Herd Behaviour in Financial Markets – An Experimental Approach

Thien Kim Nguyen

Supervisors:

Professor Thorsten Chmura

Dr Hang Le

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Introduction

Herd behaviour is one of the major issues in behavioural finance, especially in the context of financial investment. The existence of herd behaviour is extensively confirmed in financial markets where participants are supposed to be intelligent and rational (see, e.g. Anderson and Holt, 1997; Christie and Huang, 1995). This behaviour is also claimed to be one of the factors for price volatility and bubbles in the recent financial crises (see, e.g. Chiang and Zheng, 2010). Despite the potential risks, the literature on this behaviour is still controversial. On the one hand, the validity of the empirical method is uncertain. For example, Cipriani and Guarino (2005) argued that herd behaviour could not be empirically estimated since there is no information on investors' private information. Therefore, insights which information the investors based on to make their own decisions are unknown. Fama (1998) concluded that there is a lack of direct connection between empirical specifications and theoretical frameworks on this behaviour.

Bikhchandani and Sharma (2000) indicate that experiments could be a better approach to examine herd behaviour. Particularly, herding decisions could be tested with a group of homogenous participants; each member could observe the trade of others and the group should not be too large. Through the experimental approach, the experimenters could control the flow of information released to the participants and could identify precisely the situation people make the following decisions. The three experiments we introduce in this thesis, which are asset market, information cascade and Holt and Laury (2002), could deliver all requirements of an appropriate approach to test for the presence of herd behaviour. Also, the consequences of this behaviour are investigated via the experiment. The results taken from this thesis could be applied to financial markets.

The standard experiment used to examine herd behaviour in the literature is information cascade. This experiment allows the researchers to identify precisely which situation participants make decisions based on their private information and which situations they make decisions by simply following others in the markets. In other words, this experiment allows the experimenters to separate between private and public information. However, the problem with this experiment is that it does not include a price mechanism in the design. Participants do not have to pay to make decisions and to choose an asset, which is inappropriate in financial markets where investors pay for their assets. Cipriani and Guarino (2005) indicate that information cascade could not be used to examine herd behaviour in financial markets. They tried to add a price mechanism in the standard design where the price reflects the number of orders for a specific asset. However, they found that herd behaviour disappears in the market with a price mechanism. Instead, participants make decisions based on the offered price. The results in the literature leave us a lot of room to develop another approach since we believe that the disappearance of herd behaviour is due to the inappropriate design of the experiments. We introduce three separate experiments in this thesis and expect that the experiments would produce similar results, which support the presence of herd behaviour. More specifically, we use asset market experiment, information cascade with a price mechanism and Holt and Laury (2002). Asset market experiment is widely used in behavioural finance to replicate financial markets. We could find a number of papers using this experiment to examine different issues in financial markets (see e.g. Noussair, Robin and Ruffieux, 2001; Oechssler, Schmidt and Schnedler, 2011; Sutter, Huber and Kirchler, 2012; Haruvy, Noussair and Powell, 2013; Corgnet et al., 2014; Eckel and Füllbrunn, 2015). Interestingly, this is the first study using this experiment to examine the existence of herd behaviour in financial markets. The experiment not only allows us to replicate financial markets but also is appropriate to measure the consequences of herd behaviour. More specifically, we could test for the correlation between herd behaviour and price bubble formation, volatility and market efficiency using this design. Again, this study makes the first attempt to investigate the consequences of herd behaviour experimentally. Information cascade is considered as the standard experiment to test for herd behaviour. However, we add a price mechanism in this study to the experiment. Participants must pay for the asset they choose. The price mechanism in this study does not reflect the number of orders for a specific asset but reflect the fundamental value of an asset, calculated by Bayes' rule based on the available information supporting the success of that particular asset. We assume that the price in the market follows the efficient market hypothesis. This assumption also helps us to test for the validity of this hypothesis in the experimental market. The purpose of introducing the price mechanism in the standard experiment is to make it more appropriate with the mechanism in financial markets. For the last experiment, we decide to use Hold and Laury (2002). This experiment is easy to conduct and allows us to test for individual risk preferences. In this context, we use this experiment to examine whether participants change their risk preferences after knowing the risk preferences of others. The results from this experiment could confirm the existence of herd behaviour, not only with the investment decisions but also with individual preferences.

We expect the results from these experiments could support the existence of herd behaviour and its characteristics in financial markets. We also test for the effects of individual traits and personalities on herding decisions. We believe that results from this study are beneficial for both researchers and practitioners. We are aware of one possible issue with the experimental approach is that we could not control for many variables at the same time since each treatment is designed to test for one parameter. However, we include essential variables in the experiments by developing different treatments for each experiment.

The first essay is entitled "Herding decision: is it good for the market? An examination of herd behaviour and financial literacy using asset market experiment". In this essay, we use the asset market experiment, which is introduced firstly by Smith, Suchanek and Williams (1988) and widely used in experimental finance, to investigate the presence and consequences of herding. The advantage of this experiment is that it captures the financial markets adequately. Therefore, although the existence of herding behaviour in financial markets is already examined experimentally, the results from this paper are more applicable in the financial markets. Also, the impacts of herding decisions on bubble formation, volatility and efficiency are examined. We record the performance and decisions taken by the leaders, who are three participants earning the highest payoff, in each period. This information is released in the following period to the markets with and without a price. The results show that most participants do not pay to get additional information. However, since they do not pay for the information, they believe that there is information asymmetry in the market, which leads to significant lower bubbles. When the participants get information for free, they follow the leaders substantially, especially following the first-ranked leaders. Herd behaviour reduces bubble and price volatility while improving market efficiency. The individual differences express significant impacts on herding decisions. We find that risk-loving, math skills, self-monitoring ability and financial literacy are negatively correlated with herding decisions.

The second essay is entitled "Herd behaviour in financial markets: an experimental approach with information cascade experiment". Different from the first essay, we use the standard experiment to examine herd behaviour, which is information cascade (Anderson and Holt, 1997). This experiment is claimed to be not appropriate to apply in financial markets since there is no price mechanism in the design. Particularly, participants choose between two assets, which are Asset A and Asset B, based on their private information and public information. In the standard design, participants do not pay anything to get the asset, which is controversy with financial markets where people pay for assets. We introduce a price mechanism, which captures the available information in the markets to the standard information cascade experiment. By adding the price mechanism, the results from this setting are applicable in the markets, which is the main contribution of this essay. Also, the price-mechanism design helps us to test the "famous" efficient market hypothesis. The results show that participants herd in their decisions; however, the magnitude of herding is decreasing. Interestingly, many participants purchase an asset which they do not believe in the successful potentials of the asset, mainly to get a lower price. This purchasing behaviour strictly violates the validity of the efficient market hypothesis. Again, individual differences express significant effects on decision making. Specifically, the following magnitude of Western participants is significantly thin. Male make more against-belief decisions while the opposite result is found with overconfident participants.

The third essay is entitled "Risk-preference shifting – Do decisions of others matter?". We start with a different approach to measure herding in this essay. Specifically, we apply the Holt and Laury, 2002 experiment to examine the risk preferences of participants. After that, we inform the risk preferences of other participants, which are significantly prone to risk-loving and risk-averse. The results are interesting, which show that participants update their beliefs and shift their risk preferences after knowing the risk preferences of their peers. Individual differences, again, show significant impacts on decision making. The results show that overconfidence, risk preference, major of study and income significantly determine herding decisions.

In the fourth essay, which is entitled "Big five personality traits and financial decision making", we would like to measure the big five personality traits of participants and correlate with herding decisions. The measure of big five is conducted in the previous experiments. We find that big five express significant impacts on herding decisions. For instance, extravert and open-to-experience participants are less likely to make herding decisions, while the open-to-experience participants are willing to make irrational decisions to earn higher payoffs. The neurotic people pay a relatively high amount of money to get additional information; however, they do not use the data later. Agreeable people are less likely to purchase an asset against their beliefs while the extravert ones do. The big five personality traits are found to have significant correlations with the self-monitoring ability, risk preferences, trust and life satisfaction.

This thesis contributes to the literature on different strands. Firstly, this is the first study to use the asset market experiment, which could replicate the financial markets, to measure herd behaviour. The experiment also allows us to measure price bubble formation, bubble magnitude, volatility and market efficiency, which are potentially considered as the consequences of herd behaviour. The design of the asset market experiment would help to overcome the current limitations of the applied experiments to examine herding decisions in financial markets. By allowing participants to trade simultaneously with each other or keep the asset for dividend, the experiment could partly replicate what is happening in the financial markets. Also, we record the leader-board and provide to the market to measure whether participants take the decisions of the leaders into account before making decisions or not. This design is phenomenal in the context of testing herding decisions experimentally.

Secondly, the price mechanism adding to the standard experiment used to measure herding is unique. One of the limitations of the information cascade experiment is a lack of a price mechanism; therefore, the results could not be applied to financial markets. Cipriani and Guarino (2005) constructed a price mechanism which reflects the number of orders in the markets to this experiment and finds no support for herd behaviour. We believe that the price should reflect the fundamental value of the asset. Also, participants may herd in their beliefs but make a decision against their belief to earn abnormal returns. In other words, they are willing to take risks by investing in an asset that they do not believe it would be successful. In our setup, we allow the price mechanism to reflect the success probability of an asset, based on the available information (Bayes' rule). Our design is backed by the efficient market hypothesis. Also, we separate participants' beliefs and their decisions to make sure whether they make decisions against their beliefs or not. We believe that this is the first experiment to add the price mechanism according to the efficient market hypothesis to the information cascade experiment and separate between participants beliefs and their decisions. By doing this, we make the results to be more applicable in financial markets. Also, we are able to indicate whether participants herd in their beliefs or not.

Thirdly, this study is the first to use Holt and Laury (2002) experiment to examine risk-shifting decisions, which is considered as a form of herd behaviour. Individual preferences should not change regardless of the preferences of their peers. However, with the third design, we would like to prove that participants would change their risk preferences after being informed about the risk preferences of their peers. Finally, this study is among the rare papers to examine the impacts of individual differences, including overconfidence, self-monitoring and big five personality traits, on financial decisions and herd behaviour.

From the essays, we could come to a firm conclusion on the presence of herd behaviour in financial markets. The characteristics and personalities of participants express a significant impact on herding decision. The results from this research are not only beneficial for the practitioners, including the investors and financial institutions but also act as a useful reference for the market policymakers. It is hard to remove herding out of the markets; the best practice we could do is understanding the behaviour and manage toward a more efficient market.

