Article

Effect of Response to Stock Price Changes on the Persistence of Reputation-Based Herding

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Abstract
The existence and extent of herding behavior in the financial market is an important topic to analyze, since herding impedes efficiency in the operation of the financial system, and more importantly, increases the risk of financial crisis. This paper discusses one type of herding behavior, namely reputation-based herding. Based on the model developed by previous researchers who focused on asset market in which price is fixed, I adapted the model to simulate the behavior of fund managers in stock market to capture the impact of price responses on the persistence of herding. This paper takes a purely theoretical approach. By building a model in Python to track the behavior of investors, I found that the increase in stock price followed by the bids of previous investors dampens herding behavior, although the extent of this dampening impact depends on several features of the stock market in consideration.

Keywords: Herding Behavior, Financial Market

1. Introduction

Herding is a problem that has long been seen in financial markets. Its negative consequences include reducing efficiency, exacerbating volatility and systematic risk, and increasing the likelihood of financial crisis occurring in the economy. These can severely impact the living standard of the population, which have been made clear by the traumatic consequence of the reoccurrence of financial crises throughout the recent history (Bikhchandani and Sharma, 2000).

To be more specific, Acharya and Yorulmazer pointed out that herding increases the ex-ante systemic risk in the financial system, because it makes the joint failure among financial institutions more likely to occur. Herding also increases the ex-post systemic risk as it induces information contagion (Acharya and Yorulmazer, 2008).

This proves the importance of analyzing the causes of this phenomenon and finding possible remedies for it. While there are many factors that can trigger herding behavior, this paper focuses on a particular type of them, namely reputation-based herding.

The paper takes a purely theoretical approach to analyze the persistence of reputation-based herding in stock market. It examines how the behavior of rational investors changes when stock price rises, due to previous purchases, which reduces the profitability of investment in that stock. This price increase provides a disincentive for investors to imitate the behavior of the previous decision makers, compared to a scenario where stock prices stay constant.

The rest of this paper will take the following structure: Section 2 provides a discussion of existing literature on herding behavior in the financial markets. Section 3 illustrates the inspiration of the theoretical approach used in this paper. Section 4 shows the details of the model used in this paper. Section 5 discusses the results obtained from Python simulation based on the model in Section 4. Section 6 discusses the limitations of the model and the scopes of further research. Section 7 concludes the main findings of this paper.

2. Literature Review

2.1. Defining Herding Behavior

Before exploring the details of herding, it is worthwhile to precisely define the actual intentional herding, to distinguish it from spurious herding, which is the efficient behavior of investors making similar decisions when facing similar information. This paper follows the definition of Bikhchandani and Sharma, who defined 'herding' as the behavior of investors to rationally and intentionally imitate others, making different decisions compared to when they were to make investment decisions without observing the actions of others (Bikhchandani and Sharma, 2000).

2.2 The Development of Research in Herding

The early analysis of herding behavior in the field of economics can be traced back to The Theory of Moral Sentiments, the book published by Adam Smith in 1759 (Filiz et al, 2019). Since then, there have been various of research papers exploring the causes and consequences of herding.

Some researchers assume partial rationality when modelling the decision-making process of investors. For instance, Shleifer and Summers assumed that investors are not fully rational. They examined the impact of investor sentiment on asset prices, assuming that arbitrage is limited (Shleifer and Summers, 1990).

This section mainly discusses literatures on herding caused by fully rational behaviors only. There are three main factors that can lead to rational herding (Bikhchandani and Sharma, 2000) – imperfect information and the resulted information cascade (Banerjee, 1992), compensation structures (Roll, 1992), and reputational concerns from fund managers (Scharfstein and Stein, 1990).

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2.2.1 Information-Based Herding

Banerjee analyzed information-based herding. He assumed fixed asset price for all investors and that each investor has some free private information about the quality of the project. In this setting, Bayesian updating implies that, the information revealed by the decisions of the first few investors is a better predictor of the quality of the project than the private information of each subsequent investor. Consequently, all subsequent investors will follow the decisions of the previous investors. This impedes efficiency since the decisions made by the later investors no longer reflect their private information (Banerjee, 1992). Since the decision of the first few decision makers is not necessarily correct, this can lead to mistaken allocation of financial resources, resulting in a Pareto inefficient outcome (Bikhchandani and Sharma, 2000).

