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Herding with leading traders: Evidence from a laboratory social trading platform

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ABSTRACT

We provide novel evidence about herd behavior and its impact on asset price bubbles in an experimental financial market. We find that traders imitate quotes of those with the highest wealth increases as ranked on the leader-boards, despite that no traders possess private value-related information and that wealth increases are not due to trading skills. Most remarkably, we find that herd behavior does not produce more price bubbles and the awareness of information asymmetry leads to fewer bubbles as risk-averse traders become more cautious and do not quote prices too far from the fundamental value. We also find that participants with financial training have a lower herding tendency and markets with these participants exhibit less mispricing.

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1. Introduction

Interests in the mechanism that leads investors to herd and whether/how herd behavior could produce asset price bubbles and increase the fragility of the financial system have shown no sign of abating in the past decades (see, Bikhchandani and Sharma 2000, Hirshleifer and Teoh 2003, Venezia et al. 2011, Cipriani and Guarino 2014). The recent phenomenal growth in social trading platforms that aggressively promote imitating as a dominant strategy raises new and important yet unanswered questions about herd behavior.

In the traditional setting, herding occurs when investors follow recommendations and/or trading activities of sophisticated investors, such as security analysts and fund managers (Welch, 2000; Brown et al., 2014) who devote considerable resources to stock analysis, believing such research would lead to profitable strategies (Barber et al., 2001). Retail investors, should they wish to receive detailed recommendations in a timely manner, would need to become clients of investment firms. Furthermore, most investors do not know if sophisticated investors trade on stocks that they recommend, i.e. 'put money where their mouth is'.

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In contrast, on social trading platforms, such as *eToro* or *Zulutrade*, millions of users could automatically replicate the trading of top-performing traders at no extra cost[1]. There are attempts to set up regulatory frameworks for operators of platforms offering copy trading in the US, UK and the EU, some in response to concerns for retail investors in these platforms[2]. Yet, there is very little evidence on the extent of herding and its consequences on these platforms, not least because studying herd behavior in financial markets and particularly in online trading platforms is empirically challenging due to the lack of data on private information available to investors (Cipriani and Guarino, 2005, 2009; Venezia et al., 2011). In this paper, we design an experimental financial market that resembles an online social trading platform, which allows us to overcome challenges that empirical studies face addressing the following questions: Do traders follow leaders in the absence of value-related information asymmetry? Does herd behavior produce asset price bubbles? Does the cost of information affect herd behavior and, subsequently, bubble formation? Do participants with financial training trade differently in terms of herding tendency and bubble formation?

There are several prominent theoretical models of herd behavior. In the information-based models (Banerjee, 1992; Bikhchandani et al., 1992) investors disregard their private information and follow other investors. Cipriani and Guarino (2014) show that rational herding arises due to informational uncertainty. In the reputation-based models (Froot et al., 1992), managers imitate one another to maintain their reputation as ability is unobservable. In the compensation-based models (Maug and Naik, 2011), managers follow the market to maintain compensation relative to benchmarks. While there is considerable empirical research on herd behavior among security analysts (Graham, 1999; Jegadeesh and Kim, 2010; Frijns and Huynh, 2018), mutual funds (Lakonishok et al., 1992; Grinblatt et al., 1995; Koch, 2017) and individual investors (Venezia et al., 2011; Zheng et al., 2021), the overall evidence is inconclusive. This is to a great extent due to a lack of data on the private information available to investors, which makes it difficult to distinguish between intentional herding from spurious herding (when investors react to the same information), or to examine herd behavior independently of underlying reasons for incidental clustering of actions (Cipriani and Guarino, 2005, 2009).

The laboratory setting has been used to study aspects of herd behavior that would otherwise be difficult to examine using actual data from financial markets. In laboratory experiments, one can observe the decisions of participants while controlling fundamentals and private information (Drehmann et al., 2005; Sutter et al., 2012). Using the sequential asset market model of Avery and Zemsky (1998) and Cipriani and Guarino (2005) design an experiment that allows subjects to have private information on the fundamental value of an asset and trade this asset with a market maker, who in turn, updates the price according to the trading history. They find that subjects make decisions based on the offered price and do not follow others (see, also Cipriani and Guarino 2009). Similarly, Drehmann et al. (2005) construct a price mechanism based on the number of offers for a particular asset in the market. They show that the mechanism in which price is set by the market maker prevents herding.

The experiment we report in this paper was designed to assess the prevalence of herd behavior in a setting where copying is actively promoted and its impact on asset price bubbles. We filtered out spurious herd behavior by ensuring that no new value-related information was disseminated (privately or publicly) during the whole experiment. We only provided information about the fundamental value of assets at the start of the experiment to all participants. As such we eliminated any possible spurious herding due to participants reacting to new information in a similar manner. We recruited participants to take part in a standard experimental asset market with dividends using the double auction mechanism as in Smith et al. (1988) [3]. We designed four different treatments, each containing six markets. In each market, we endowed participants with assets and experimental money at the beginning of the experiment. Participants then traded in real-time, posting bids/asks or accepting the best bids/asks posted by others in fifteen periods.

An innovative feature of our experiment is the variations in information cost. We created leader-boards at the end of each period, which contained details about quotes made by each participant and their ranking by the period change in wealth[4]. The leader-boards were provided to all participants at no cost in two treatments and only to participants who were willing to pay in one treatment. Our setup allowed participants to utilize the leader-board information, without framing and pushing the decisions to copy the leaders' strategies. We are confident that our design closely resembles key features of a social trading platform while at the same time addressing issues that would otherwise have not been possible using empirical data[5]. Our experiment design is different from studies that examine herd behavior in a laboratory. For example, Cipriani and Guarino (2005, 2009) and Drehmann et al. (2005) use the market maker mechanism but do not allow actively-promoted copying. Apesteguia et al. (2020), while setting an asset market experiment that allows imitation of leading traders, do not

[1] *eToro* claims to have twenty million registered users while other platforms report a fewer number of users, e.g. one million users in *Zulutrade*, 90,000 in *Collective2*, 30,000 in *Wikifolio*. There are several other smaller platforms, all operating with the same principle such as *Sprinklebit, StockTwits, Estimize, Covestor, Quantopian*, and *Avondo*.

[2] https://commonslibrary.parliament.uk/the-rise-of-armchair-retail-trading-risks-and-regulation/; https://ec.europa.eu/commission/presscorner/detail/en/MEMO_14_305; https://www.fca.org.uk/firms/copy-trading; https://www.sec.gov/news/public-statement/enforcement-tm-statement-potentially-unlawful-online-platforms-trading.

[3] The experimental literature has used the asset market design to examine behavioral biases such as irrationality and beliefs (Ackert et al., 2012), gender difference (Eckel and Füllbrunn, 2015), traders' expectation (Haruvy et al., 2007), probability judgment error and speculation (Ackert et al., 2009), heterogeneity of beliefs and trade (Carlé et al., 2019), and capital constraints (Coppock et al., 2021).

[4] A sample leader-board is provided in the Online Appendix 1.2.

[5] Other studies that examine herd behavior in a laboratory such as Cipriani and Guarino (2005, 2009) and Drehmann et al. (2005) use the market maker mechanism; Apesteguia et al. (2020) conduct an asset market experiment in which participants cannot trade with each other.

allow participants to trade with each other. Their attention is on how the risk profile of traders who copy influences and is influenced by herd behavior. Our paper is related to but substantially differs from these studies as we examine whether herd behavior is influenced by value-unrelated uncertainty without framing and imposing a strategy (as in e.g. Apesteguia et al. 2020). Furthermore, our participants trade in real-time and the leader-boards in each market are produced at the end of every trading period. This enables us to shed light on whether herd behavior produces asset price bubbles, which would not be possible in previous studies. By focusing on the consequences of actively promoted herd behavior, our findings are more generalizable compared to other studies tailored towards online trading platforms and present highly relevant policy implications.