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- JFK

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ESSAY 1: HERDING DECISION: IS IT GOOD FOR THE MARKET? AN EXAMINATION OF HERD BEHAVIOUR AND FINANCIAL LITERACY USING ASSET MARKET EXPERIMENT

Abstract: *We examine the existence, features and consequences of herd behaviour due to reputational externality in an experimental financial market. Information on performance-based ranking and historical trading (leaderboard) were provided with and without a cost. When the leaderboard is released without a cost, participants follow the decisions made by first-ranked leaders. Financial literate students studying finance herd at a significantly smaller magnitude compared to non-financial literate students from other disciplines. Interestingly, herd behaviour reduces the size of bubbles and price volatility while enhancing market efficiency. In the costly leaderboard treatment, most participants are not willing to pay for additional information. However, since participants are aware of asymmetric information, assets are traded at a remarkably lower price, which leads to significantly smaller bubbles. In other words, the belief in asymmetric information reduces the magnitude of price bubbles. Individual differences affect earnings and herding decisions. The implications for financial markets are also discussed.*

JEL Classification: C91, D81, G41

Keywords: Asset market, herd behaviour, information asymmetry, bubble formation.

1.1. Introduction

Herd behaviour is one of the major bias in behavioural finance, which is considered as a source of exacerbating volatility, creating bubbles and crashes and increasing the fragility of the financial system (see, e.g. Morris and Shin, 1999; Persaud, 2000; Chiang and Zheng, 2010). One example is the herd in the real estate market in the U.S., which is claimed as one of the main causes of the financial crisis in 2007-2009. Another example is the social trading communities, which are advertised as an achievement of Fintech and promised to change the way people invest in financial markets. ETORO is the largest community, with nine million users in 2018 (Phillip Securities Research, 2018). Users could include stocks, indices, commodities, currencies, ETFs and even cryptocurrencies in their portfolios without any information and financial literacy. ETORO develops the CopyTraderTM technology, which records the top leaders measured by their returns, and the other users invest by merely copying these "leaders". ETORO is not the only platform that introduces this copying mechanism. This mechanism is one of the leading competitive factors of most social trading communities, such as Zulutrade, Collective2, Wikifolio and many more[1]. Çelen and Kariv (2004) define herd behaviour as a situation when people make identical decisions. In the case of social trading communities, it is unknown whether it is efficient to the financial markets when maintaining a platform in which herd behaviour is a dominant investing strategy and whether it is beneficial to the individual investors by applying this strategy. The questions become critical when the market of cryptocurrencies, included in the portfolio, is found to be correlated with high volatility and bubbles (Cheah and Fry, 2015 and Urquhart, 2016).

The presence and consequences of herd behaviour in financial markets are difficult to examine using empirical data (Cipriani and Guarino, 2005) since there is no data on the private information which is available to the traders. Therefore, we cannot know whether traders use their information or imitate others. Also, it is not easy to

[1] Zulutrade claims to have 1 million users (Phillip Securities Research, 2018); Collective2 has 90,000 registered users until 2018 (Collective2 website); Wikifolio has more than 30,000 users registered between 2012 to 2014 (Wikifolio website). Other similar platforms are Sprinklebit, StockTwits, Estimize, Covestor, Quantopian, Avondo. In Germany alone, there are 14 social trading platforms with the market size in 2015 is EUR190m (Dorfleitner et al., 2017). The volume significantly increases in 2019; however, there is very little data.

distinguish between intentional herding and spurious herding in practice (Mobarek, Mollah and Keasey, 2014). Spurious herding is the situation participants make identical decisions in responding to a policy change or market shock but not necessarily follow others. Bikhchandani and Sharma (2000) show that the underlying fundamentals in financial markets are difficult to control, therefore, lack of a direct link between empirical specifications used to test for herding and theoretical discussion of this behaviour (Fama, 1998).

Experiments allow to shed light on the influence of information in different treatments and allow to generalise. With a lab experiment, we could control the information informed to the participants and measure whether they follow their private information or follow the crowds. Anderson and Holt (1997) construct an experiment, following the models of Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992), to examine herd behaviour due to information externality (information cascade[2]). Although this experiment confirms the presence of herd behaviour and is developed to captures herding characteristics (see, e.g. Drehmann, Oechssler and Roider, 2007; Hung and Plott, 2001; Kübler and Weizsäcker, 2004; Fahr and Irlenbusch, 2011), Cipriani and Guarino (2005) argue that this experiment cannot be used to examine herd behaviour in financial markets since there is a lack of a price mechanism in the design. The authors develop another experiment following the model of Glosten and Milgrom (1985), where participants pay for their decisions and conclude that herd behaviour disappears in the market. Avery and Zemsky (1998) indicate that herd behaviour does not exist in a market where the price is flexible. In such an environment, participants make decisions based on the offering prices and do not consider the decisions of others.

Despite the fact that herd behaviour is a significant issue in financial markets, the results are still controversial. This paper adds to the herding literature by making three contributions. Firstly, this is the first paper examines herd behaviour in financial markets using the asset market experiment, which replicates the financial markets. We also include a leaderboard in the design to examine whether participants follow the best performers in the markets. Secondly, the design of the experiment is the pioneer to experimentally examine the consequences of herd

[2] Information cascade is the situation participants disregard their private information to follow the market.

behaviour, including price bubbles, volatility and market efficiency. Finally, the impacts of individual differences on herding are investigated, especially the correlation between financial literacy and herding decisions.

The asset market experiment is developed by Smith, Suchanek and Williams (1988) (hereafter SSW) and popularly used to examine decision-making in financial markets. The experiment is designed based on the mechanism of the double auction and is considered as one of the most appropriate experiments to replicate financial markets and measure bubbles. It includes a certain number of periods, in which participants trade their assets using a given amount of money. By holding assets, participants may earn dividend after each period. The amount of dividend may be constant or fluctuate with a certain probability. The dividend structure determines the fundamental values of assets. The differences between market trading prices and fundamental values are considered as mispricing or bubbles.

Bikhchandani and Sharma (2000) show that herding can be tested with a group of homogenous participants, who trade actively and act similarly. Each member can observe the trades of other members, and the group should not be too large. In this paper, these requirements are fulfilled by using the experimental approach. In particular, the asset market experiment is employed to examine the presence and consequences of herd behaviour in financial markets due to compensational and reputational externalities. The design of this experiment replicates the mechanism in financial markets and allows to control for the influence of information. A leaderboard is recorded at the end of each period and informed to the markets at the beginning of the next period, with and without a cost (*costly-information* and *leaderboard* treatment, respectively). In the *leaderboard* treatment, we could measure whether participants follow the prices offered by the leaders in the market. Given the symmetric information among participants, we could identify herding decisions due to reputational effect. Also, we could recognize whether participants pay a relatively high cost (approximately 7% of their initial cash allowance) to buy the leaderboard and whether they follow the asymmetric information (*costly-information* treatment). We strongly believe that using this experiment to examine herd behaviour in financial markets, the results are more in line with what happening in the markets and are more applicable.

The beauty of the asset market experiment is that it allows the experimenters to measure price bubbles, which are the positive differences between the trading prices and fundamental values. As a result, this paper is the pioneer to experimentally examine the consequences of herding decisions, including bubble formation, price volatility and market efficiency.

Finally, we measure individual differences by introducing a questionnaire at the end of the experiment. We want to test whether personalities affect herding decisions. The personalities included in the questionnaire are overconfidence, risk preference, maths skill, self-monitoring ability and other demographic characteristics. More importantly, we conduct the *leaderboard* treatment with finance students studying master and PhD in finance and investment and students from mixed disciplines at the University of Nottingham to find out the impacts of financial literacy on herd behaviour. The social trading communities mentioned at the beginning allows people without any financial knowledge to invest in sophisticated financial products such as ETFs or cryptocurrencies. We believe that finance students are a perfect proxy for financial literacy.

The paper is followed by a literature review (section 2), experimental design (section 3), results and discussions (section 4) and a conclusion (section 5).

1.2. Related Literature

The model of herd behaviour constructed independently by Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) indicates that information cascade is an explanation for herd behaviour. More specifically, individuals tend following others disregarding their private information in the situation of asymmetric information. Avery and Zemsky (1998) show that herd behaviour does not exist in the presence of price uncertainty. In the market with price mechanism, individuals adjust their behaviours to capture the price fluctuation and do not follow others. The authors show that herd behaviour may occur in a market with more than one uncertainty dimension apart from price uncertainty. Bikhchandani and Sharma (2000) add to this point by showing certain circumstances that herd behaviour can occur in financial markets, which are information asymmetry, compensation and reputation externalities. For example, investment decisions may be affected by the belief that others know something about the return on the investment and their decisions reveal this information. Similarly, a financial agent, investing on behalf of the others, may imitate if his reputation and compensation are credited by comparing his performance to a benchmark. More specifically, the financial agent will mimic the benchmark to protect his reputation and compensation scheme. In the ETORO example, the investors who choose to follow the investment strategy of the "leaders" believe in the competences of the "leaders", and herding decisions are mainly motivated by monetary incentives, which could be considered as compensation and reputation externalities.

This research contributes to several strands of the current literature on examining herd behaviour in financial markets. Firstly, the examination of herd behaviour in financial markets is more appropriate by applying the experiment which can replicate the mechanism of the markets. Secondly, the consequences of herding can be investigated, especially the controversial correlation between herding and price bubbles.

Herd behaviour is empirically examined in financial market through two main types of data, which are data on decisions of portfolio investors (Lakonishok, Shleifer and Vishny, 1992; Welch, 2000; Walter and Weber, 2006) and data on aggregate market (Christie and Huang, 1995; Chang, Cheng and Khorana, 2000; Chiang and Zheng, 2010; Wang, 2008; Mobarek, Mollah and Keasey, 2014).

For the individual- and fund-level data, Lakonishok, Shleifer and Vishny (1992) indicate that money managers herd relatively little in large stocks in comparison with small stocks, but the magnitude of herding is far from dramatic. Welch (2000) examine the herd behaviour of brokers in the U.S. market and conclude that the buy or sell recommendations of a security analyst has a strong positive impact on the recommendation of the next two analysts. Walter and Weber (2006) also confirm the presence of herd behaviour among mutual fund managers in Germany.

For the aggregate market data, Christie and Huang (1995) fail to detect herd behaviour in daily and monthly equity returns in both positive and negative movements of average prices. Similarly, Chang, Cheng and Khorana (2000) cannot find herd behaviour in the U.S. and Hong Kong markets while Chiang and Zheng (2010) confirm the results for the U.S. and Latin American markets. Interstingly, Chiang and Zheng (2010) examine the behaviour in international markets and show that most investors follow the U.S. market. Mobarek, Mollah and Keasey (2014) use liquid constituent indices in European markets in 2001-2012 and conclude that while herd behaviour is insignificant in the whole period, it is found to be significant during the periods of crises and highly asymmetric information.