Some researchers further suggested that information cascade is more likely to form when each investor must incur some cost to receive private information (Bikhchandani et al, 1998). Apart from that, Avery and Zemsky relaxed the assumption of fixed asset price in the original model and applied the new model to the stock market. They have shown that price adjustments effectively dampen information-based herding (Avery and Zemsky, 1998).

2.2.2 Compensation-Based Herding

Roll suggested that when the compensation for a fund manager is linked to the relative performance of other investors, a rational manager has incentive to choose an inefficient portfolio (Roll, 1992).

Later, Maug and Naik provided a more detailed model of herding. They found that a risk-averse investment manager has incentive to mimic the portfolio choice of his or her colleagues if his or her compensation is based on relative performance. This result is obtained under the assumption that there is only one risky asset (Maug and Naik, 1995).

2.2.3 Reputation-Based Herding

As early as in 1936, Keynes pointed out that the fear of reputation loss is likely to encourage investors to align their decisions with the majority (Filiz et al, 2019).

Later, Scharfstein and Stein provided a more formal analysis of reputation-based herding under the assumption of fixed asset price. They defined reputation-based herding as the herding behavior of investors induced by the uncertainty about the competency of managers and the ability-related compensation scheme. If neither the money manager himself nor his employer know the ability of the money manager to select the profitable stocks, the manager may attempt to avoid the risk of revealing potentially low ability of him. Consequently, he has incentive to maintain conformity with other investors to preserve this uncertainty (Scharfstein and Stein, 1990).

In their paper, Scharfstein and Stein proved that, without concerns for reputation, all managers will respond to both the public information revealed by the behavior of the previous investors, as well as their private information about the quality of the stock. The financial market will aggregate as much as information as possible from all the investors. The result of their investment decisions will be efficient (Scharfstein and Stein, 1990).

However, when reputational concern is introduced and the asset price stay fixed, only the first investor will consider his or her private information. The first decision maker will invest if and only if he or she has received a signal indicating good perspective of the project, and the project will be rejected if otherwise. After the decision made by the first decision maker, the second investor always has incentive to adopt the same behavior as the first investor, regardless of his private signal. This is because making the same decision as the first investor always provides the second manager with a higher probability to be regarded as competent than making the opposite decision. The second investor will either always decide to invest (an ‘invest cascade’ starts), or he will always reject the investment (a ‘reject cascade’ starts). This implies that the subsequent investors can inform no new information about the quality of the project from the decision of the second investor. Therefore, they are effectively in the same position as the second decision maker. All investors will make the same decision as the first investor – herding persists and the financial market fail to utilize all the available formation, the market becomes inefficient (Scharfstein and Stein, 1990).

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Avery and Chevalier modified the model of Scharfstein and Stein to capture the fact that fund managers gradually become aware of their own ability over time. They found that, consistent with the predictions from Scharfstein and Stein, managers tend to herd in the early stage of their careers since they have no information about their own ability. However, once the managers have sufficient information about their ability, they 'anti-herd', that is, they deliberately make the opposite decision to other investors (Avery and Chevalier, 1999).

Villatoro applied the analysis of reputational herding to the behavior of financial intermediaries. He found that financial intermediaries with relatively high reputation make investment decisions according to their private information, while those lack of reputation tend to herd (Villatoro, 2009).

2.3. The Negative Consequences of Herding

Many researchers have shown the negative consequences of herding, which proves the importance of exploring the causes and patterns of herding behaviour, and to figure out feasible ways to dampen it.

Some researchers suggested that when investors follow the trading decision of others, the volatility in return tend to increase, which will destabilize the financial market (Demirer et al, 2010). Apart from that, herding behavior induced by Bayesian learning can lead to price bubbles, even without any speculative incentive, which can increase the fragility of the financial system (Hott, 2009).

More recent research also proves the existence and prevalence of herding behavior. Hasan et al. successfully showed the prevalence of intentional herding and the resulted increase in systemic risk (Hasan et al, 2023).

As a result, herding can cause increased burden on authorities which targets financial stability, as it amplifies the vulnerability of the economy to financial instability (Liang, 2013).