Theoretical models on herding such as Banerjee (1992), Bikhchandani et al. (1992) and Avery and Zemsky (1998) would predict that there would be no herding tendency in our setting as all participants had the same information about uncertainty in the fundamental value. Yet, we document a strong tendency to imitate top traders on the leader-boards. More startling is the finding that some participants were willing to purchase the leader-boards and to follow top traders, despite knowing that no traders had private information about the fundamental value. This suggests that participants may still imitate if they believe that others may do the same. Furthermore, we find that it is not necessarily the case that participants copy those traders who may have superior trading skills. This is in line with the propositions that participants may deviate from rational Bayesian decisions due to heuristics (Huck and Oechssler, 2000; Drehmann et al., 2005) and that individual behavior is subject to conformity, i.e. how they view the rationality of others (Alevy et al., 2007). Cipriani and Guarino (2005) argue that traders herd possibly because of value-related uncertainty in the market. We show that traders herd even if uncertainty is unrelated to the fundamental value.

Bikhchandani and Sharma (2000)'s model predicts that information-based herd behavior can lead to asset price bubbles. Similarly, Lei et al. (2001) attribute bubbles to systematic errors in decision-making resulting from irrational behavior[6]. In contrast, we find that asset price bubbles decrease with herd behavior and with information asymmetry: (i) markets where participants are asymmetrically informed have smaller bubbles than markets where participants are either symmetrically informed or symmetrically uninformed and (ii) markets where participants herd have smaller bubbles than those where participants do not. Our findings are consistent with previous studies such as Porter and Smith (1995) and Sutter et al. (2012). However, in these studies information (a)symmetry refers to knowledge about future dividends which affects assets' fundamental values whereas our results are based on information (a)symmetry about other participants' trading and about others' decisions to purchase such information. This lends further support to Porter and Smith's notion that behavioral and strategic uncertainty about other traders' behavior is the driving force for asset price bubbles. We argue that the novel design of our experiment in which the leader-boards serve as a mechanism to encourage herd behavior but without providing information about fundamental value is a key driver of the results generated. We show that uncertainty appears to encourage risk-averse traders to become more cautious, not quoting prices too far from the fundamental value, hence reducing asset bubbles.

Another interesting result in our paper comes from an important variation in our subject pool. We assigned all participants who were studying for a postgraduate finance degree (Master or PhD) in one treatment (the LB-Finance treatment) and participants who were studying for non-finance degrees in the other three treatments[7]. We used this subject pool to guarantee similar knowledge about financial markets and trading behavior. This might seem clinical but is of great importance for understanding the variations in place. Whilst non-student pools are very heterogeneous in their performance, history and success, our subject pools allow the results to be more controlled and therefore, differences and effects more robust. We are interested in studying if herd behavior and asset price bubble formation vary with financial training and knowledge acquired from formal education, or the lack of it. Previous studies suggest that trading behavior of professional investors could be different from that of individual investors due to the formers' experience and training and also other factors such as career- and compensation-concerns (see e.g. Hirshleifer and Teoh 2003, Venezia et al. 2011). Weitzel et al. (2020) show less overpricing and fewer and smaller bubbles in markets with professionals than markets with students. This has also led to the question about the validity of using students in laboratory financial experiments who might act differently compared to practitioners in the real financial market (Cipriani and Guarino, 2009).

Our experimental design facilitates an investigation of a possible effect of financial training and knowledge in the absence of career- and compensation-concerns. After controlling for differences in personality traits, demographic and ability characteristics, we find that herding tendency among participants with financial training is much less prevalent compared to those without such training. We also find interesting differences between the two groups. Participants with financial training were more likely to herd with leaders who gain from trading than with those who gain from receiving dividends. Participants without financial training did not make this distinction. Less herding is also associated with higher payoffs among participants with financial training. This is not the case in the treatments with participants with no financial training. We find that markets where participants have financial training and knowledge have fewer asset price deviations. This is consistent with Weitzel et al. (2020)'s finding that the markets with financial professionals are more efficient and this is due to their real-world experience rather than their cognitive skills.

[6] See Brunnermeier (2001) for surveys about bubbles and herding.

[7] In an experiment designed to examine irrational diversification, Baltussen and Post (2011) indicate that the task is demanding and therefore recruited students who completed basic courses in statistics, microeconomics and finance.

Our paper is related to the emerging literature on the role of social trading, internet message boards and the wisdom of crowds in the financial markets. This literature has focused on the effect on price and trading volume of these activities (Antweiler and Frank, 2004; Das and Chen, 2007), and growing reliance of investors on social media outlets for investment advice and for information production, evaluation and dissemination (Golub and Jackson, 2010; Chen et al., 2014).

The remainder of the paper is structured as follows. Section 2 presents the experimental design. Section 3 discusses results and Section 4 concludes.

2. Experiment design

2.1. The experiment and procedure

We conducted the experiment at the laboratories at a major university in the UK. We recruited 216 participants who were students in different disciplines at the university *via* ORSEE (see Greiner 2015). In total, we ran four treatments, *Base*, Leader-Board (*LB*), Leader-Board with Financial Knowledge (*LB-Finance*) and Leader-Board with Costly-Information (*LB-Cost*). For each treatment, we ran 6 independent markets with 9 participants in each market, making a total of 54 participants per treatment. We assigned 54 students who were studying for MSc Finance and PhD Finance at the university to the *LB-Finance* treatment[8] and 162 students in non-finance disciplines to the other three treatments. Participants were unaware of how we assigned them to different treatments nor did they participate in the asset market games prior to the experiment. Our experiment was designed and programmed using z-tree (Fischbacher, 2007). Our procedure in each market was as follows:

1. We read instructions to participants (See Online Appendix 1)[9].
2. Each market consists of 15 trading periods. Each period lasted for 120 seconds. Every participant was endowed with 280 ECUs (experimental currency units) and 4 units of an asset at the beginning of the session[10].
3. *Dividend:* At the end of each period, participants received dividends from the units of asset that they held in this period. Dividend per unit of the asset was a random outcome from the following set (0, 8, 16, 40) where each outcome was equally likely. Participants were informed of the probability distribution of dividends at the start of the experiment and of the actual dividends they received at the end of each period.
4. *Trading:* During each period, participants could quote bid/ask prices to indicate their willingness to buy or sell assets. Short-selling and borrowings were not allowed. Participants could choose not to trade. Trading prices were determined by the double auction mechanism.
5. *Wealth:* The wealth that each participant accumulated at the end of each period was the sum of the money they had (after trading and receiving dividends) and the fundamental value of the units of asset they owned at the end of this period[11].
6. *Period change in wealth*: The change in wealth of each participant at the end of each period was the difference between wealth at the end of this period and wealth at the end of the previous period.
7. After Period 15, we asked participants to complete a questionnaire to collect demographical information and to measure personality traits of participants. This lasted approximately 15 min.
8. At the end of the session, we calculated the wealth that each participant accumulated at the end of Period 15 and converted them into pound sterling at the rate of 124 ECUs = 1 GBP. Participants were paid immediately after the experiment.