Although the empirical approach is widely applied to examine herd behaviour, the main issue with this method is data. Cipriani and Guarino (2005) argue that herd behaviour is hard to examine empirically since there is no data on private information. People may make identical decisions based on their private information or in responding to a piece of news, a policy change or a market shock (spurious herding). Mobarek, Mollah and Keasey (2014) state that it is not easy to distinguish between intentional herding and spurious herding in practice. These issues explain the controversial results on the presence of herd behaviour.

Recently, the evolution of the experimental approach is considered as a solution for the limitations of the empirical method in examining behavioural finance. Anderson and Holt (1997) are the pioneers who develop an experiment to study herd behaviour, which is information cascade. The experiment is designed based on the herding model developed by Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992). More specifically, participants make decisions to choose between two Urn, A and B. Before making the decision; they can access the decisions of other participants and the private information, which is available to them only. Anderson and Holt (1997) show that in the situation herd behaviour exists when participants find it is optimal to follow the market regardless of their private information. Many studies follow this approach with modifications to examine different aspects of herding decisions[3].

Although this experiment is widely applied to examine herd behaviour, Avery and Zemsky (1998) argue that the concept of information cascade cannot be applied in the financial markets because there is a lack of a price mechanism. More specifically,

[3] For example, Alevy, Haigh and List (2007) use the experiment with students and financial professionals in gain and loss domains. The results show that market professionals are better at recognizing the quality of signals and are not affected by the domain of earnings (gain and loss). Nöth and Weber (2002) add qualities of information, including strong and weak features to each signal and find that participants make decisions deviating Bayesian rule. The suggested explanation for this deviation is that the participants are too overconfident and decide to follow their own information irrationally. Ziegelmeyer et al. (2010) make Urn design with low informed and high informed participants and stated that cascades are not fragile since informed participants decide to follow despite their advantage information. Also, other features of herding are examined by employing this format, including payoff externalities and reputation (Drehmann, Oechssler and Roider, 2007); majority rule of group effect (Hung and Plott, 2001); depth of reasoning (Kübler and Weizsäcker, 2004); group size and group effect (Fahr and Irlenbusch, 2011).

whenever there is a price in the market, people make decisions based on the offered price and do not follow others. Cipriani and Guarino (2005) confirm this point by examining herd behaviour in a laboratory financial market. They allow their participants to have private information on the fundamental value of an asset and trade this asset with a market maker in sequence. The market maker, in turn, updates the price according to the trading history. They find that herd behaviour disappears since the participants make trading decisions based on their informed price only. Similarly, Drehmann, Oechssler and Roider (2007) construct a price mechanism, which captures the number of offers for a particular asset in the market. They apply the concept of information cascade experiment with a price mechanism to replicate the financial markets. By conducting an internet experiment, they conclude that the price mechanism prevents herding. These results have challenged the presence of herd behaviour in financial markets.

Avery and Zemsky (1998) state that price is only one uncertainty in the market. If the market has other uncertainties, herd behaviour may occur. Scharfstein and Stein (1990) add to this point by introducing the role of reputation on herd behaviour among managers. In particular, those managers may mimic the decisions of others to increase their reputations. If the decision is successful, they would be regarded as smart, but if the decision is unsuccessful, they could reduce the "blame" by sharing with others. Brandouy, Barneto and Leger (2003) use a simulated stock market to examine the impact of asymmetric information and communication on herding. They conclude that other factors, apart from informational noise, can be the determinants of herd behaviour, but further research should be conducted.

In this paper, we use the asset market experiment to examine herding. This experiment is considered as one of the most appropriate designs which replicate the financial markets more appropriately. The presence of herding in this context is motivated by reputational and compensational externalities, rather than information uncertainty.

Asset market experiment is popularly used to examine decision-making in financial markets. The fundamental value is decreasing after every period and becomes zero at the end of the last period. This design is the standard and is applied in most research using asset market experiment (see, e.g. Sutter, Huber and Kirchler, 2012; Haruvy, Noussair and Powell, 2013; Corgnet et al., 2014). Another design, which is pioneered by Noussair, Robin and Ruffieux (2001), sets the fundamental value to be constant. This format allows the authors to measure the determinant of bubbles. Additionally, Oechssler, Schmidt and Schnedler (2011) stated that declining fundamental values is atypical for real financial markets. Other research combines the declining and constant underlying structure such as Kirchler, Huber and Stöckl (2012) conclude that the confusion on fundamental values create mispricing. Similarly, Stöckl, Huber and Kirchler (2015) which confirm that the efficient pricing is observed in markets with constant fundamental values while overvaluation is found in markets with decreasing fundamental values. Apart from the two previous approaches, some research allows fundamental value fluctuates differently. For example, Kirchler (2009) and Huber, Angerer and Kirchler (2011) applied stochastic fundamental values while Lin and Rassenti (2012) used fluctuated fundamental values. The primary motivation for those formats is that the authors try to replicate the Bearish, Neutral and Bullish markets. In this research, we keep the original design of SSW (1998) by allowing the fundamental value to be declining. We believe that with the available information, participants can infer the value of the offered assets. This design is more appropriate to measure bubbles, which is correlated with the magnitude of herding.

1.3. Experimental design

Although there are extensive literature using asset market to measure different issues in behavioural finance such as irrationality and beliefs (Ackert, Kluger and Qi, 2012), gender difference (Eckel and Füllbrunn, 2015), traders' expectation (Haruvy, Lahav and Noussair, 2007) and team decision making (Cheung and Palan, 2012), no study uses this experiment for examining herd behaviour. This study is the first attempt to apply this experiment to investigate the existence of herd behaviour in the financial markets and its consequences.

Three independent treatments were conducted, which are *base*, *leaderboard* and *costly-information*.

Treatment 1: BASE

Treatment 1 follows the third design, class 1 of SSW, which is considered as the base case. Nine participants play the asset market for 15 periods. A period lasts for 120 seconds. Every participant is endowed with a certain amount of cash and assets at the beginning. In SSW, three classes of the endowment are introduced to replicate different market sizes. In this treatment, we adopt the first class, in which every participant is endowed with 4 assets and 280 ECUs. Participants receive dividend by holding the assets after each period. The dividend structure is (0, 8, 16, 40) in each period with the probability of ¼, which makes the expected dividend return in each period is 16, and the intrinsic value of each asset is 240 (16x15). According to Kirchler, Huber and Stöckl (2012), the cash to asset ratio (C/A) should not be too high; otherwise, the market may become overvalued. They revealed that the best performed C/A ratio is approximately 1/3. The endowment selected in this treatment is in line with this result. This design also adopts the concept of the declining fundamental values of SSW without buyout policy at the end of the last period. In other words, the asset's value is zero at the end of period 15. Short-selling and borrowing are not allowed in this set-up. In terms of information, participants know the probabilistic structure of dividend and total trading periods but do not know the actual dividend payment at the end of each period. During the treatment, participants will make decisions to buy and sell the assets by putting bid-ask prices. The *Wealth* of participants at the end of each period is the total money they have plus the fundamental value of total assets they own, which is calculated by the following formula:

Wealth = *Money* + Number of Asset * 16 * (15 - *Period*)

The *Profit* is calculated by taking the differences between participants' wealth in the current period and the previous period.

Profit = *Wealth* in the current period – *Wealth* in the previous period

Treatment 2: LEADERBOARD

In this treatment, we design a leaderboard, which includes participants' performance-based ranking and historical trading. Participants receive the information freely at the end of each period. Through the leaderboard, participants know which participant in their group made the highest profit in the previous period and this participant's trading behaviour. We expect participants to take this information into account and follow the top-ranked leaders. We consider the first three leaders in the market as the top-ranked leaders, including the first-ranked, second-ranked and third-ranked leaders. Bikhchandani and Sharma (2000) state that herd behaviour may exist due to reputational externality. Top-ranked leaders are considered as the ones who have the highest reputation; therefore, participants are expected to follow their decisions. The level of herding is correlated with the magnitude of price bubbles since herd behaviour is suggested as the root of price bubbles and crashes (Lux, 1995).

The hypothesis tested using this treatment include:

H1: Herding occurs in asset market experiment due to reputational effect.

H2: Herding increases bubble magnitude.

TREATMENT 3: COSTLY-INFORMATION

In this treatment, the leaderboard is not freely delivered to the participants. Instead, if participants are interested in this information, they can buy the leaderboard at the end of each period for 20 ECU. This price is relatively high compared to the amount of cash in their endowment (7%)[4]. We expect participants only decide to buy when they think this information is significantly important to them. We also expect that they follow the top leaders when they get the information from the leaderboard. This design creates an informational-asymmetric market. More specifically, if a participant does not pay for the leaderboard, she believes that other members in the market may have more information. The impact of information asymmetry has been already examined in the literature using asset market experiment. Sutter, Huber and Kirchler (2012) investigate the relationship between bubbles and information. They allow a certain number of participants in the market to know about the future dividend while others do not have this information. Markets with asymmetrically informed participants have significantly smaller bubbles compared to the symmetric ones. This issue is revisited in this experiment.

The following hypotheses would be tested using this treatment:

H3: Participants are interested in the leaderboard and pay a relatively high amount of money to buy this information.

H4: Asymmetric information decreases bubble magnitude.

The three treatments allow the experimenters to examine the existence of herding, the consequences of herding in terms of earnings, bubble formation and the impact of informational asymmetry. At the end of each treatment, participants are asked to complete a questionnaire which measures participants' personality traits including

[4] The full-service brokers normally charge 1% to 1.5% of total assets managed for a client per annum (Moskowitz, 2019).

overconfidence, maths skill, self-controlling ability and demographic information. Additionally, we conduct the Holt and Laury (2002) experiment to measure the individual risk preference. These measures are expected to correlate with herding decisions. According to Daniel, Hirshleifer and Subrahmanyam (1997), overconfident investors are the ones who are unrealistically optimistic about their evaluation ability. There are three types of overconfidence, which are miscalibration, unrealistically positive self-evaluations and the illusion of control.