Furthermore, research has shown that herding may cause investors to misinterpret the expected value of assets (Cipriani and Guarino, 2014). Herding can also cause the price of stocks to deviate from their fundamental values (Yüksel, 2015).

3. Inspiration of the Model

Researchers have pointed that observing the final decision of individuals reveals little information about their thinking process and the motivation behind their decisions (Manski, 2000). This suggests that it is difficult to empirically distinguish between the three types of herding, evening if herding behaviour can be identified. Therefore, this paper only takes a theoretical approach.

Also, Avery and Zemsky have shown that price adjustments effectively dampen information-based herding (Avery and Zemsky, 1998), but little literature analyzes the impact of flexible price on reputation-based herding (Bikhchandani and Sharma, 2000). Therefore, this paper attempts to incorporate price responses to the original model of reputation-based herding to explore if fluctuations in prices can also mitigate this type of herding.

To adapt the baseline model to cover the effect of price changes, it is natural to focus on stock market rather than an asset market with fixed price. Luckily, Scharfstein and Stein pointed out that, with some slight moderations, their model would be suitable for stock market (Scharfstein and Stein, 1990).

Avery and Zemsky proves that, in a stock market, the market maker has incentive to set a higher price when higher demand increases bid price (Avery and Zemsky, 1998). Therefore, during the process of herding, if the first decision maker decides to buy the stock, the second investor will confront with a higher cost of investing. If the second investor also invests, the third person will face an even high price, and so on. On the contrary, if the first investor chooses not to invest, the second investor will face the same price as the first investor, and the price faced by the third investor depends on the decision of the second investor, and so on.

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Empirical research has shown that the return of stocks tends to follow a normal distribution (Andersen et al., 2001) or a power-law distribution (Amaral et al., 2000). This indicates that the probability of obtaining a certain return falls with the value of the return. Therefore, when the price of a stock increases, it becomes less likely to be profitable -- a higher return will be required to compensate for the higher stock price and the opportunity cost, but the probability of obtaining a higher return is lower than the probability of obtaining the initial level of return. When making decisions, investors may interpret this as a fall in the subjective probability of benefiting from purchasing that stock.

In the case of herding in stock market, this suggests that, if the first investor invests, the increased stock price imposes a force against herding on the second investor. Then, if the second investor still herds, the price increases further and the third investor faces an even stronger force against herding, and so on. This process may eventually stop herding from persisting.

On the contrary, if the first decision maker chooses not to invest, the stock price will be unchanged and the second investor will herd (not invest), and the same happens to the third investor, and so on.

Therefore, under this situation, price changes may be effective to stop reputation-based herding, but only in the case of an ‘invest cascade’.

A more detailed description of the model used in this paper is provided in next section.

4. Methodology

This section describes the framework of a theoretical model, which is used to examine how the extent of price response (e) affects the number of investors that will rationally choose to herd. It takes the idea from Scharfstein and Stein (Scharfstein and Stein, 1990), with slight moderations to take the impact of price responses into account.

Section 3.1 describes the players in this model and the information that the players know. Section 3.2 describes the dynamic decision-making process of the managers and the way information is updated. Section 3.3 provides a mathematical derivation of the condition for herding to be a rational choice for a certain decision maker. A summary of all the variables and symbols used is included in the appendix.

4.1 Framework of the Model

Assume that there is a series of M+1 fund managers, who will decide whether to invest in a certain stock. Denote the first manager as manager 0, the second manager as manager 1, the third one as manager 2, and so on (m=0, 1, 2, …, M). Assume that these managers invest in sequence, where manager 0 makes the decision first, followed by manager 1, and so on.

Before making their decisions, the managers each observe a signal that conveys information of the likely future return of the investment. Each manger belongs to one of the two types – either ‘Smart’ (S), that is, the one who receive informative signals about the return of the stock; or ‘Dumb’ (D), whose signals received are purely noisy.

Initially, neither the employer of these fund managers nor the managers themselves know their types. For each manager, the ex-ante probability of him or her being ‘Smart’ is k. Assume that the utility of the managers depends only on the ex-post probability of being regarded as ‘Smart’, since that is what affect their reputation hence future wages.