2.2. The experimental design

The base treatment *(Base)* followed the procedure described above. For the other three treatments, at the end of each period, we created a leader-board which contained information about the trading history and performance ranking based on the period change in wealth of all participants in a market in that period. The leader-board was provided to all participants in the market before the next period started. In the *LB* and *LB-Finance* treatments, leader-boards were provided to all participants in the market at *no cost*. In the *LB-Cost* treatment, we informed participants about the opportunity to purchase leader-boards, including the information that is contained and its cost of 20 ECUs per leader-board[12]. We set the price per leader-board with reference to the fee structure in the fund management industry. The price of 20 ECUs per leader-board is

[8] For this group, the experimenters distributed invitation leaflets about the experiment at several lectures in the finance programmes. Participants in the *LB-Finance* treatment were not aware that they were targeted as a separate group, or that they would be in the treatment with finance students only.

[9] In the instruction, we use the example "you buy one stock at the price of 20 ECU and sell one stock at the price of 30 ECU" during period 1, which may affect the starting market prices in the first period. However, we do not believe that the low starting price in our experiment could be entirely attributed to this potential bias. Our starting price is low but comparable to those in other asset market papers (e.g. Palan 2010, Corgnet et al. 2010, Huber and Kirchler 2012, Cheung et al. 2014, Lugovskyy et al. 2014, Haruvy et al. 2014).

[10] Following Kirchler et al. (2012) we set the level of cash to asset endowment ratio as 1/3 to prevent overvaluation.

[11] Asset fundamental value was calculated as *Assets*16*NumberOfPeriodsLeft* where *Assets* was the number of assets that the participant owned at the end of this period, 16 was the expected dividend of each asset and *NumberOfPeriodsLeft* was the number of periods left in the session after this period. Following Smith et al. (1988), we set asset value at zero at the end of the last period, i.e. Period 15 (i.e. declining fundamental value).

[12] If a participant decided to purchase a leader-board at the end of every period (except at the last period) the total cost would equal the total initial cash endowment (20*14 = 280 ECUs).

Table 1
Herding with leaders.

Panel A: Herding quotes (total)					
	Base	LB	LB-Finance	LB-Cost	LB-Cost (All)
F1 *(number)*	288	518	404	33	309
F2 *(number)*	159**	365**	104***	13***	126***
F3 *(number)*	89***	144***	107***	7***	84***
All herding quotes	536	1.027	615	53	519
All quotes	3368	4916 (*p*-value = 0.000)	4036 (*p*-value = 0.008)	296	3424 (*p*-value = 0.000)
Herding quoted as % of all quotes	15.91%	20.89% (*p*-value = 0.012)	15.24% (*p*-value = 0.002)	17.91%	15.15% (*p*-value = 0.057)
F1 *(as % of all quotes)*	8.55%	10.54% (*p*-value = 0.224)	10.00% (*p*-value = 0.370)	11.14%	9.02% (*p*-value = 0.342)
F2 *(as % of all quotes)*	4.72%	7.42% (*p*-value = 0.148)	2.58% (*p*-value = 0.000)	4.39%	3.68% (*p*-value = 0.005)
F3 *(as % of all quotes)*	2.64%	2.93% (*p*-value = 0.073)	2.65% (*p*-value = 0.421)	2.36%	2.45% (*p*-value = 0.227)
Panel B: Herding quotes (period mean)					
	Base	LB	LB-Finance	LB-Cost	LB-Cost (All)
F1 *(number)*	3.20	7.00 (*p*-value = 0.005)	5.32 (*p*-value = 0.022)	0.37	3.43 (*p*-value = 0.012)
F2 *(number)*	1.77**	5.62** (*p*-value = 0.025)	2.08*** (*p*-value = 0.000)	0.14***	1.40*** (*p*-value = 0.000)
F3 *(number)*	0.99***	3.20*** (*p*-value = 0.043)	3.06*** (*p*-value = 0.757)	0.08***	0.93*** (*p*-value = 0.123)
Panel C: Herding participants					
	Base	LB	LB-Finance	LB-Cost	LB-Cost (All)
Total herding participants	53	53	46	20	53
Total *(as % of all participants)*	98.15%	98.15%	85.19% (*p*-value = 0.000)	68.97%	98.15%
F1 *(period mean)*	1.95	2.64 (*p*-value = 0.101)	1.82 (*p*-value = 0.010)	0.21	2.03 (*p*-value = 0.000)
F2 *(period mean)*	1.17***	1.82*** (*p*-value = 0.098)	0.51*** (*p*-value = 0.000)	0.09***	0.97*** (*p*-value = 0.000)
F3 *(period mean)*	0.63***	0.83*** (*p*-value = 0.110)	0.54*** (*p*-value = 0.343)	0.08**	0.63** (*p*-value = 0.000)
N	54	54	54	54	54

This table presents herding statistics in the *Base, LB, LB-Financ*e and *LB-Cost* treatments. The LB-Cost column presents data of participants who bought the leader-boards only while the LB-Cost (All) column reports data of all participants in this treatment. Panel A reports the total number of herding quotes in each treatment where F1, F2 and F3 are herding decisions following first-ranked, second-ranked and third-ranked leaders (We do not include the copying quotes from the leaders in the next period, i.e. a leader copies himself/ herself). Panel B reports the per-period average number of herding quotes. Panel C reports the total and per-period average number of herding participants. Herding participants in the *Base, LB, LB-Finance* and *LB-Cost* treatments are those who herd at least once during the whole experiment. ***, **, and * indicate *p*-value < 0.01, *p*-value < 0.05 and *p*-value < 0.1 for the null hypothesis that herding measures for F1 and F2 are equal and for F1 and F3 are equal using *Wilcoxon signed-rank test. p*-values in brackets are for the null hypothesis that herding measures in the *Base* and *LB; LB* and *LB-Finance; LB* and *LB-Cost* treatments are equal using *Mann Whitney U-test*.

equivalent to 1.61% of a participant's total wealth (cash and assets) at the start of the trading session. This is in line with the on-going charges set by leading fund management firms in the UK[13]. The concept of costly information in the asset market was introduced by Huber et al. (2011) who designed a costly newsletter with the distribution of information levels among traders. The information cost in our markets was set at a relatively more expensive level (1.61% compared to 0.15%) as we aimed to incentivize participants to be more cautious with their purchasing/information-acquiring decisions.

3. Results

3.1. Evidence of herd behavior

In line with Celen and Kariv (2004)'s definition of herd behavior, we define herding quotes as quotes made in a period that are the same as those made by the top three leaders in the previous period's leader-board in the same market. For example, a participant's quote of an asset at 100 in period two after knowing that the top trader traded at this price in period one is classified as a herding quote. Panel A Table 1 presents the total number of herding quotes in the *LB, LB-Finance* and *LB-Cost* treatments following leaders ranked first, second and third (F1, F2 and F3), excluding the copying quotes made by the leaders in the subsequent periods. It is evident that herding is prevalent in all three treatments and there is a herding hierarchy where F1 leaders attract the highest level of following. In the *LB* treatment, out of 4916 quotes made, there are 1027 herding quotes. Half (518) of the herding quotes are F1 quotes and the other half are F2 and F3 quotes. While herding appears less prominent in the *LB-Finance* treatment compared to the *LB* treatment (15.24% and 20.89%, respectively with $p = 0.001$), the number of herding quotes is still large and with a similar level of herding hierarchy (a total of 615 herding

[13] For example, JP Morgan's total charge is 1.68% per total assets managed (where the asset management charge is 1.5% and the operation and administration expenses 0.18%). For details see https://am.jpmorgan.com/gb/en/asset-management/gim/per/guidance-and-planning/choosing-your-investments/fund-management-charges. Legal & General's charges range between 0.04% and 1.79%. For details see https://www.legalandgeneral.com/investments/funds/prices-and-reports/charges-and-fees/charges-and-fees-for-our-funds/.

quotes of which two thirds, i.e. 404, are F1 quotes). In the *LB-Cost* treatment, a substantial proportion of quotes made by participants who purchased leader-boards is herding quotes (17.91%) and there are more F1 quotes than F2 and F3 quotes.