This study uses the measure of Biais et al. (2005) for miscalibration. More specifically, participants are asked to give their responses to 10 questions, which they are 90% confident that the result is allocated in a certain range. If the participants are rational, they should provide a wide range for the answers in response to the questions they do not know so that the answers fit in the correct interval. Overconfident participants provide a narrower range, which does not include the correct answer. The second measure for overconfidence in this study is unrealistically positive self-evaluations (or we call better-than-average in this context). In particular, we ask participants to evaluate their performance compared to others in the asset market. They can evaluate themselves in top 5%, top 10%, top 20%, middle 50%, lower 30%, lower 20% and lower 10%. Overconfident participants are the ones who rank themselves higher than their actual performance. We expect overconfident participants follow less in the *leaderboard* treatment and do not buy the leaderboard in the *costly-information* treatment. Corgnet et al. (2014) indicate that participants with low cognitive ability earn less and buy more when the price is above the fundamental price while Biais et al. (2005) indicate that self-monitoring ability increases trading performance. In this paper, we measure maths skill (Eckel and Füllbrunn, 2015) and self-monitoring ability (Biais et al., 2005) and correlate with earnings as well as herding. We expect participants who are better in maths and self-monitoring earn more and follow others less. In contrast, we expect risk-averse participants, which is measured by Holt and Laury (2002) experiment, earn less and follow others more.

H5: Individual differences affect herding decisions

We run 6 independent markets for each treatment, which results in 54 participants for each treatment and 162 participants in total. The participants are recruited via ORSEE (Greiner, 2015) and are students from different disciplines studying at The

University of Nottingham. Additionally, we conduct the *leaderboard* treatment with another 54 students who study master and PhD in Finance at the University of Nottingham. Market professionals are believed to make different decisions compared to general students. For example, Alevy, Haigh and List (2007) indicate that market professionals could distinguish good and bad signal; therefore, they make better decisions. Similarly, Nikiforow (2010) shows that training on behavioural finance could help to reduce conformity while Dufwenberg, Lindqvist and Moore (2005) and Fama (1998) believe that professional stock investors are not prone to biased judgements. In this research, we consider finance students as market professionals. These students are Master students in Finance and Investment, which is a prestigious finance programme in the U.K. and PhD students in finance. We believe that these students are a proper proxy for market professionals. The hypothesis in this context is:

> *H6: Market professionals perform better and herd at a significantly lower magnitude.*

The experiment is designed using z-tree (Fischbacher, 2007) and conducted at The Centre for Research in the Behavioural Sciences (CRIBS), Jubilee Campus, University of Nottingham.

1.4. Results and Discussions

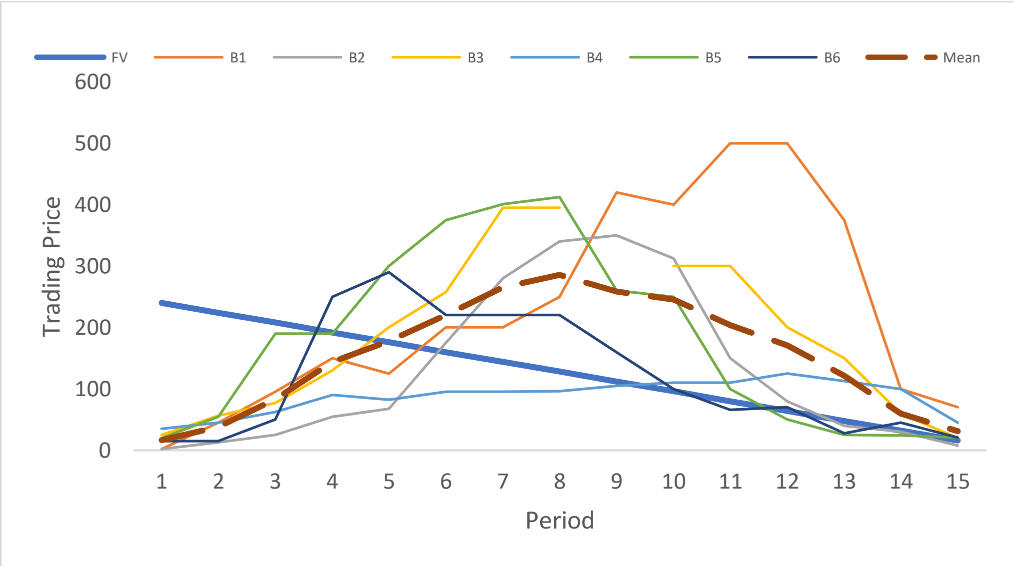
1.4.1. Bubble formation

Bubbles are measured in the asset market experiment by estimating the differences between trading prices and fundamental values. Bubbles are formed in most treatments at a certain point, which is relatively high in the *base* treatment and relatively low in the *costly-information* treatment, shown in Figure 1.1.

Figure 1. 1 - Bubble formation in the three treatments

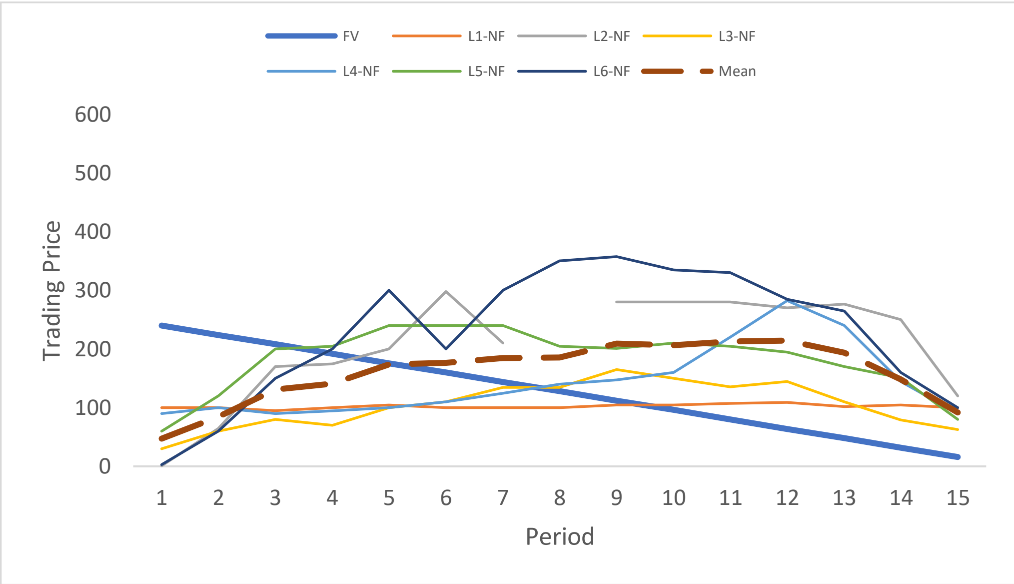
This figure expresses the price level in the *base*, *leaderboard* and *costly-information* treatments. In every treatment, the figure shows the median executed prices in 6 single markets and the mean value of the six markets.

(A) The *base* treatment



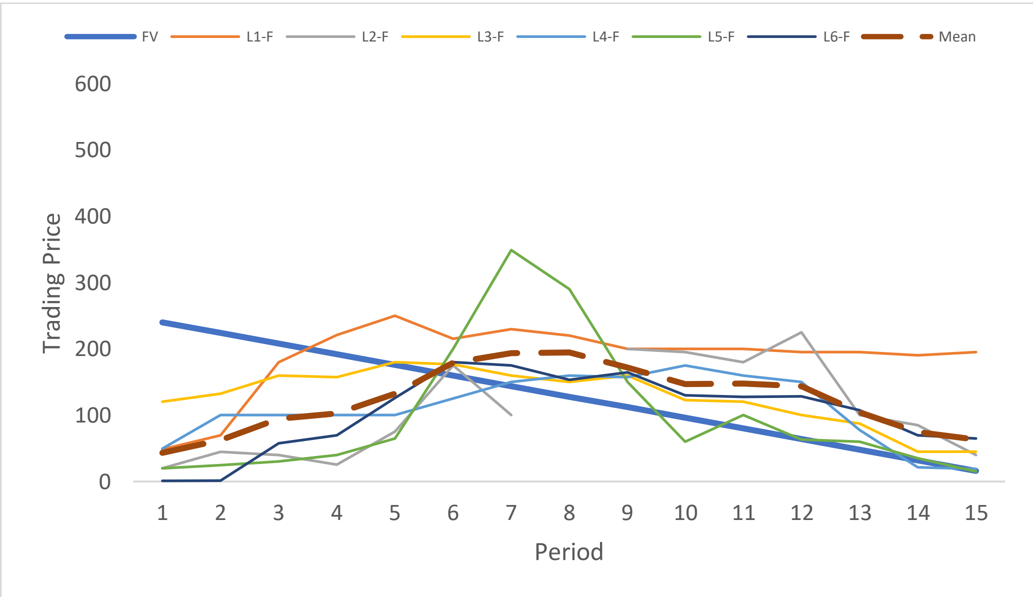
B1-B6 are the median prices in individual markets in the *base* treatment. FV indicates fundamental value and Mean indicates the average value of all individual markets.

(B) The *leaderboard* treatment



L1-NF-L6-NF are the median prices in individual markets in the *leaderboard* treatment with non-finance students. FV indicates fundamental value and Mean indicates the average value of all individual markets.

(C) The *costly-information* treatment

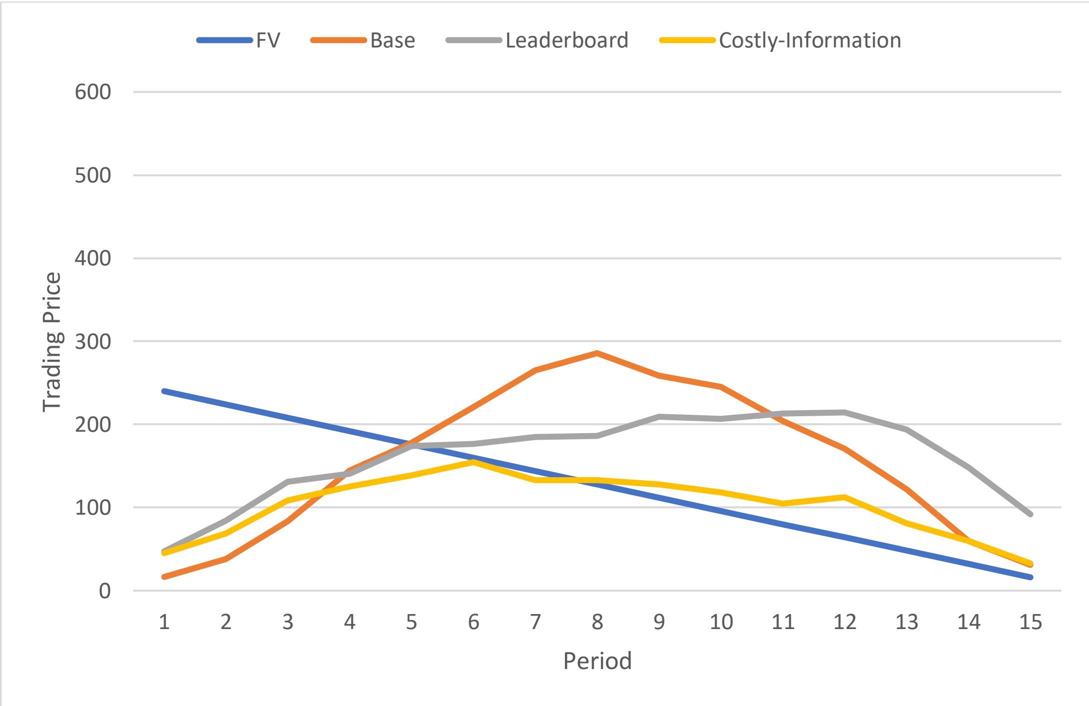


CI1-CI6 are the median prices in individual markets in *costly-information* treatment. FV indicates fundamental value and Mean indicates the average value of all individual markets.