There are two possible outcomes of purchasing the stock: 1) a ‘High State’ (H) – the return is high enough so that it is worthwhile to buy that stock at the price faced by that investor, 2) a ‘Low State’ (L) – the return is not high enough. The prior probability of these states is a and (1-a), respectively.

Before making their decisions, each manager receives a signal, which is either ‘Good’ (G), or ‘Bad’ (B). If the manager is ‘Smart’, the signal received by him or her is informative – a ‘Good’ signal is more likely to be received if the return would be high enough, vice versa.

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For a 'Smart' manager, the probability that a 'Good' signal is received prior to a 'High State' is p, denote this as $\mathrm{P(G|H,S)} = p$. The probability that a 'Good' signal is received prior to a 'Low State' is q, denote this as $\mathrm{P(G|L,S)} = q$. According to the assumption, $p > q$. For simplicity, assume also that $p = 1 - q$.

If the manager is 'Dumb', the signals received by him or her is completely random, which means that the probability of receiving a 'Good' signal prior to a 'High State' is the same as receiving a 'Good' signal prior to a 'Low State'. Denote this as $\mathrm{P(G|H,D)} = \mathrm{P(G|L,D)} = z$.

Suppose that, if one manager is 'Smart' and the other is 'Dumb', or if they are both 'Dumb', the signals that they receive will be independent. However, if they are both 'Smart', they will always receive the same signal.

Assume that the probability of receiving any particular signal is the same for both types of managers, so that they cannot deduce their types based on the signal that they received, i.e. $\mathrm{P(G|S)} = \mathrm{P(G|D)}$. Using Bayes' theorem, it can be seen that $z = ap + (1-a)q = ap + (1-a)(1-p)$.

Assume that if a manager invests, the labor market interprets this as the manager has received a 'Good' signal, vice versa.

Once all the managers have made their decisions, the return is realized and the labor market reevaluates the ability of managers based on their performance (whether the return to the stock is high enough relative to the purchasing price if the investor bought the stock), as well as whether the investors have made the same decision as their colleagues.

Use K to denote the updated probability of the manager being 'Smart' after the labor market examines his or her trading decision. Assume that the future wages (*w*) of the managers are set based on their revealed ability (K). Assume also that w is proportional to K. Suppose that the managers are rational and risk neutral, this incentivizes managers to manipulate their decision to maximize K hence maximizing *w*.

4.2 Decision Making Process

The first investor (manager 0) makes decision only based on the signal that he or she received – he or she will invest if and only if a 'Good' signal is observed.

After that, the second manager (manager 1) makes decision. Manager 1 also receives a signal. In addition, manager 1 can observe the decision of manager 0. This provides additional information to manager 1 – if manager 0 has decided to invest, this implies that manager 0 has received a 'Good' signal, vice versa. Manager 1 invests if and only if the ex-post probability for him or her to be regarded as 'Smart' is higher when investing than not investing.

The same process continues for all investors – manager 2 observes the behavior of manager 0 and manager 1, as well as receiving his or her own signal, and so on.

After all the managers have made trading decisions in the stock market, the labor market updates its beliefs about the type of each manager based on 1) the return of stock relative to the price, 2) whether one manager's decision is consistent with the decision of his or her colleagues.

Criteria 2) is a result of the 'sharing-the-blame' effect. At any given level of return-to-price ratio, the perceived ability of one manager is higher if he or she makes the same decision as the majority. Because a low profit may be attributed to a systematically unpredictable shock which worsens the return and makes the decision of all managers to turn out to be wrong, even if they are all smart. This provides the incentive for reputation-based herding (Scharfstein and Stein, 1990).

The 'sharing-the-blame' effect also occurs since 'Smart' managers tend to receive perfectly correlated signals of the return of the stock, while the 'Dumb' managers receive independent random noisy signals. Therefore, each investor (apart from the first one), has incentive to imitate the behavior of the previous decision makers. Because this implies

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that it is likely that they have received correlated signals. The labor market is then more likely to perceive that manager as a 'Smart' one.

4.3 Bayesian Learning Process

As mentioned in Section 3, the price adjustment will only make a difference to the persistence of an 'invest cascade'. Therefore, the following part will only consider the case under which manager 0 has invested.