The statistics for herding per period and herding participants presented in Panel B and Panel C corroborate those in Panel A. Herding with top leaders (F1) is more pronounced than with second and third leaders (F2 and F3) and overall herding is higher in the *LB* treatment than in the *LB-Finance* treatment. On average, there are 7 F1 herding quotes per period in the *LB* treatment, compared to 5.32 in the *LB-Finance* treatment ($p = 0.022$). Similarly, there are 5.62 F2 quotes in the LB treatment, compared to 2.08 in the *LB-Finance* treatment ($p = 0.000$). Results in Panel C show that most of the participants in the *LB* and *LB-Finance* treatments copied at least once in the whole experiment. In the *LB* treatment, 53 out of 54 participants did so compared to 46 of 54 participants in the *LB-Finance* treatment. In the *LB-Cost* treatment, 29 out of 54 participants purchased at least one leader-board and 20 copied at least once using the information from the leader-board that they purchased. The average per-period number of participants who followed F1 and F2 leaders in the *LB* treatment is significantly higher than those in the *LB-Finance* treatment.

Our design allows participants to observe trading by other participants when they trade with each other in real-time, post bids/asks and/or accept the best bids/asks posted by others in fifteen periods. This is different from Apesteguia et al. (2020)'s design which allows imitation of leading traders but does not allow participants to trade with each other. Consequently, while herding decisions in the *LB, LB-Finance* and *LB-Cost* treatments could be driven by the 'availability of the leader-board', it is possible that in all treatments, including the *Base* treatment, such decisions are also driven by the 'trading activity information' effect and 'availability of the leader-board' effect.

To disentangle the 'availability of the leader-board' effect, which could be present in the *LB, LB-Finance* and *LB-Cost* treatments, from the 'trading information' effect, we calculated the leader-boards and herding quotes in the *Base* treatment in the same manner that we did for other treatments despite the fact that participants in this treatment did not receive any information about the trading and performance of top traders. We then compared the number of quotes that were similar to the quotes of top traders in the *Base* treatment with the herding quotes in the *LB* treatments. The differences reported in Table 1 are statistically significant, which indicates that the herding behavior observed in the three *LB* treatments can be attributed to the 'availability of the leader-board' effect. Quotes in the *Base* treatment that are the same as those made by the top three leaders in the previous period could be attributed to the 'trading information' effect[14].

Our results provide strong evidence of the existence of a tendency to herd when this behavior is encouraged in the form of available information about top traders' activities. While information-based herding theories (Banerjee, 1992; Bikhchandani et al., 1992) point to uncertainty about value-related private information in the market as the mechanism leading to herd behavior, our results suggest that uncertainty unrelated to private information could also be a source of herding. In our experiment, it is evident that the behavior of participants depends on one another. Participants who are rational in the sense that they think that trading of top traders reveals neither skills nor private information may still herd if they believe that other participants will follow these traders. As Drehmann et al. (2005) conclude, 'sometimes an intuition for the possibly irrational behavior of others seems to be more important than being able to apply Bayes' rule' (page 1422).

3.2. Herd behavior and financial knowledge and training

Results in the previous section show that herd behavior is more pronounced in the *LB* treatment than in the *LB-Finance* treatment. A possible explanation could be that the *LB-Finance* participants have acquired extensive training about finance and financial markets as well as the presence of cognitive and psychological bias in financial markets from their study and thus are more likely to decide against herding[15]. To test this proposition, we first compare demographical, personality traits and abilities of the two sets of participants. We then examine if the decision to herd varies with one's financial training and knowledge, or the lack of it, controlling for differences in individual-specific characteristics that might affect herding decisions. Previous research, in both laboratory and non-laboratory settings, shows that demographical characteristics, personality traits, and cognitive ability may influence how individuals invest and trade. For example, Nöth and Weber (2002) find that overconfident individuals are less likely to follow others while Grinblatt et al. (2012) show that individuals who perform better on IQ tests are less prone to judgmental biases. Chevalier and Ellison (1999) find that young fund managers with less experience are more likely to herd while Menkhoff et al. (2006) show that high risk-taking and overconfident fund managers are less likely to herd.

We collected participant-specific characteristics from the end-of-treatment questionnaire. We used Biais et al. (2005)'s test for miscalibration and self-monitoring[16], Eckel and Füllbrunn (2015)'s test for math skills, and Holt and Laury (2002)'s experiment for risk preferences. We also asked participants to compare their performance to that of others in the experiment. For nationality, we distinguish Western and non-Western participants. Western participants are anyone coming from European countries and North America (the U.S. and Canada) while non-Western participants are from the rest of the world. Psychological literature suggests that conformity is more likely in hierarchical cultures such as East Asia, where people live in small towns and know each other. For example, Kim and Markus (1999) show that while the advertisements in the U.S.

[14] We thank an associate editor and an anonymous referee for pointing this possible effect.

[15] Both MSc and PhD in Finance programmes at the university cover behavioral finance in their curriculum.

[16] Miscalibration refers to the tendency to underestimate uncertainty in future outcomes while self-monitoring refers to the level of attentiveness to social cues.

Table 2
Demographical information, personality traits and ability of participants.

	All	Non-finance	Finance	*p*-value
Miscalibration	20%	18.3%	25.9%	0.171
Self-evaluation	26.07%	33.33%	46.94%	0.160
Math skills	3.92	3.81	4.12	**0.030**
Self-monitoring	8.66	8.76	8.35	0.752
Risk preference	6.38	6.83	5.71	**0.056**
Gender	44.55%	42.59%	51.02%	0.394
Western countries	33.18%	46.30%	16.33%	**0.001**

This table presents the characteristics of participants and compares them between participants in the *LB* and *LB-Finance* treatments. *p*-values are for the null hypothesis that characteristics of participants in the *LB* and *LB-Finance* treatments are equal using the Mann–Whitney–Wilcoxon test.

Table 3
Herding and participant-specific characteristics.

Dep. Var.	*F1_Quotes* (1)	*F123_Quotes* (2)
Base	-3.695*** (1.420)	-5.609** (2.173)
Finance	-2.046 (1.541)	-4.629* (2.359)
Miscalibration	0.144 (0.341)	0.016 (0.522)
Self-evaluation	-0.269 (1.377)	1.475 (2.107)
Math skills	-1.117** (0.505)	-0.864 (0.773)
Self-monitoring	-0.021 (0.166)	-0.345 (0.253)
Risk preference	-0.617** (0.270)	-0.464 (0.414)
Gender	1.477 (1.179)	3.090* (1.804)
Western countries	-2.888** (1.289)	-4.123** (1.973)
Constant	17.31*** (3.117)	24.21*** (4.771)
N	211	211
R-sqr.	0.087	0.075

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, This table reports the estimation results of herding decisions regressed on participant characteristics. The dependent variables are the total number of F1 herding quotes *F1_Quotes* (in model 1) and of all herding quotes *F123_Quotes* (in model 2) made by a participant in the whole experiment. *Base* is a dummy variable that takes a value of 1 in the Base treatment and 0 otherwise. *Finance* is a dummy variable that takes a value of 1 if the participant took part in the *LB-Finance* treatment and 0 otherwise. Other demographical, personality traits and ability variables are collected from the end-of-treatment questionnaire.

focus on uniqueness, the advertisements in Korea focus more on conformity, i.e. the percentage of people who make the same decisions. We then compared the ranking by participants with their actual performance to evaluate the tendency to unrealistically self-evaluate positively.