Bubbles start from period 5 in the *base* and *leaderboard* treatments and period 8 in the *costly-information* treatment, shown in Figure 1.2. While bubbles reach a peak level at period 8 in the base case, period 12 is the peak point of bubbles in the *leaderboard* and *costly-information*. However, the magnitude of bubbles is significantly small in the case historical information is costly.

Figure 1. 2 - Bubbles in the base, leaderboard and costly-information treatment

This figure compares the price level in the three treatments



To estimate the magnitude of bubbles, we adopt the measures introduced by Stöckl, Huber, and Kirchler (2010), which are relative absolute deviation (*RAD*) and relative deviation (*RD*). The authors indicate that *RAD* and *RD* are the most appropriate measures for mispricing in the asset market experiment since these measures correlate the fundamental value and price and are comparable across different designs. More specifically, *RAD* shows the differential value between the average price and the average fundamental value, which perfectly capture mispricing while *RD* indicates whether the average prices are overvalued or undervalued.

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

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

Where N is the number of periods, $\overline{P_p}$ is the mean price of period p, FV_p is the fundamental price of period p and $\overline{FV}$ is the mean fundamental price.

In addition to *RAD* and *RD*, we use other measures of bubbles including amplitude, average bias, total dispersion, positive (negative) deviation, boom (burst) duration and turnover (the description can be found in Appendix 1.1).

Bubble measures in the three treatments are shown in Table 1.1. The results of *RAD* indicate that prices in the three treatments are mispricing. In particular, the level of mispricing in the *base* treatment and *leaderboard* treatment is 0.9 and 0.81, respectively, which is significantly higher than the mispricing in the *costly-information* treatment (0.52). Similarly, prices in the *base* and *leaderboard* are overvalued (*RD* = 0.18 and *RD* = 0.23, respectively) while prices in the *costly-information* treatment are undervalued (*RD* = -0.23). In other words, the bubble magnitude is significantly smaller in the case of *costly-information* compared to the *base* and the *leaderboard* treatment (Figure 1.2). The possible explanation in this context is asymmetric information. More specifically, the information in the *base* treatment and *leaderboard* treatment is symmetric, which means every participant has the same information. However, in the *costly-information*, participants are asked to pay for the information on ranking and historical trades. As a result, a participant who does not pay to get extra information may think others have more information. This thought makes them hesitate to offer a higher price, which causes price undervaluation in the market. This result is in line with the finding of Sutter, Huber and Kirchler (2012) about the impact of information asymmetry on bubble magnitude. In their setup, there is a group of informed investors and another group of uninformed investors who know and does not know the structure of future dividends. Interestingly, we find that information asymmetry is just a belief in our experiment. The frequency participants pay for the leaderboard is significantly lower (less than 8%), shown in Figure 1.3, which means the information is symmetric in most periods. The wealth of participants in the *base* treatment and *costly-information* treatment is not significantly different (p = 0.773, Spearman's rank correlation), indicating that participants have an equal amount of money to invest in assets. This result adds to the literature of information asymmetry and bubble formation. The belief of asymmetric information could reduce the magnitude of bubbles.

Table 1. 1 – Magnitude of bubbles in the three treatments

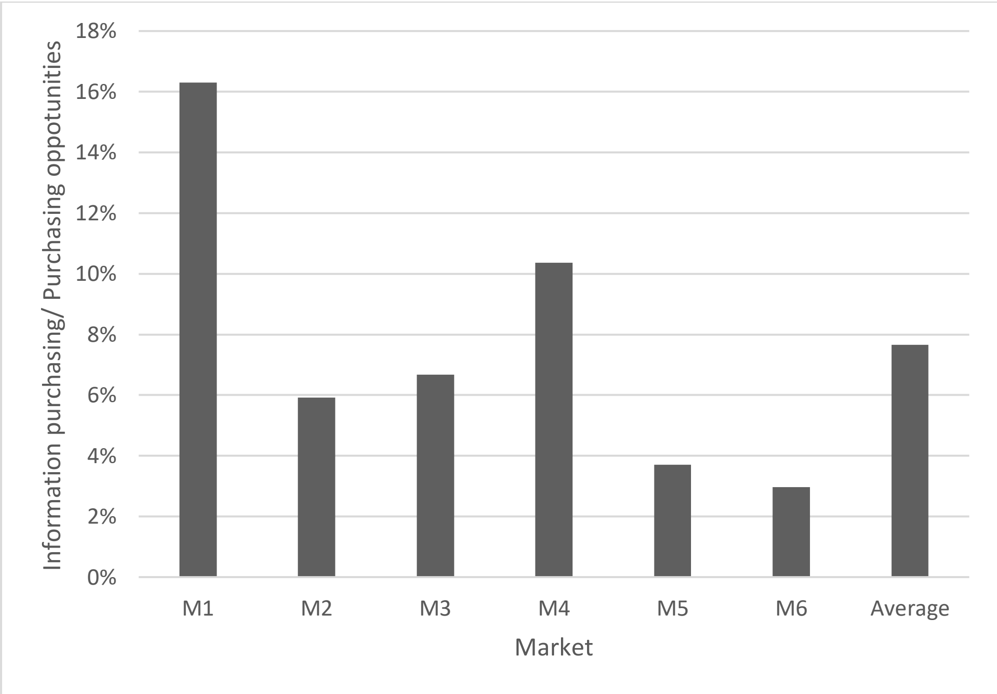
This table reports the magnitude of price bubbles in the three treatments using RAD and RD measures.

Treatment	Group	*RAD*	*RD*
1	1	1.44	0.76
1	2	0.93	0.01
1	3	1.01	0.33
1	4	0.60	-0.33
1	5	0.88	0.41
1	6	0.57	-0.08
Average		**0.90**	**0.18**
2	1	0.51	-0.21
2	2	1.08	0.46
2	3	0.54	-0.09
2	4	0.77	0.08
2	5	0.71	0.41
2	6	1.24	0.74
Average		**0.81**	**0.23**
3	1	0.59	0.15
3	2	0.84	-0.52
3	3	0.45	-0.28
3	4	0.39	-0.16
3	5	0.38	-0.36
3	6	0.46	-0.19
Average		**0.52**	**-0.23**
p-value (T12)		0.521	0.809
p-value (T13)		**0.016****	**0.054***
p-value (T23)		**0.054***	**0.037****

RAD and *RD* are relative absolute deviation and relative deviation.
p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. 3 – Proportion of participants pay to purchase extra information

This figure shows the frequency participants purchase the *leaderboard* in the *costly-information* treatment.



M1, M2, M3, M4, M5 and M6 represennt Market 1 to Market 6 in the *costly-information* treatment

To examine how the bubble formation changes during the 15 periods of the asset market, we divide each market into 3 phases, in which phase 1 starts from period 1 to period 5, phase 2 from period 6 to period 10 and phase 3 from period 11 to period 15 (Appendix 1.2). The result shows that *RAD* is significantly higher in the *base* treatment compared to the *leaderboard* treatment in the first phase, but not in the second and third phase. Trading volume in the first two phases of the *leaderboard* treatment is significantly higher than in the *base* treatment. The differences in price magnitude between the *base*, *leaderboard* treatment and the *costly-information* treatment start in the last two phases. This result implies that while the leaderboard might reduce bubble formation in short-run, information asymmetry creates the effect in long-run. The magnitude of bubbles is highest in the last phase of the *leaderboard* and be relatively higher than the other two treatments, which should not be the case since the fundamental value of the asset is declining toward zero.

1.4.2. Herding counting

1.4.2.1. Herding counting with non-finance students

The design of the *leaderboard* treatment allows participants to observe the performance-based ranking and historical trading activities at the end of each period. Participants can compare their performance to the performance and trading decisions of the leaders. We expect that participants follow the prices made by the top leaders in the market, including the first-ranked, second-ranked and third-ranked leaders. The ranking is recorded based on participants' profit in a period. Çelen and Kariv (2004) state that herd behaviour exists when participants make identical decisions. In this context, we regard the decisions of following the prices offered by the top leaders as herd behaviour.

The average following times in 6 markets with the *leaderboard* design is shown in Table 1.2. We estimate the number of times participants follow the exact prices offered by the first, second and third-ranked leaders. The number of herding decisions is examined in the executed case and in total, with both executed and non-executed offers. The results indicate that 24% of total offers in the market are made, based on the exact prices offered by the leaders in the previous period. This number is 37% in the case of executed offers. The number of times participants follow the first-ranked leaders is significantly higher than the second-ranked and third-ranked leaders.

Table 1. 2 - Herding the exact prices offered by the top leaders

This table reports the number of times participants herd the exact prices offered by the first, second, third-ranked leaders and the top three leaders together and percentage of herding the case of executed offers and total offers.