4.3.1 In case of 'High State' and investor 0 invested (investor 0 received G):

-- if investor 1 chooses not to invest (which would reveal that investor 1 receives B), these two investors must be of different types, and the only case under which investor 1 is 'Smart' is when investor 0 is 'Dumb'. Using Bayesian updating, the posterior probability of investor 1 being 'Smart' is shown below:

$$\mathrm{K(G,B,H)} = \mathrm{P(D,S|G,B,H)} = \frac{z(1-p)k(1-k)}{z(1-p)k(1-k)+p(1-z)k(1-k)+z(1-z)(1-k)^2}$$

K(G,B,H) is a symbol for the probability that investor 1 is 'Smart', given that investor 0 received a 'Good' signal, investor 1 received a 'Bad' signal, and 'High State' is revealed. P(D,S│G,B,H) is a symbol for the probability that investor 0 is 'Dumb', investor 1 is 'Smart', given that investor 0 received a 'Good' signal, investor 1 received a 'Bad' signal, and 'High State' is revealed. The same rule of labelling applies to the posterior probabilities in the rest of the paper.

-- if investor 1 also invests (which implies that investor 1 received G), there are two cases under which investor 1 is 'Smart' – either both investor 0 and investor 1 are 'Smart', or investor 0 is 'Dumb' and investor 1 is 'Smart'. The posterior probability of investor 1 being 'Smart' in this case is shown below:

$$\mathrm{K(G,G,H)} = \mathrm{P(S,S|G,G,H)} + \mathrm{P(D,S|G,G,H)} = \frac{pk^2+zpk(1-k)}{pk^2+zpk(1-k)+pzk(1-k)+z^2(1-k)^2}$$

4.3.2 In case of a 'Low State' and investor 0 invested (investor 0 received G):

-- if investor 1 chooses not to invest (which shows that investor 1 received B), these two investors must be of different types, and the only possible case for investor 1 to be 'Smart' is when investor 0 is 'Dumb'. The posterior probability of investor 1 being 'Smart' is shown below:

$$\mathrm{K(G,B,L)} = \mathrm{P(D,S|G,B,L)} = \frac{zpk(1-k)}{zpk(1-k)+(1-p)(1-z)k(1-k)+z(1-z)(1-k)^2}$$

-- if investor 1 also invests (which indicates that investor 1 received G), there are two possible cases under which investor 1 is 'Smart' – either both investors are 'Smart', or investor 0 is 'Dumb' and investor 1 is 'Smart'. The posterior probability of investor 1 being 'Smart' is shown below:

$$\mathrm{K(G,G,L)} = \mathrm{P(S,S|G,G,L)} + \mathrm{P(D,S|G,G,L)} = \frac{(1-p)k^2+z(1-p)k(1-k)}{(1-p)k^2+z(1-p)k(1-k)+(1-p)zk(1-k)+z^2(1-k)^2}$$

To examine whether investor 1 has incentive to herd, we need to consider the behavior of investor 1 when he or she observes a different signal compared to investor 0, i.e. when investor 0 observes G and investor 1 observes B.

Conditional on this, the probability of a 'Low State' occurring is shown below:

$$\mathrm{P(L|G,B)} = \frac{(1-a)[(1-p)(1-z)k(1-k)+zpk(1-k)+z(1-z)(1-k)^2]}{(1-a)[(1-p)(1-z)k(1-k)+zpk(1-k)+z(1-z)(1-k)^2]+a[z(1-p)k(1-k)+p(1-z)k(1-k)+z(1-z)(1-k)^2]}$$

Since the investment of investor 0 will push up the stock price, investor 1 will require a higher return for the investment to be worthwhile and a higher return will occur with a lower probability compared to the level of return required by investor 0. Assume that investor 1 will capture this change by assigning a lower subjective conditional probability to 'High State', i.e. a higher subjective conditional probability to 'Low State'. Assume for simplicity that

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the impact of price on the subjective conditional probability is linear, i.e. P(L|G,B)will increase by e, where e is an arbitrary small number.