Table 2 presents the summary statistics of participant characteristics and compares non-finance participants with finance participants. The two groups are not significantly different in terms of miscalibration and self-monitoring scores or gender distribution. However, 46.94% of finance participants unrealistically believed that their performance in comparison to others' performance in the market was better than it actually was. Only 33.33% of non-finance participants believed so ($p = 0.160$). Finance participants also scored better on the math test ($p = 0.030$) and showed a more risk-taking attitude ($p = 0.056$) than non-finance participants[17].

Table 3 reports the estimation results of herding decisions regressed on participant characteristics. The dependent variables are the total number of F1 herding quotes *F1_Quotes* (in model 1) and of all herding quotes *F123_Quotes* (in model 2) made by a participant in the whole experiment. To formally differentiate the 'availability of the leader-board' effect from the 'trading information' effect, in the case of the *Base* treatment we still count herding quotes as quotes similar to those of leaders in the previous periods although participants did not receive information about trading of top traders. We include a dummy variable *Base* that takes a value of 1 if the participant took part in the *Base* treatment and 0 otherwise. We run the regression for the full sample consisting of all participants who took part in the four treatments and completed the end-of-experiment questionnaire. Our other variable of interest is *Finance*, a dummy variable that takes a value of 1 if the

[17] Online Appendix 2 provides details about the end-of-treatment questionnaire. On average, our participants were more miscalibrated than those reported in Biais et al. (2005), but scored lower in the self-evaluation test compared to those in Pikulina et al. (2017). They scored lower in the maths test compared to those in Eckel and Füllbrunn (2015) but for the self-monitoring and risk preference tests their average scores were similar to those in Biais et al. (2005) and Holt and Laury (2002).

Table 4
Herding and leaders' trading skills.

	Performing traders	Non-performing traders	p-value
LB treatment			
Herding quotes	6.25	8.00	0.452
Herding participants	3.65	3.30	0.754
LB–Finance treatment			
Herding quotes	5.80	3.92	0.023
Herding participants	2.80	1.92	0.024

This table compares the number of herding quotes and herding participants following performing and non-performing trading first-ranked leaders. Performing/Non-performing trading leaders are those with trading gains in the top/bottom quartile where trading gains are measured as $(W_t - W_{t-1} - D_t)$. p-values are for the null hypothesis that herding measures in the *LB* and *LB-Finance* treatments are equal using the Mann–Whitney–Wilcoxon test.

participant took part in the *LB-Finance* treatment and 0 otherwise. We also include other participant-specific characteristics as detailed in Table 2 as explanatory variables.

The negative and statistically significant coefficients of *Base* in both models indicate that participants in the *Base* treatment are less likely to follow the first-ranked leaders and top three leaders. The more following decisions in the *LB*, *LB-Finance* and *LB-Cost* treatment could be attributed to the "availability of ranking" effect apart from the "trading activity information" effect. The coefficients of *Finance* are negative though only statistically significant in model (2), which indicates that knowledge about financial markets and behavioral bias, or the lack of it, could explain differences in herd behavior, even after controlling for differences in individual characteristics of participants. The results in both models show that the characteristics that statistically distinguish between non-finance and finance participants, i.e. math skills, risk preferences[18] and country of origin, are associated with herding behavior although they are not always significant at the standard levels.

Our finding that participants in the *LB-Finance* treatment herd less compared to those in the *LB* treatment is consistent with previous research comparing the behavior of financial professionals and retail investors. For example, Alevy et al. (2007) suggest that the behavior of professionals may differ from that of students due to the formers' training and/or expertise while Dufwenberg et al. (2005) believe that professional investors are not prone to biased judgements. Venezia et al. (2011) attribute less herding proclivity among professional investors relative to amateur investors to the former's superior financial training. While Venezia et al. focus on how herding varies with asset-specific characteristics (firm size and risk), we show that this tendency holds even after individual-specific characteristics are taken into account[19].

3.3. Herd behavior and leaders' trading skills

Participants in our experiment exhibit a tendency to follow those ranked as top leaders, i.e. those with the largest increase in their wealth. By design, change in wealth is comprised of dividends received in the period, which is a random outcome from a pre-determined distribution, and gains/losses from trading. As such, one may imagine that participants would be more likely to follow leaders whose period change in wealth could be attributed to trading skills. For example, a leader whose period change in wealth is 50 ECUs, of which 40 ECUs come from trading gain could be perceived as having better trading skills and thus may attract more followers than a leader whose change in wealth is also 50 ECUs but by luck receiving 40 ECUs from dividends and only 10 ECUs from trading. To test this proposition, we rank all F1 leaders by trading performance which is the period change in wealth minus dividends received in the period $(W_t - W_{t-1} - D_t)$. We call leaders in the top quartile of trading gains as 'best performing traders' and those in the bottom quartile as 'worst-performing traders'. We then compare the number of herding quotes and herding participants following best and worst-performing traders. Table 4 shows that in the *LB* treatment, the average number of quotes following best-performing traders is not statistically different from that of quotes following worst-performing traders. Similarly, the number of herding participants following the two groups are also indifferent. In contrast, in the *LB-Finance* treatment, best-performing traders appeared to attract more followers and more herding quotes than worst-performing traders. In other words, finance participants are more likely to follow performance traders.

[18] We also examine the effect of the traders' risk attitude and their trading decisions. First, for each treatment we measure the deviation of quotes from the fundamental value as the absolute value of the differences between the quoting prices and the fundamental values (*Diff*). We then compare this deviation across three groups of traders, risk-averse, risk-neutral and risk-seeking as measured by Holt and Laury (2002). The results reported in the Online Appendix 5 indicate that the deviation from fundamental values in quotes by risk-taking traders is larger than those in quotes by risk-neutral or risk-averse traders. Second, to establish a causal relationship between risk preferences and the deviations between quotes and fundamental values, we perform a regression analysis in which the dependent variable is *Diff*. We include *Risk preference* and all other explanatory variables as in the specifications in Table 3. In the results reported in the Online Appendix 5, the coefficient of *Risk preference* is negative and significant, indicating that traders' risk attitude causes them to become more cautious in trading by not quoting prices too far from the asset's fundamental value.

[19] Drehmann et al. (2005) report differences in behavior of student subjects in different disciplines. They find that physicists perform best in terms of 'rationality' (i.e. behaving according to theory prediction) but worst in terms of profits while psychologists perform worst in rationality but best in profitability.

Table 5
Herding and payoff.