(A) All offers

Market	F1 All	F2 All	F3 All	Total All	Total Offers	Percentage
1	17.77	9.33	3.44	30.55	81.77	**37%**
2	4.77	2.77	.66	8.22	75	**11%**
3	19.11	13.22	3.77	36.11	153	**24%**
4	5.55	3.44	3.33	12.33	59.88	**21%**
5	13.33	5.88	2.44	21.66	70.11	**31%**
6	3.66	2.88	1	7.55	45	**17%**
Mean	**10.70**	**6.25**	**2.44**	**19.40**	**80.79**	**24%**
p-value (F1 vs. F2)				**0.000***		
p-value (F1 vs. F3)				**0.000***		
p-value (F2 vs. F3)				**0.000***		

F1, F2, F3 (All) the numbers of times participants follow the exact prices offered by the first, second and third-ranked leaders regardless the offers are executed or not
p-values are taken from the Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

(B) Executed offers

Market	F1 Executed	F2 Executed	F3 Executed	Total F Executed	Executed Offers	Percentage
1	5.88	5.77	1.0	12.66	23.11	**55%**
2	1.22	0.77	.11	2.11	8.88	**24%**
3	2.22	1.66	.33	4.22	16	**26%**
4	2.0	1.22	1.55	4.77	16	**30%**
5	6.22	3.33	0.77	10.33	23.44	**44%**
6	0.66	0.44	0.44	1.55	9.22	**17%**
Mean	**3.03**	**2.20**	**0.70**	**5.94**	**16.11**	**37%**
p-value (F1 vs. F2)				**0.054***		
p-value (F1 vs. F3)				**0.000***		
p-value (F2 vs. F3)				**0.000***		

F1, F2, F3 (Executed) is the number of times participants follow the exact prices offered by the first, second and third-ranked leaders and the offers are executed.
p-values are taken from the Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

Table 1. 3 - Herding the prices with 5% interval offered by the top leaders

This table reports the number of times participants herd the prices with 5% interval offered by the first, second, third-ranked leaders and the top three leaders together and percentage of herding the case of executed offers and total offers

(A) All offers

Market	F1In All	F2In All	F3In All	Total Fin (All)	Total Offers	Percentage
1	36.66	10.55	1.88	49.11	81.77	**60%**
2	11.55	4	1.44	17	75	**23%**
3	25.22	18	6.11	49.33	153	**32%**
4	13.77	5.55	4.33	23.66	59.88	**40%**
5	32.88	5.22	0.77	38.88	70.11	**55%**
6	8.22	4	1	13.22	45	**29%**
Mean	**21.38**	**7.88**	**2.59**	**31.87**	**80.79**	**39%**
p-value (F1 vs. F2)				**0.000*****		
p-value (F1 vs. F3)				**0.000*****		
p-value (F2 vs. F3)				**0.000*****		

F1in, F2in, F3in (All) is the numbers of times participants follow the exact prices with 5% interval offered by the first, second and third-ranked leaders in general.
p-values are taken from the Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

(B) Executed offers

Market	F1in (Executed)	F2in (Executed)	F3in (Executed)	Total Fin (Executed)	Traded Offers	Percentage
1	12.66	5.11	0.33	18.11	23.11	**78%**
2	1.88	1	0.11	3	8.88	**34%**
3	3	1.33	0.77	5.11	16	**32%**
4	4.22	1.77	2.11	8.11	16	**51%**
5	14.44	1.33	0.33	16.11	23.44	**69%**
6	1.66	0.55	0.44	2.66	9.22	**29%**
Mean	**6.31**	**1.85**	**0.68**	**8.85**	**16.11**	**55%**
p-value (F1 vs. F2)				**0.000*****		
p-value (F1 vs. F3)				**0.000*****		
p-value (F2 vs. F3)				**0.006*****		

F1in, F2in, F3in (Executed) is the number of times participants follow the exact prices with 5% interval offered by the first, second and third-ranked leaders and the offers are executed.
p-values are taken from the Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. 4 - Numbers of times participants follow the exact prices and prices with 5% interval offered by the leaders (All offers)

Number of times participants follow the exact prices and price with 5% interval offered by the leaders. This figure considers all the offers when counting herding.

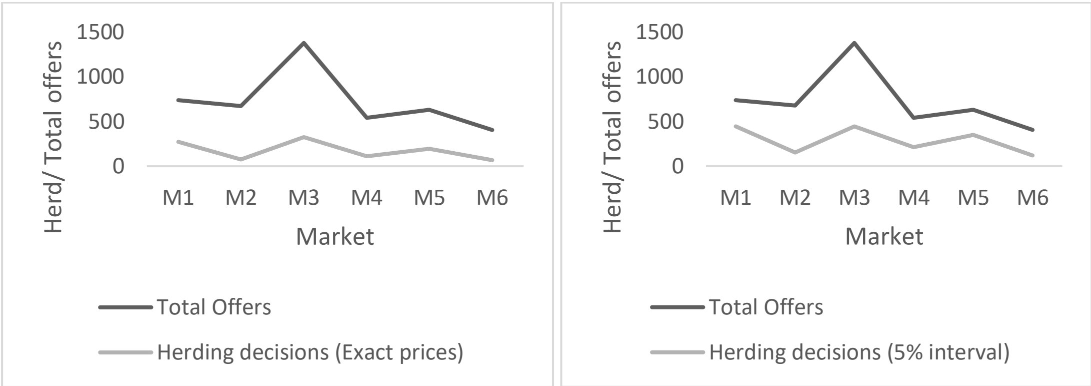
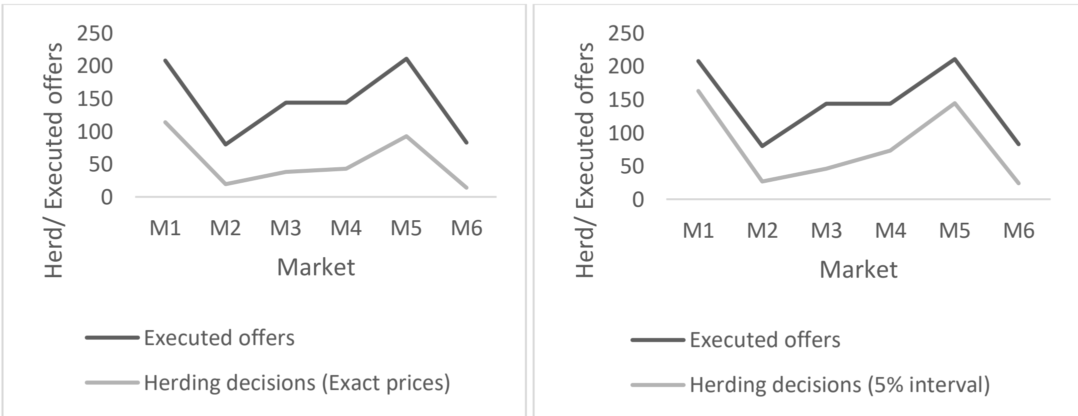


Figure 1. 5 - Numbers of times participants follow the exact prices and prices with 5% interval offered by the leaders (Executed offers)

Number of times participants follow the exact prices and price with 5% interval offered by the leaders. This figure considers executed offers only.



We examine situations in which participants choose to follow and modify the offered prices in a specific interval to make the prices more competitive, but still, keep track of what the top leaders did. For example, participants may observe that the first-ranked leader bought an asset at 100 ECU. In the next period, they might make an offer to purchase at 101 or 102. We choose the price interval at 5%. This interval is small enough to be comparable with the exact prices offered by the top leaders but still be competitive enough to attract other participants in the market. The number of time participants follows the top leaders significantly increases in the case of 5% interval is shown in Table 1.3. More specifically, 55% of executed offers and 39% of total offers are based on the prices within the 5% interval offered by the top leaders, respectively. These numbers indicate that the top leaders significantly lead the trading prices in the markets. Similar to the case of following the exact prices, in the case of following the prices within 5% interval, the number of times participants follow the first-ranked leaders is significantly higher than the number of times participants follow the second and third-ranked leaders. Bikhchandani and Sharma (2000) indicate that herding could happen due to reputational externality. More specifically, people follow the ones with high reputation. In this case, the first-ranked leader is the one who generates the highest profit in a particular period. The fact that participants choose to follow the first-ranked leaders emphasises the validity of reputational externality in the context of herd behaviour. We could doubt that participants do not follow the leaders, but simply follow the average executed prices in the market. The results reported in Appendix 1.3 show that the number of times participants follow the leaders is significantly higher than the number of times participants follow the average executed prices, both in the case of the exact prices and the prices with 5% interval (p=0.000, Wilcoxon signed-rank test). In other words, decision-making is led by the top performers, not by the whole market. Another doubt is that a few single participants in the market exhibit herd behaviour. However, the result shows that most participants in the market make herding decisions, shown in Table 1.4. More specifically, 3 participants choose to follow the exact prices offered by the first-ranked leaders, 2 participants decide to follow the second-ranked leaders, and 1 participant chooses to follow the third-ranked. These numbers are 4, 2 and 1, respectively in the case of following the prices with 5% interval. The numbers show that herding is not only from any specific participant but from the whole market.

Table 1. 4 - Number of participants herds the top leaders

This table reports the number of participants herds the exact price and price with 5% interval offered by the first, second and third-ranked leaders.

Market	F1	F2	F3	F1In	F2In	F3In
1	4.06	2.73	1.00	6.53	2.73	0.80
2	1.80	1.06	0.40	2.66	1.60	0.46
3	2.40	2.80	0.80	3.13	3.00	1.26
4	2.20	1.40	1.60	3.93	1.86	1.60
5	4.73	2.33	1.13	6.80	2.20	0.26
6	1.80	1.26	0.53	2.86	1.53	0.46
Mean	**3**	**2**	**1**	**4**	**2**	**1**

F1, F2, F3 indicates the number of participants follows the exact prices offered by the first, second and third-ranked leaders while F1In, F2In, F3In indicates the number of participants follows the prices with 5% interval offered by the first, second and third-ranked leaders

1.4.2.2. Financial Literacy: The comparison in herding between finance and non-finance students

The example of ETORO at the beginning of this study shows that individuals without financial literacy could be an investor by merely copying the investment strategy of the best performers in the market. In this section, we examine the differences in decision-making, particularly herding decisions between finance and non-finance students. The purpose of this section is examining whether finance students, who have better financial literacy, make better decisions? Although this finding is beneficial to improve the efficiency and stability of the markets, the results are still controversial. It is widely believed that professional stock investors with better expertise are not prone to bias judgements (see, e.g. Dufwenberg, Lindqvist and Moore, 2005 and Fama, 1998). However, Carhart (1997) suggest that even professional investors are prone to judgement biases. Venezia, Nashikkar and Shapira (2011) indicate that the propensity to herd is lower in the case of professional investors compared to amateur investors. Professional investors are less sensitive to the firm's systematic risk and size, which is considered as the leading causes of herding. However, Cipriani and Guarino (2008) examine herd behaviour with market professionals and conclude that the result is not different from the identical experiment they conducted in 2005 with undergraduate students (Cipriani and Guarino, 2005). Nikiforow (2010) provides evidence on the impact of training on behavioural finance on the perception and investment behaviour of professional fund managers. The author shows that training reduces conformity tendency, leading to less dependence on colleagues and other market participants. Similarly, Caldwell and Dolvin (2012) find that increased education in both general and targeted behavioural education reduces the likelihood and impact of herding.

