light of the results of our paper, investors will have less chance to herd on successful others, and volatility clustering will be muted. In addition, if the hedge funds are out of the market, the market may become more stabilized since there will be fewer investors in the market, who trade larger amounts of stock shares. We may raise several other arguments in relation to effect of the hedge fund regulations, but the actual effect would be more complicated and remain uncertain.

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Appendix

Table 6 summarizes the results of the robustness check explained in footnote 14. It gives the results from herding and non-herding economies with different parameter values.

Table 6 Test results for volatility clustering

	Herding economy			Non-herding economy		
	ARCH test	GARCH (1, 1) model		ARCH test	GARCH (1, 1) model	
	ARCH(1)	GARCH	ARCH	ARCH(1)	GARCH	ARCH
$N = 50$	68.61	0.980	0.018	2.28	0.426	0.012
	[1]	(0.005)	(0.005)	[0.1]	(0.374)	(0.011)
		[1]	[1]		[0.35]	[0.15]
$N = 150$	19.05	0.989	0.009	2.48	0.267	0.010
	[0.7]	(0.003)	(0.003)	[0.05]	(0.358)	(0.009)
		[1]	[1]		[0.15]	[0.1]
$\bar{\sigma}^2 = 7,500$	25.49	0.988	0.011	1.48	0.410	0.011
	[0.85]	(0.003)	(0.002)	[0.05]	(0.386)	(0.008)
		[1]	[1]		[0.4]	[0.1]
$\bar{\sigma}^2 = 25,000$	25.11	0.986	0.011	2.98	0.379	0.014
	[0.9]	(0.009)	(0.004)	[0.15]	(0.370)	(0.012)
		[1]	[1]		[0.4]	[0.2]
		[1]	[1]		[0.3]	[0.15]
$g_{1,\max} = 0.15$	27.59	0.987	0.012	1.19	0.302	0.008
	[0.9]	(0.003)	(0.003)	[0.05]	(0.359)	(0.008)
		[1]	[1]		[0.25]	[0.05]

Table 6 continued

	Herding economy			Non-herding economy		
	ARCH test	GARCH (1, 1) model		ARCH test	GARCH (1, 1) model	
	ARCH(1)	GARCH	ARCH	ARCH(1)	GARCH	ARCH
$g_{1,\max} = 0.4$	70.82	0.987	0.012	6.92	0.437	0.021
	[1]	(0.003)	(0.002)	[0.45]	(0.294)	(0.012)
		[1]	[1]		[0.4]	[0.45]
$n_{\max} = 0.5$	25.25	0.990	0.008	2.23	0.387	0.011
	[0.8]	(0.003)	(0.003)	[0.1]	(0.342)	(0.009)
		[1]	[1]		[0.2]	[0.05]
$n_{\max} = 1.1$	31.49	0.987	0.012	3.04	0.301	0.016
	[0.95]	(0.003)	(0.003)	[0.2]	(0.353)	(0.009)
		[1]	[1]		[0.2]	[0.25]
$\sigma_{g_2} = 1$	36.65	0.987	0.012	1.18	0.439	0.008
	[1]	(0.003)	(0.003)	[0]	(0.393)	(0.006)
		[1]	[1]		[0.35]	[0.05]
$\sigma_{g_2} = 5$	48.73	0.987	0.011	9.80	0.232	0.02
	[0.95]	(0.004)	(0.004)	[0.2]	(0.312)	(0.025)
		[1]	[1]		[0.15]	[0.15]
$L_{\max} = 50$	35.86	0.987	0.011	1.86	0.326	0.01
	[0.95]	(0.003)	(0.003)	[0.1]	(0.366)	(0.011)
		[1]	[1]		[0.4]	[0.25]
$L_{\max} = 250$	24.19	0.987	0.012	2.98	0.345	0.013
	[0.85]	(0.005)	(0.004)	[0.1]	(0.340)	(0.011)
		[1]	[1]		[0.25]	[0.15]
$p_m = 0.01$	90.96	0.981	0.018	2.17	0.447	0.013
	[1]	(0.010)	(0.010)	[0.05]	(0.376)	(0.008)
		[1]	[1]		[0.45]	[0.1]
$p_m = 0.12$	13.21	0.989	0.008	1.91	0.386	0.010
	[0.6]	(0.003)	(0.002)	[0.05]	(0.385)	(0.010)
		[1]	[1]		[0.35]	[0.15]

N number of agents, $\bar{\sigma}^2$ conditional variance, ω memory parameter, $g_{1,\max}$ max. value of a parameter for the fundamental component, $n_{\max}$ max. value of a parameter for the noise component, σ_{g_2} std of a parameter for the chartist component, $L_{\max}$ time horizon in the chartist component, and p_m probability of mutation. The numbers reported are the means of the test statistics over 20 runs. The numbers in brackets are the fractions of runs rejecting the null hypotheses at the 99% confidence level. The numbers in parentheses are the standard errors of estimates over the 20 runs

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