	High herding activities	Low herding activities	p-value
LB treatment			
End-of-treatment wealth	1529.33	1932.00	0.391
Period-average wealth	1335.79	1628.78	0.373
LB–Finance treatment			
End-of-treatment wealth	947.76	1372.76	0.029
Period-average wealth	1038.277	1429.75	0.003
LB–Cost treatment			
End-of-treatment wealth	978.47	1106.54	0.428
Period-average wealth	1075.27	1164.82	0.450

This table compares the end-of-treatment and period-average wealth of participants with high and low herding activities. In the *LB* and *LB-Finance* treatment, participants in the high/low herding activities groups are those with the total number of herding quotes higher/lower than the treatment median herding quote. In the *LB-Cost* treatment, participants in the high herding activities group are those purchased leader-boards and made herding quotes. Participants in the low herding activities group include those purchased leader-boards and did not make herding quotes and those did not purchase leader-boards. *p*-values are for the null hypothesis that wealth measures of the two groups are equal using the Mann-Whitney-Wilcoxon test.

3.4. Herd behavior and payoffs

We explore if payoffs vary with herding tendency. Bosch-Domènech and Vriend (2003) indicate that individual payoff would be worsened by following the more successful participants while Apesteguia et al. (2007) conclude that imitating a more successful action increases the payoff differences. In this study, we rank participants in each treatment by the total number of quotes following F1 leaders that they made in the whole treatment and divide them into two groups: the ‘high herding participants’ are those with higher than median herding quotes and the ‘low herding participants’ are those with lower than median herding quotes[20]. We then compare the average end-of-treatment wealth and period-wealth of each group. In the *LB-Cost* treatment, we compare payoffs of participants who purchased leader-boards and herded with the rest.

Given that leaders do not possess value-related information, we do not expect any difference in the payoffs of the two groups. This prediction is corroborated by results in Table 5. In the *LB* and *LB-Cost* treatments, participants who herded more received lower payoffs than those who herded less but the difference is statistically insignificant. In the *LB-Finance* treatment, we observe a significantly higher payoff among participants who herded less[21].

3.5. Herding and asset price bubbles

We use several measures of asset price bubbles as in Kirchler et al. (2012) and Corgnet et al. (2015) to check for differences between treatments and to examine if bubble characteristics vary with herding among participants:

(1) Relative absolute deviation (*RAD*): measures mispricing, i.e. the size of price deviations compared to the fundamental value.

$$RAD = \frac{1}{N}\sum_{p=1}^{N}\frac{\left|\overline{P_p} - FV_p\right|}{\left|\overline{FV}\right|} \tag{1}$$

(2) Relative deviation (*RD*): measures overvaluation.

$$RD = \frac{1}{N}\sum_{p=1}^{N}\frac{\overline{P_p} - FV_p}{|\overline{FV}|} \tag{2}$$

(3) Amplitude: measures the magnitude of peak-to-trough price deviations compared to the fundamental value.

$$Amplitude = \max\frac{\left(\overline{P_p} - FV_p\right)}{FV_1} - min\frac{\left(\overline{P_p} - FV_p\right)}{FV_1} \tag{3}$$

(4) Boom (Burst) duration: measures the largest number of consecutive periods where the price is above (below) the fundamental value.

(5) Turnover: measures the volume of share transactions relative to the number of shares in the market.

$$Turnover = \frac{\sum_{t=1}^{T} Q_t}{36} \tag{4}$$

[20] The ‘low herding participants’ group includes participants with no herding quotes.

[21] The payoffs in the *LB* treatment on average are higher than in other treatments due to differences in the level of dividends received (for example the average dividend in the *LB* treatment is 97 ECUs compared to 60 ECUs in the *LB-Finance*). The average lower payoff in the *LB-Cost* treatment is due to the money spent on purchasing leader-boards.

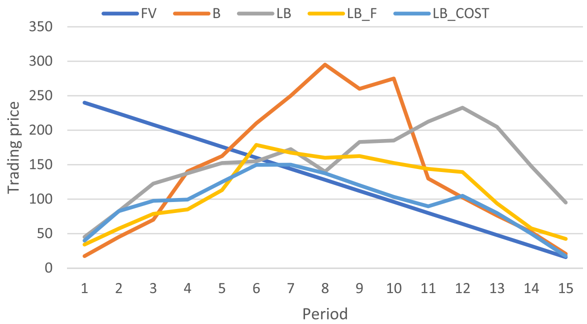

Fig. 1. Bubble formation in the treatments, This figure shows the bubble formation in the four treatments, *Base*, *LB*, *LB-Finance* and *LB-Cost*. B, *LB*, *LB_F* and *LB_COST* are median prices in each market in the *Base*, *LB*, *LB-Finance* and *LB-Cost* treatments. FV indicates fundamental value.

Table 6
Bubble characteristics.

	RAD	RD	Amplitude	Boom	Burst	Turnover
LB	0.81	0.23	1.45	9.00	6.00	4.02
LB-Finance	0.63	-0.05	1.32	9.00	6.00	2.98
LB-Cost	0.52	-0.23	1.10	7.00	7.50	2.49
Base	0.91	0.18	1.87	9.00	6.00	2.55
p-value (LB = LB-Finance)	0.336	0.146	0.521	0.934	0.934	0.261
p-value (LB = LB-Cost)	**0.054***	**0.037****	0.109	0.143	0.168	0.108
p-value (LB-Finance = LB-Cost)	0.336	0.261	0.262	0.124	0.144	0.422
p-value (LB=Base)	0.521	0.809	0.109	0.509	0.509	0.126
p-value (LB-Finance=Base)	**0.065***	0.261	**0.078***	0.410	0.410	0.336
p-value (LB-Cost = Base)	**0.016****	**0.054***	**0.016****	0.219	0.286	0.872

This table reports the characteristics of bubbles in the *LB*, *LB-Finance* and *LB-Cost* treatments. *p*-values are for the null hypothesis that the bubble characteristics in the two treatments are equal using the Mann–Whitney–Wilcoxon test.

where, N is the number of periods, $\overline{P_p}$ is the mean price of period p, FV_p is the fundamental value of period p, $\overline{FV}$ is the mean fundamental value. Q_t is the total executed offers in a market.

In Fig. 1, we plot per-period median executed prices in all four treatments. We observe significant and similar patterns of mispricing in all the treatments: Prices started below the fundamental value, then converged towards the fundamental value until period 5 (or 6), rose above the fundamental value and converged back to the fundamental value towards the end of treatment. Bubbles were formed in all markets in all treatments although they were different in magnitudes (see Appendix A). Price deviations were visibly larger in the Base and LB treatments compared to the LB-Finance and LB-Cost treatments.

Table 6 reports and compares measures of bubble characteristics in each treatment. The positive values of *RAD* in all four treatments indicate that prices differed from the fundamental value in these treatments. The lowest value of *RAD* is in the *LB-Cost* treatment, indicating that prices in this treatment were closer to the fundamental value relative to the other treatments. The value of *RAD* in the *Base* treatment suggests that prices in this treatment were farthest from the fundamental value. Price deviations in the *LB-Cost* treatment are significantly lower compared to the *Base* treatment ($p = 0.016$) and to the *LB* treatment ($p = 0.054$). The price deviation in the *LB-Finance* is also significantly lower compared to the *Base* treatment ($p = 0.065$). The sign of *RD* suggests that deviation was overpricing in the case of the *Base* and *LB* treatments (0.18 and 0.23, respectively) but underpricing in the case of the *LB-Finance* and *LB-Cost* treatments (-0.05 and -0.23, respectively). The *LB-Cost* treatment also has the lowest value of *Amplitude* whereas the *Base* treatment has the highest value. Other bubble measures, *Boom*, *Burst* and *Turnover*, do not differ significantly across treatments when considering standard significance levels[22].