We expect that finance students make better decisions. In this context, better decisions mean participants should make an offer based on the fundamental value of the asset in each period and should not merely follow the leaders. To examine this hypothesis, we conduct 6 asset markets using the *leaderboard* design with finance students only, which results in 54 finance students in total. They are master students in Finance and Investment, which is one of the prestigious master programmes in Finance in the UK, and PhD students in Finance studying at the

Nottingham University Business School. The comparison of herding the exact prices offered by the top leaders between finance and non-finance students are shown in Table 1.5. The results show that finance students follow 22% in executed offers and 18% in total offers. These numbers are significantly lower than in the case of non-finance students (p=0.000, Mann Whitney U-test). In other words, finance students follow the exact prices offered by the top leaders significantly less, which is consistent with the hypothesis. The similar results are found in the case of following the price with 5% interval (Table 1.6). Although the rate of following is relatively high in this case, which is 33% and 28%, respectively with traded offers and total offers, these numbers are significantly lower than the case with non-finance students (p=0.000, Mann Whitney U-test). Alevy, Haigh and List (2007) state that market professional can distinguish between bad and good signal. In this experiment, finance students with a better understanding of financial markets, are less likely to make herding decisions.

Table 1. 5 - Comparison on herding the exact prices offered by the top leaders between finance and non-finance students.

This table reports the number of times participants herd the exact prices offered by the top leaders and the percentage of herding with two participant pools, finance students and non-finance students. Market 1-6 are conducted with non-finance students while market 7-12 are conducted with finance students.

Market	Ftimes Executed	Executed Offers	Percentage	Ftimes All	Total Offers	Percentage
1	12.66	23.11	55%	30.55	81.77	37%
2	2.11	8.88	24%	8.22	75	11%
3	4.22	16	26%	36.11	153	24%
4	4.77	16	30%	12.33	59.88	21%
5	10.33	23.44	44%	21.66	70.11	31%
6	1.55	9.22	17%	7.55	45	17%
Mean	**5.94**	**16.11**	**37%**	**19.40**	**80.79**	**24%**
7	3.44	11.77	29%	10.66	58	18%
8	2.11	15.77	13%	14.33	90.77	16%
9	3.55	14.44	25%	12.88	61.88	21%
10	2.33	9.11	26%	6.33	52.55	12%
11	3	9.77	31%	17.44	82.77	21%
12	1.55	10.55	15%	12	60.55	20%
Mean	**2.66**	**11.90**	**22%**	**12.27**	**67.75**	**18%**
p-value	**0.000*****	**0.012****	**0.012****	**0.004*****	**0.06***	**0.001*****

Ftimes (Executed) is the number of times participants follow the exact prices offered by the leaders and the offers are executed; Ftimes (All) is the number of times participants follow the exact price offered by the leaders, we consider total offers in this case.
p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

Table 1. 6 - Comparison on herding the prices with 5% interval offered by the top leaders between finance and non-finance students.

This table reports the number of times participants herd the prices with 5% interval offered by the top leaders and the percentage of herding with two participant pools, finance students and non-finance students. Market 1-6 are conducted with non-finance students while market 7-12 are conducted with finance students.

Market	Ftimesin Executed	Executed Offers	Percentage	Ftimesin All	Total Offers	Percentage
1	18.11	23.11	78%	49.11	81.77	60%
2	3	8.88	34%	17	75	23%
3	5.11	16	32%	49.33	153	32%
4	8.11	16	51%	23.66	59.88	40%
5	16.11	23.44	69%	38.88	70.11	55%
6	2.66	9.22	29%	13.22	45	29%
Mean	**8.85**	**16.11**	**55%**	**31.87**	**80.79**	**39%**
7	4.22	11.77	36%	13.22	58	23%
8	2.55	15.77	16%	18.66	90.77	21%
9	6.11	14.44	42%	21.66	61.88	35%
10	4.88	9.11	54%	21.55	52.55	41%
11	3.22	9.77	33%	19.22	82.77	23%
12	2.77	10.55	26%	19.66	60.55	32%
Mean	**3.96**	**11.90**	**33%**	**19**	**67.75**	**28%**
p-value			**0.000***			**0.003***

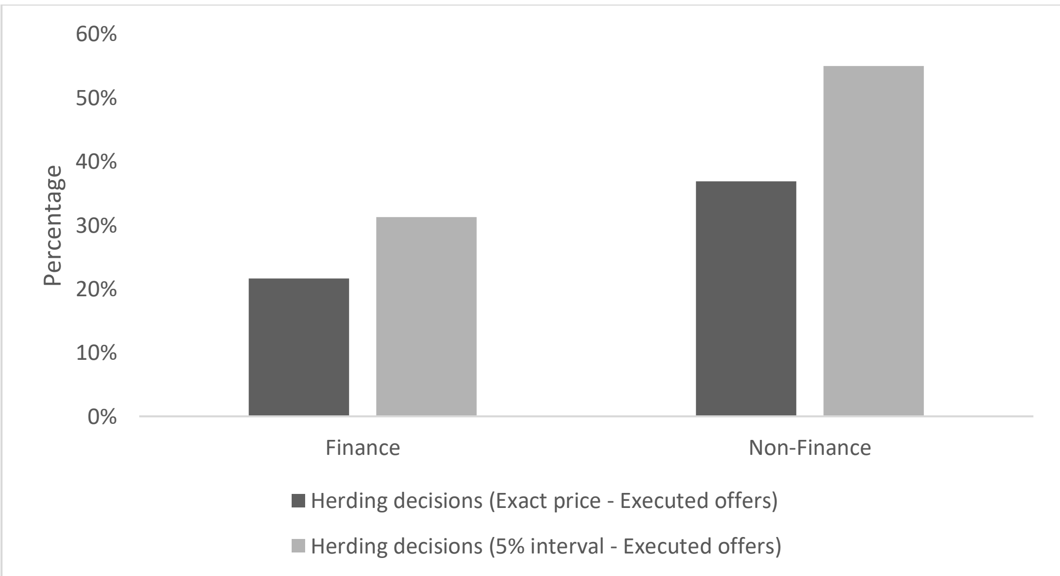
Ftimesin (Executed) is the number of times participants follow the exact prices with 5% interval offered by the leaders and the offers are executed; Ftimesin (All) is the number of times participants follow the exact price with 5% interval offered by the leaders, we consider total offers in this case.
p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. 6 - Comparison of herding decisions between non-finance and finance students (Total offers and Executed offers)

This figure expresses the percentage of herding decisions out of total offers in the market. The figure shows the level of herding in 6 markets with finance students and another six markets with non-finance students.

(A) Total offers

(B) Executed offers



1.4.2.3. The consequences of herding

Herding is claimed to be the cause of market volatility, destabilisation and fragility of the financial markets (see, e.g. Morris and Shin (1999), Persaud (2000) and Shiller (1990). Bikhchandani and Sharma (2000) show that information-based herd behaviour can lead to price bubbles and mispricing. Also, herding can lead to volatility since investors make reversed decisions after realising that they made wrong decisions by herding. This situation is more likely to happen when investors are experienced or when new information comes out. Similarly, Venezia, Nashikkar and Shapira (2011) indicate that herding causes market volatility. However, other authors (see, e.g. Allen and Gale, 2000a, and Brunnermeier, 2001) show that there are rational models of bubbles and crashes which have nothing to do with herding. Similarly, Avery and Zemsky (1998), present via their model that herd behaviour need not distort prices. However, complex information structures can lead to herd behaviour and make price bubbles possible. In this paper, we examine the correlation between herding and bubble magnitude, price volatility and market efficiency. Bubbles are mainly measured by *RAD*, *RD* and other measures such as amplitude, average bias, total dispersion, positive dispersion, negative dispersion, boom duration and burst duration. Market volatility is measured by the average of absolute returns across each trading period (Hanke et al., 2010).

$$y_{j,k} = \frac{\sum_{\theta=1}^{\Theta} |Ret_{j,k,\theta}|}{\Theta}$$

In which,

$$\left|Ret_{j,k,\theta}\right| = |\ln\left(P_{j,k,\theta}\right) - \ln\left(P_{j,k,\theta-1}\right)|$$

Where θ stands for each transaction and Θ is the total number of transactions within a certain period *k* and market *j*.

Market efficiency is measured by the absolute deviation between the average price within a trading period ($\bar{P}$) and the fundamental value (*V*), standardized over its average per market and period.

$$y_{j,k} = \frac{|\bar{P}_{j,k} - V_{j,k}|}{(\sum_{k=1}^{15}\left|\bar{P}_{j,k} - V_{j,k}\right|/15}$$

The correlation between the number of times participants follows the exact price and price with 5% interval offered by the first, second and third-ranked leaders and different measures of bubble magnitude, turnover, market volatility and efficiency, shown in Table 1.7. In general, herding is negatively correlated with bubble magnitude. The correlation is relatively high and significant in many cases. For example, the number of times participants follow the exact price offered by the first-ranked leaders is negatively and significantly correlated with overvaluation (RD), average bias (AB) and total dispersion (TD). The number of times participants follow the price with 5% interval offered by the first-ranked leaders is significantly and negatively correlated with most of the bubble measures. This result indicates that herding is not a reason for bubble formation in this context. In contrast, herding is helping to reduce the magnitude of bubbles. The suggested reason is that participants choose the right person to follow in this case. Therefore, herding stabilises the market. This finding can be tested by estimating the correlation between herding and price volatility and market efficiency. Herding is negatively and significantly correlated with volatility and market efficiency in most of the cases, shown in Table 1.7 (1% significant level with volatility and 5% with market efficiency in the case of herding decisions within 5% interval). It means that the high magnitude of herding could reduce market volatility and improve market efficiency. This result indicates that herding is not a reason for market destabilisation; at least in the case the market chooses the right person to follow.

Table 1. 7 - Consequences of herd behaviour

This table reports the correlations between herding decisions and price bubbles, turnover, volatility and market efficiency.