Investor 1 will only choose to react to his or her private information (a 'Bad' signal) and decide not to invest if this offers him or her a higher posterior probability of being considered as 'Smart', which is represented by the condition below:

$\mathrm{K(G,B,H)P(H|G,B)} + \mathrm{K(G,B,L)P(L|G,B)} \geq \mathrm{K(G,G,H)P(H|G,B)} + \mathrm{K(G,G,L)P(L|G,B)}$ (Condition 1)

If the above condition fails to hold, investor 1 will ignore his or her private signal and simply imitate the behavior of investor 0. An 'invest cascade' starts. In this case, the behavior of investor 1 reveals no information of the signal received by him or her. When investor 2 starts to make decision, he or she is confronted with the same amount information as investor 1, apart from that P(L|G,B) will be reduced by one more e. Because the investment of investor 1 will push up the stock price further. The condition for investor 2 to decide whether to herd is the same as investor 1.

The same logic applies to all the rest of the investors.

The 'invest cascade' will only stop when the impact of price adjustment is strong enough so that the condition shown above starts to be satisfied.

I simulated the above process in Python to model when the 'invest cascade' stops, for different extent of price response (e), different probability of a 'Smart' manager receiving 'Good' signal prior to a 'High State' (p), different prior probability of 'High State' (a), and different proportion of 'Smart' investors in the population (k). The result is shown in the section below.

The code of the Python simulation is provided in the appendix.

5. Results from Python Simulation

Below presents the results from the simulation. It shows the first investor who will find it rational to not herd. That is, the first investor where condition 1 in Section 3.3 fails.
Various paces of price adjustment (e) are included to examine the impact of change in price response on the persistence of herding.

5.1 a=0.5, k=0.5, Impact of Different Sensitivity to Price Changes at 5 Different Levels of p

This subsection shows the impact of the probability of a 'Smart' manager receiving 'Good' signal prior to a 'High State' (p) on the persistence of herding.

Table 1 -- *a*=0.5, *k*=0.5, Impact of Price Changes at 5 Different Levels of *p*

e	Herding Stops At				
	p=0.6	*p*=0.65	*p*=0.7	*p*=0.75	*p*=0.8
0.0001	170	137	116	100	87
0.0002	120	97	82	71	61
0.0003	98	79	67	58	50
0.0004	85	68	58	50	43
0.0005	76	61	52	45	39
0.0006	69	56	47	41	35
0.0007	64	52	44	38	33
0.0008	60	48	41	35	31
0.0009	57	46	39	33	29
0.0010	54	43	37	32	27
0.0011	51	41	35	30	26

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0.0012	49	39	33	29	25
0.0013	47	38	32	28	24
0.0014	45	36	31	27	23
0.0015	44	35	30	26	22
0.0016	42	34	29	25	22
0.0017	41	33	28	24	21
0.0018	40	32	27	24	20
0.0019	39	31	27	23	20
0.0020	38	31	26	22	19