We conduct the phase analysis by dividing the 15 periods into 3 phases, Phase 1 (Period 1–5), Phase 2 (Period 6–10) and Phase 3 (Period 11–15). The results in the Online Appendix 7 show that trading volume is also significantly higher in the three phases of the *LB* treatment compared to those in the *Base* treatment. It is plausible that participants compete to become the leaders in the next period, or they are more confident about having more information from the leaderboards. We also observe that the structure of bubbles changes during the course of the experiment. More particularly, the magnitude of bubbles is significantly lower in Phase 1 of the *LB* treatment compared to that in the *Base* treatment while

[22] Other measures such as market efficiency and volatility (as in Corgnet et al. 2015) do not differ significantly across treatments. Results are not reported here for brevity.

significantly higher in Phase 3 of the *LB* treatment compared to that in the *Base* treatment. The availability of information on the leader-boards in the *LB* treatment could be attributed to this phenomenon.

The differences in bubble characteristics indicate that markets where participants are asymmetrically informed (*LB-Cost*) have smaller bubbles than both markets with symmetrically informed participants (*LB*) or uninformed participants (*Base*)[23]. It appears that our experimental design in which uncertainty is highest in the *LB-Cost* treatment is the key driver for these differences. In this treatment, not only participants who purchased the leader-boards were aware that they would have an informational advantage compared to those who did not purchase; those who chose not to purchase the leader-boards also knew that other participants might do so and thus would have more information than they did. In addition, no participants knew how many traders in the market purchased the leader-boards and seemingly had an informational advantage.

It is, however, not possible to accurately quantify this belief or awareness that the participants who did not purchase the leader-board had. Previous studies such as Sutter et al. (2012), predetermine the level of asymmetric information in their experiments by means such as letting half of the participants know the dividend structure while half participants do not. Our design, which allows participants to choose whether to purchase information, not only makes our setting more similar to 'real' financial trading, but also offers interesting insights into how perceived information asymmetry affects trading behavior. To understand the magnitude of the belief/awareness of information asymmetry, we compare the number of quotes, trading volume and deviation of quotes from fundamental values of two groups of participants in the *LB-Cost* treatment[24] (the Online Appendix 6). We find that on average participants who did not purchase the leader-boards have significant smaller trading volumes and their quotes deviated less from fundamental values than participants who purchased the information[25].

Our finding is in line with that of Sutter et al. (2012) who also find that markets with information asymmetries have smaller and shorter bubbles than markets with symmetrically informed traders. Yet our finding differs from their work in an important way. In Sutter et al. (2012) (and in other papers about bubbles in financial markets), information asymmetry refers to knowledge about future dividends which affect assets' fundamental values. In our paper, information asymmetry refers to knowledge about trading behavior of participants in the market. In 'real' financial markets, trading activities may reveal market aggregated information about firm fundamentals and trading behavior of sophisticated traders may be indicative of their skills, i.e. ability to analyze and pick stocks. By design, information about the fundamental value is symmetric in our experiment, i.e. all participants knew about the dividend distribution at the start of the experiment. As such, trading behavior of leaders in our experiments is not related to skills nor indicative of any knowledge about the future prospect of the asset. Our analysis reveals that investor psychological bias, i.e. knowing that other traders may have information regardless of whether such information is related to fundamental value, may have an effect on market efficiency.

Next, we investigate if herd behavior explains differences in bubble characteristics in treatments, controlling for differences in information asymmetry by treatment design. Bikhchandani and Sharma (2000) argue that information-based herd behavior can lead to price bubbles and mispricing, especially when investors make reversed decisions after realizing that they have made wrong decisions by herding (see also Lux 1995). This situation is more likely to happen when investors are experienced or when new information comes out. However, other authors (see e.g. Brunnermeier 2001) show that there are rational models of bubbles and crashes which have nothing to do with herding. Similarly, Avery and Zemsky (1998) show in their model that herd behavior needs not to distort prices but complex information structures can lead to herd behavior and make price bubbles possible.

Table 7 reports the estimation results of *RAD* (in models 1 to 3) and *RD* (in models 4 to 6) on herding. We include three dummy variables to compare the *LB, LB-Finance* and *LB-Cost* treatments with the *Base* treatment. Our variable of interest is *F1_Quotes_Period* which is the total number of F1 herding quotes in the period. We also use *F123_Quotes_Period* which is the total number of all herding quotes in the period as an alternative variable. We run the regression for the sample consisting of 360 periods (15 periods per market, 6 markets per treatment for 4 treatments).

The negative coefficients of *LB-Cost* confirm what could be observed previously. Prices systematically deviated from the fundamental values in the *LB-Cost* treatment compared to the *Base* treatment. Markets with heterogeneously informed traders, even if the available information is unrelated to market fundamentals, are less prone to bubbles than when such information is symmetrically distributed or not available at all. Our results are indicative that the two levels of uncertainty, one relating to fundamental value and the other relating to trading behavior or other participants, may drive our mostly risk-averse traders to act with more caution. The negative coefficients of *LB-Finance* (although only significant at standard levels in models (1) and (2) suggest that price deviations were also smaller in this treatment). Given this treatment is not different from the *LB* or the *Base* treatments in terms of information symmetry, a possible explanation could be that only participants in the *LB-Finance* treatment have financial training compared to participants in the other three treatments. Previous research finds that knowledge, as acquired by experienced traders participating many times in the same type of

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[23] One can argue that the smaller bubbles in *LB-Cost* are caused by the lower wealth level of participants in this treatment. However, we find that the wealth levels of participants in *LB-Cost* are not significantly different compared to that in other treatments (Mann Whitney U-test, $p = 0.773$; $p = 0.375$, respectively) since there are not many participants who pay to buy leader-boards.

[24] We thank an anonymous referee for suggesting this analysis.

[25] This is in line with the results reported in the Online Appendix 5 in which we report that risk averse traders are more cautious in trading by not quoting prices too far from the asset's fundamental value.

Table 7
Herding and bubbles characteristics.

Dep. Var.	*RAD*			*RD*		
	(1)	(2)	(3)	(4)	(5)	(6)
LB	-0.097 (0.505)	-0.071 (0.670)	0.064 (0.694)	0.047 (0.796)	0.128 (0.509)	0.173 (0.383)
LB-Finance	**-0.276 (0.060)**	**-0.255 (0.082)**	-0.179 (0.228)	-0.233 (0.205)	-0.169 (0.327)	-0.158 (0.380)
LB-Cost	**-0.383 (0.009)**	**-0.382 (0.006)**	**-0.375 (0.007)**	**-0.409 (0.026)**	**-0.404 (0.020)**	**-0.402 (0.020)**
F1_Quotes_Period		-0.005 (0.320)			**-0.014 (0.007)**	
F123_Quotes_Period			**-0.014 (0.006)**			**-0.011 (0.077)**
Constant	0.905 (0.000)	0.905 (0.000)	0.905 (0.000)	0.183 (0.158)	0.183 (0.220)	0.183 (0.220)
N	360	360	360	360	360	360
R-sqr.	0.294	0.313	0.410	0.286	0.340	0.371

This table reports the estimation results of bubble characteristics regressed on herding. The dependent variables are *RAD* (in models 1–3) and *RD* (in models 4–6). *F1_Quotes_Period* and *F123_Quotes_Period* are the total numbers of F1 herding quotes and of all herding quotes made by participants in each period. *LB, LB-Finance* and *LB-Cost* are dummy variables indicating the treatment that a period belongs to. *p*-values are reported in the brackets. We report results of GLS random-effects regressions.

market, reduces 18bubbles substantially (Smith et al., 1988; Dufwenberg et al., 2005). Our results show that knowledge acquired from formal education could have similar effects on bubble formation.