Figure 1 - the Sensitivity to Price Rise and the Persistence of Herding

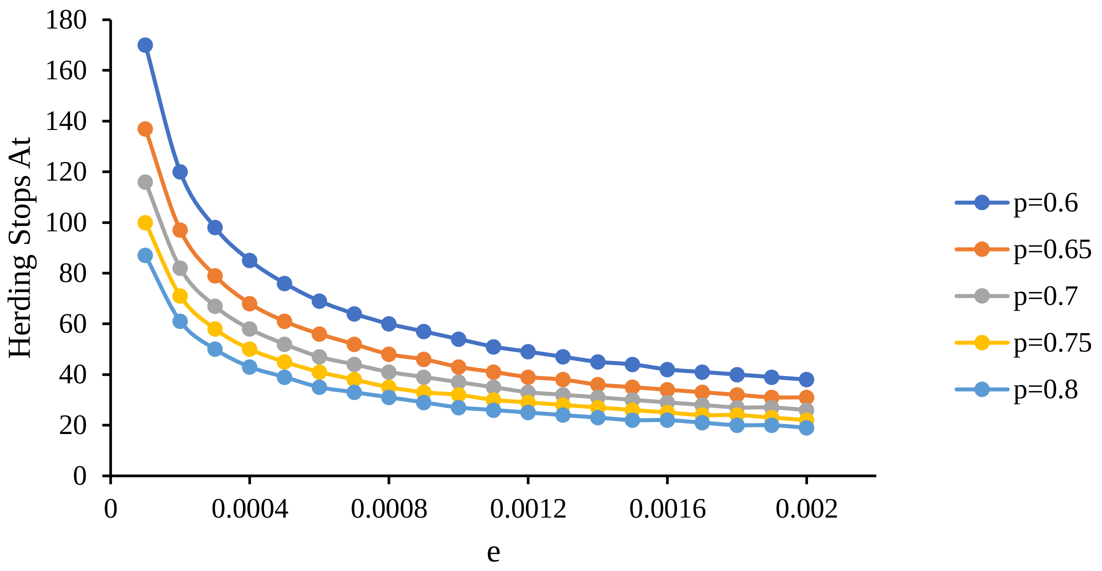

Table 1 shows the simulation result when a=0.5, k=0.5. The number in the cell under the columns ‘Herding Stops At’ indicates the first investor who starts to react to his or her private signal instead of simply following the decision of the previous investors. This is where Condition 1 in Section 4.3 begins to be satisfied. For example, the number ‘170’ in the first cell in the column ‘p=0.6’ means that when a=0.5, k=0.5, and p=0.6, the ‘invest cascade’ will ends at investor 170.

Figure 1 is a graphical representation of the result shown in Table 1. It can be seen from Figure 1 that the price increase caused by the purchase of stock of previous investors is effective in dampening the ‘invest cascade’, provided that the subsequent investors reduce their perceived subjective conditional probability of the investment being worthwhile (e). This result holds for any level of informativeness of a ‘Good’ signal for a ‘Smart’ investor, and the larger the extent to which the subsequent investors adjusting their subjective probability following the price rise, the earlier the ‘invest cascade’ stops. However, the effect of increase in sensitivity of investors to changes in price on the ‘invest cascade’ is diminishing, as reflected by the flattening of the paths shown in Figure 1.

Figure 1 also shows that for any given level of response to price adjustment, herding behavior will stop earlier when p is higher. This is reasonable because a higher p means a ‘Smart’ investor is more likely to receive a ‘Good’ signal prior to a ‘High State’ – if a manager is indeed ‘Smart’, it is more unlikely that he or she will receive a ‘Bad’ signal prior to a ‘High State’. Therefore, for any probability that a particular manager is ‘Smart’, a ‘Bad’ signal is likely to be a stronger predictor of a potential ‘Low State’, compared to when ‘Good’ signal is less likely to be received. Therefore, each manager may pay more attention to their private signal when p is higher, which will impede herding.

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5.2 k=0.5, p=0.6, Impact of Different Sensitivity to Price Changes at 5 Different Levels of a

Section 4.2 shows how the persistence of herding evolves at 5 difference levels of prior probability of 'High State' (a).

Table 2 -- *k*=0.5, *p*=0.6, Impact of Price Changes at 5 Different Levels of *a*

e	Herding Stops At				
	a=0.5	*a*=0.55	*a*=0.6	*a*=0.65	*a*=0.7
0.0005	76	75	74	74	73
0.0010	54	53	53	52	52
0.0015	44	43	43	43	42
0.0020	38	38	37	37	36

Table 2 shows the simulation result when k=0.5, p=0.6. It indicates that the response to price rises effectively impedes reputation-based herding for any level initial probability of a 'High State' to occur. The effectiveness increases with the sensitivity of the subsequent investors to the price increase. Also, the herding behavior will stop earlier if the initial probability of a 'High State' is higher. This is because, ceteris paribus, a higher initial probability can only occur when the level of return required by investor 0 is relatively low. Therefore, as price of the stock increases as the subsequent investors buy the stock, the return will fall below the level required by the investor who faces a higher price sooner. However, the impact of this is relatively limited, as shown in the table.

5.3 a=0.5, p=0.6, Impact of Different Sensitivity to Price Changes at 5 Different Levels of k

This subsection includes 5 different proportions of 'Smart' investors in the population (k) and examine the impact of that on herding.

Table 3 -- *a*=0.5, *p*=0.6, Impact of Price Changes at 5 Different Levels of *k*

e	Herding Stops At				
	k=0.5	*k*=0.55	*k*=0.6	*k*=0.65	*k*=0.7
0.0005	76	80	84	88	91
0.0010	54	57	60	62	65
0.0015	44	46	49	51	53
0.0020	38	40	42	44	46

Table 3 shows the simulation result when a=0.5, p=0.6. It indicates that the response to price changes reduces herding for any proportion of 'Smart' fund managers in the population. This impact becomes greater when the responsiveness of investors to the price changes increases. However, a higher proportion of 'Smart' investors in the population, ceteris paribus, will cause the 'invest cascade' to persist longer. This is because a larger proportion of 'Smart' investors means that investor 0 is more likely to be a 'Smart' one and the following investors have a greater chance of making the correct investment decision by making the same decision as investor 0, which will increase the incentive of herding.

6. Discussion

6.1. Limitations in this Paper

The key assumption in this paper is that the response of investors to changes in stock prices is a linear decline in their perceived subjective conditional probability of the purchase of that stock being worthwhile. While this captures the basic logic of the perception of investor to the changes in stock prices, it is unlikely that investors will think about the impact of price change on probability in a linear way in reality. Because the distribution of stock return tend not to be uniform and the price of stock followed by the purchase of one investor is unlikely to increase in a linear way. Therefore, while this paper attempts to simulate the direction of the impact of price response on dampening reputation-based herding, the exact result is not practically accurate and should not be used for empirical purposes.

Also, this paper assumes rationality of the investors and that they only care about the impact of their investment decision on the way that the labor market will perceive their ability in the future. However, other factors, such as

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limited liability, or different types of compensation contracts for the fund managers, may also alter the behavior of investors, which may then stimulate or impede herding behavior (Scharfstein and Stein, 1990).

6.2. Scopes for Further Research

The model used in this paper is based on many simplifying assumptions. Therefore, future research could relax the assumptions to make the model better fit real-life scenarios and examine how the result of this paper would change.

Moreover, since this paper only takes a theoretical approach, it is natural for future research to test the result of this paper with empirical data. Also, this paper assumes that all investors have the same features and follow the same thinking process, while it would be worth analyzing the effect of heterogeneity of investors in empirical work.

7. Conclusion

This paper takes a theoretical approach to analyze the way that rises in stock prices followed by the purchase of stock of previous investors impedes reputation-based herding. Using a Python simulation, it shows that an ‘invest cascade’ will be dampened when investors adjust their judgement of the worthwhileness of purchasing a stock according to the changes in the price of that stock.

The greater the sensitivity of investors to a price rise of the stock, the sooner the herding behavior will stop. A greater chance for a ‘Smart’ fund manager to observe a ‘Good’ signal prior to a ‘High State’ will cause herding to stop sooner. Also, if the initial probability of a ‘High State’ is relatively high, herding will stop relatively sooner, although the impact of this is very limited. On the contrary, a larger proportion of ‘Smart’ managers in the population will cause the ‘invest cascade’ to persist for a longer period.

These results suggests that it is important to stimulate free trade in the stock market since it will automatically dampen reputation-based herding and hence reducing the negative consequences of herding from occurring. Government may find it beneficial to ease the access stock market, for both domestic investors and potentially foreign investors. Because this can potentially accelerate the price response hence impeding herding.

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Appendix A.

Code of the Python simulation: https://liveuclac-my.sharepoint.com/:u:/g/personal/zctphz4_ucl_ac_uk/Ee6E3Ou9dFVLrUoMoC7XrZABvVPXmHTr1zM3asXSnaSOzw?e=23WamF.

Summary of symbols used:

m = 0, 1, 2, …, M	label of managers
S	'Smart' type manager
D	'Dumb' type manager
k	ex-ante probability of any manager being 'Smart'
H	'High State' - high return of the stock
L	'Low State' – low return of the stock
a	prior probability of 'High State'
1-*a*	prior probability of 'Low State'
G	'Good' signal – a signal suggests possibly high return
B	'Bad' signal – a signal suggests possibly low return
p	the probability that a 'Smart' manager receives a 'Good' signal prior to 'High State'
q	the probability that a 'Smart' manager receives a 'Good' signal prior to 'Low State'
z	the probability that a 'Dumb' manager receives a 'Good' signal prior to either state
K	the ex-post probability of a manager being 'Smart'
w	future wages, which depends on K
e	the increase in the subjective probability of a 'Low State' due to the stock purchase of the previous investor

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