Having controlled for the differences in treatments by design, the negative and significant (in three out of four models) coefficients of the herding measures *F1_Quotes_Period* and *F123_Quotes_Period* clearly point to the role that herd behavior plays in reducing bubbles, particularly in reducing overpricing. This challenges the convention that herding may be trigger contagion and market destabilisation (see Brunnermeier 2001). As asset price bubbles represent some underlying confusion about the market environment (Dufwenberg et al., 2005; Kirchler et al., 2012; Sutter et al., 2012) our result suggests that information asymmetry (as in the case of the *LB-Cost* treatment), financial knowledge (as in the case of the *LB-Finance* treatment) and herd behavior could lessen confusion.

3.6. Robustness check and further analysis

We conduct a battery of robustness checks to ensure that our results are not influenced by how herd behavior is measured. First, we count herding quotes as those within leaders' quoted price ± 5% interval. It is possible that participants choose to follow leaders but slightly modify leaders' quotes to make their quotes more competitive. For example, as participants observed that an F1 leader bought an asset at 100 ECUs, they might make an offer to purchase at 101 ECUs in the next period. In the *LB* treatment, 37% of quotes made are within this interval compared to 21% of quotes that were exactly the same as the leaders' quotes. In the *LB-Finance* treatment, it is 25% compared to 15%. As such the results that we report previously may underestimate the true magnitude of herd behavior. We repeat all analyses using the quoted price ± 5% interval. The results (reported in Online Appendix 3) are consistent with our main findings. Second, we use a stricter measure of herd behavior, which counts only the exact herding quotes that were executed. Using this measure, only 9.5% of quotes made in the *LB* treatment, and 4.5% of quotes made in the *LB-Finance* treatment are considered as herding quotes. The results (reported in Online Appendix 4) show similar patterns of herding and similar impacts of herding on bubble formation as our main results.

4. Conclusion

In this paper, we examine herd behavior in an experimental financial market with a novel feature that resembles a social trading platform. We find that when provided with the ranking of traders based on changes in wealth, most participants imitated quotes made by those ranked with the largest increases in wealth, i.e. top leaders. Most remarkably, we find that herd behavior is associated with less asset mispricing. As the leader-boards eliminated information asymmetry about activities of other traders in the market, participants, most of whom were risk-averse, appeared to be more cautious in posting quotes that deviated too far from the fundamental value.

We also contrast the difference in the behavior of participants with financial training and knowledge (students in finance postgraduate degrees) and those without (students in other disciplines). We find that herding tendency was lower among finance participants. When they herded, finance participants chose to follow leaders who had a better trading performance and received higher payoffs. Furthermore, price deviations in the treatment with finance participants were also smaller. Our finding based on the two treatments that differed only in terms of prior financial training and knowledge of participants could shed some light on the validity of using students and professional subjects in experimental studies.

While previous studies attribute the differences in trading behavior of professional investors compared to that of individual investors to multiple factors including experience, training, and career- and compensation-concerns (see e.g. Hirshleifer and Teoh 2003, Alevy et al. 2007, Venezia et al. 2011), no study distinguishes the role, if any, of each factor. By design, our study is able to attribute the differences solely to training and knowledge. Consequently, our work lends further validity to recruiting students in laboratory financial experiments, compared to using practitioners in the real financial market (see e.g. Cipriani and Guarino 2009). By showing that participants with finance training are less likely to herd our results also provide further support for the finding in Dufwenberg et al. (2005) about professional investors are not prone to biased judgements. Another inventive feature of our study is the treatment in which we examine participants' willingness to pay for leader-boards and subsequent price deviations in the market. While not all participants purchased leader-boards, the induced information asymmetry, whereby some participants perceived that others may have more information, resulted in significantly smaller bubbles.

Overall, our findings indicate that herd behavior can be prevalent among traders when there is a mechanism that promotes copying such as those in social trading platforms. More importantly, traders herd even when leaders that they follow do not possess value-related information nor superior trading performance. However, herding and uncertainty about others' behavior may not necessarily associate with more price deviation in the market. [26]

Declarations of Competing Interest

None.

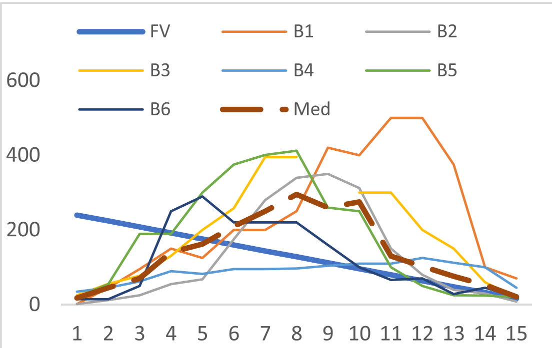
Data availability

Data will be made available on request.

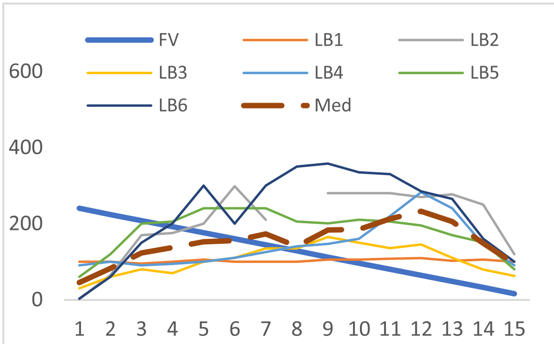
Appendix A: Bubble formation in the treatments

These figures show the bubble formation in each treatment, the *Base*, *LB*, *LB-Finance* and *LB-Cost*.

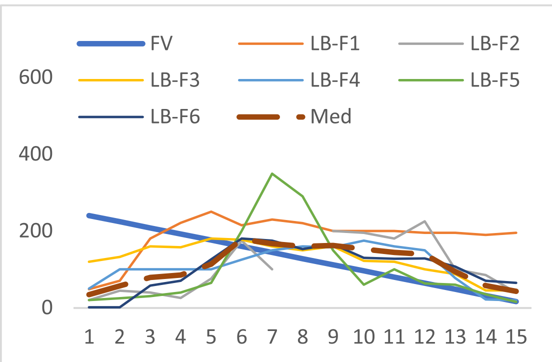
Base treatment



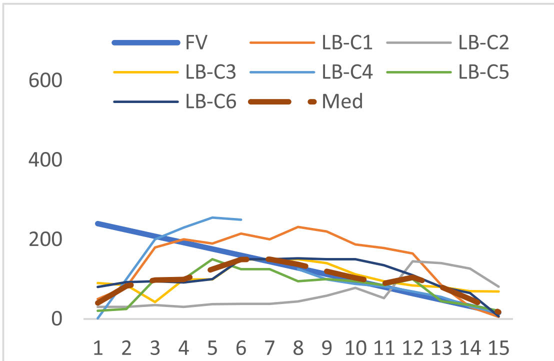
LB treatment



LB-Finance treatment



LB-Cost treatment



B1 to B6; LB1 to LB6; LB-F1 to LB-F6 and LB-C1 to LB-C6 are median prices in each market in the *Base*, *LB*, *LB-Finance* and *LB-Cost* treatments. FV indicates fundamental value and Med indicates the median value of all markets in a treatment.

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