(A) Exact prices

	Follow the 1st	Follow the 2nd	Follow the 3rd
RAD	-0.454	0.003	-0.270
RD	**-0.619****	0.074	-0.230
Amplitude	-0.426	-0.231	-0.414
AB	**-0.678****	0.077	-0.267
TD	**-0.517***	-0.056	-0.323
PD	**-0.503***	-0.021	-0.337
ND	0.370	-0.077	0.144
Boom	**-0.502***	-0.104	-0.054
Burst	**0.502***	0.104	0.054
Turnover	**0.690****	**0.513***	0.315
Volatility	-0.036	-0.110	-0.019
Market efficiency	-0.055	**-0.165****	**-0.191****

RAD stands for relative absolute deviation, RD is relative deviation, AB is average bias, TD is total dispersion, PD is positive dispersion while ND is negative dispersion. Boom and Burst and Boom duration and Burst duration. The correlations are taken from Spearman's rank correlation
*** p<0.01, ** p<0.05, * p<0.1

(B) Price with 5% interval

	Follow the 1st - In	Follow the 2nd - In	Follow the 3rd - In
RAD	**-0.636****	-0.362	-0.297
RD	**-0.591****	0.169	-0.328
Amplitude	**-0.580****	-0.485	-0.325
AB	**-0.566***	0.189	-0.395
TD	**-0.657****	-0.404	-0.339
PD	**-0.573***	-0.326	-0.430
ND	0.279	-0.316	0.357
Boom	**-0.567***	-0.088	-0.349
Burst	**0.567***	0.088	0.349
Turnover	**0.882*****	0.484	0.224
Volatility	**-0.252*****	-0.062	0.051
Market efficiency	**-0.147****	**-0.129***	**-0.170****

RAD stands for relative absolute deviation, RD is relative deviation, AB is average bias, TD is total dispersion, PD is positive dispersion while ND is negative dispersion. Boom and Burst and Boom duration and Burst duration. The correlations are taken from Spearman's rank correlation
*** p<0.01, ** p<0.05, * p<0.1

1.4.3. Individual **differences, herding and performance**

1.4.3.1. The characteristics of the participant *pool (finance and non-finance students)*

We recruited 216 students studying at The University of Nottingham, in which 54 finance students are master and PhD students in finance. The characteristics of the whole participant pool are shown in Table A1.6 (Appendix 1.4). For miscalibration, the average correct answer is 20%. This result is relatively low compared to other research. For example, Klayman et al. (1999) indicate that the value is 43%, while 36% is the result found by Biais et al. (2005). In other words, our participants are more miscalibrated. In terms of the better-than-average measure of overconfidence, it is showed that 25.94% of participants considering themselves be better than what they performed. For maths skill, participants get 3.9/6 correct answers. They can entirely control themselves in 8.72/18 situations and are prone to risk-averse (the average switching point is 6.38). 44.81% of participants are men, and 31.60% of participants come from Western countries.

The comparison between finance (54 students) and non-finance students (54 students), who participated in the *leaderboard* treatment is presented in Table A1.7 (Appendix 1.4). In general, finance participants are significantly more overconfident (better-than-average measure, 1% level of significance), perform better in the maths test (5% level of significance) and mostly come from Asian countries.

1.4.3.2. Individual differences and Performance

Chitra and Sreedevi (2011) demonstrate that the performance of the stock market is not only the results of intelligible characteristics or herd behaviour but also is due to the influence of psychological and personality traits. For example, Biais et al. (2005) prove that miscalibration reduces trading performance in an experimental financial market while Grinblatt, Keloharju and Linnainmaa (2012) show that investors with high IQ make better decisions such as market timing, stock-picking and trade execution. The first idea on this issue is shown in Table 1.8 by showing the correlations between wealth and different measures of individual characteristics. The results show that participants who are better in maths and more overconfident (better-than-average measure) can generate higher earnings. The same finding is found with male, non-finance participants. The results taking from the OLS regression[5] with the average earning wealth per participant in a particular market as the dependent variable and fixed effect and random effect regression with panel data confirm this finding (Table A1.8, Appendix 1.5). The treatment effect on wealth is also investigated. The results show that participants' wealth is significantly lower in the *costly-information* treatment (10% level of significance in OLS regression without controlling for individual differences, 5% level of significance in OLS regression with controlling for individual differences and 1% level of significance in fixed and random effect regression). Regarding the impacts of individual differences on wealth, the results from the OLS regression indicate that older participants generate lower earnings (10% level of significance). The results from the random effect regression are more in line with the Spearman Rho correlation when showing that male and non-finance students generate significantly higher income (10% level and 1% level of significance, respectively). This finding indicates that individual differences play a major role in investment performance.

[5] Ordinary Least Squares regression

Table 1. 8 - Impact of personality traits on performance

Table A reports the correlation between individual differences and wealth while table B reports the wealth earned by different groups of participants.

(A)

Individual differences	Wealth
Miscalibration level	-0.057
Maths skill	**0.222*** **
Self-monitoring ability	0.035
Risk preference	0.019

The correlations are taken from Spearman rho correlations
*** p<0.01, ** p<0.05, * p<0.1

(B)

Individual differences	Wealth
Better than average (No: 0; Yes: 1)	**3.666*** **
Gender (Female: 0; Male: 1)	**-3.047*** **
Finance students (No: 0; Yes: 1)	**1.896** **
Nationality (Asian: 0; Western: 1)	-1.445

The z values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

1.4.3.3. Individual differences and herding decisions

In this section, we examine the impacts of individual differences on herding decisions. Nöth and Weber (2002) conclude that overconfidence is the reason participants do not follow others. Culture difference is claimed as another reason. Psychological literature suggests that conformity is more likely in hierarchical cultures such as East Asian, where people live in a small town and know each other. For example, Kim and Markus (1999) show that while the ads in the U.S. focus on uniqueness, the ads in Korea focus more on conformity, i.e. the percentage of people make the same decisions. Grinblatt, Keloharju and Linnainmaa (2012), stating that investors with higher IQ are less prone to judgmental biases. The correlations between participants' characteristics and herding decisions are shown in Table 1.9. We examine the decisions of herding the exact prices and prices with 5% interval offered by the first-ranked leaders and the top three leaders in total. The results show that individual differences play a significant impact on herding decisions. More specifically, the tendency of herding is significantly low with participants who are better in maths and self-monitoring. Risk-loving participants and older participants also express a similar tendency. Indeed, while finance participants are found to follow the leaders significantly less in the case of following the exact prices, overconfident (better-than-average), male and participants come from Western countries follow the leaders substantially less in the case of following the prices with 5% interval. We conduct the random effect regression with panel data, and most of the results stay unchanged (Appendix 1.6). As we expected, participants who are smart and highly self-monitored tend to make decisions based on their judgements, but not merely follows others (5% and 10% level of significance, respectively). Male, finance and Western participants also exhibit this determination (5%, 5% and 1% level of significance, respectively). However, the correlation between the herding decisions and participants' wealth (Appendix 1.7) shows that following the first-ranked leaders increases the wealth, and this result is significant in the case of 5% interval. In fact, following the first-ranked leader in this context can be considered as rational herding.

Table 1. 9 - Correlations between participants' characteristics and herding decisions

Table A reports the correlation between individual differences and herding decisions while table B reports the herding decisions conducted by different groups of participants. Herding is measured by the number of times participants follow the first-ranked leaders and the first three leaders (first, second and third-ranked leaders) in the market. Following the exact prices and prices with 5% interval are considered in this examination.

(A)

Individual differences	F1times	Ftimes	F1timesin	Ftimesin
Miscalibration level	-0.017	-0.032	0.023	-0.009
Maths skill	**-0.091*** **	**-0.082*** **	**-0.082*** **	**-0.059** **
Self-monitoring ability	**-0.058** **	**-0.100*** **	**-0.062** **	**-0.103*** **
Risk preference	**0.047* **	**0.107*** **	**0.058** **	**0.093*** **
Age	**-0.051** **	**-0.105*** **	**-0.093*** **	**-0.143*** **

F1times is the number of time participants follow the exact prices offered by the first-ranked leaders; Ftimes is the number of times participants follow the exact prices offered by the first three leaders. F1timesin refers the number of times participant follow the prices with 5% interval offered by the first-ranked leaders while Ftimesin refers the number of times participants follow the prices with 5% interval offered by the top three leaders.
The correlations are taken from Spearman rho correlations
*** p<0.01, ** p<0.05, * p<0.1

(B)

Individual differences	F1times	Ftimes	F1timesin	Ftimesin
Better than average (No: 0; Yes: 1)	-0.697	-1.025	**-2.665*** **	**-2.038** **
Gender (Female: 0; Male: 1)	0.078	-1.049	**-2.348** **	**-2.132** **
Finance students (No:0; Yes: 1)	**4.266*** **	**7.488*** **	**5.844*** **	**7.985*** **
Nationality (Asian: 0; Western: 1)	0.852	0.931	-1.384	-0.202

F1times is the number of time participants follow the exact prices offered by the first-ranked leaders; Ftimes is the number of times participants follow the exact prices offered by the first three leaders. F1timesin refers the number of times participant follow the prices with 5% interval offered by the first-ranked leaders while Ftimesin refers the number of times participants follow the prices with 5% interval offered by the top three leaders.
The z values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

1.5. Conclusion

We make the first attempt to examine herd behaviour in financial markets using asset market experiment. We design a *leaderboard* which captures the performance-based ranking and historical trading of participants. There is one treatment in which participants receive the leaderboard without any cost at the end of each period (*leaderboard* treatment), and one treatment participants have to pay a considerably high cost to get the leaderboard (*costly-information*). We find the most participants do not pay for the leaderboard. However, since they believe that there is asymmetric information in the markets, they trade at a significantly lower price creating remarkably small bubbles and price undervaluation. This finding is in line with the research examining the impact of asymmetric information on bubbles and mispricing. The interesting finding here is that most participants do not pay to get the leaderboard; therefore, asymmetric information is just a belief. The information in the market is, in fact, symmetric. In the treatment where the leaderboard is freely informed to participants, they make decisions to follow the top three leaders. The top-ranked leaders are the ones who make the most profit in a previous period, which is considered as the most reputational participants; therefore, participants choose to follow the exact prices offered by the first, second and third-ranked leaders. To make the offers more competitive, participants change the price in a small interval. The number of times participants follow the price with 5% interval offered by the top leaders is significantly high. We test for financial literacy by comparing the herding decision-making of finance and non-finance students, and we find that finance students make a significantly lower level of herding decisions. Finance students, with a better understanding of financial literacy, choose not to follow others. However, herding is found not to be a reason for bubbles formation, high volatility and market efficiency in this context, which is one of the main findings in this paper. The result indicates that herding is not a problem in financial markets; the driving force is who is leading the markets or whom the markets choose to follow. If the markets choose to follow the rational ones, herding would be harmless to market stability. We also examine the impact of individual differences on earnings and herding decisions. Participants with excellent maths skills earn significantly more. Similarly, the earnings of non-overconfident and non-finance participants are significantly higher than the earnings of overconfident and finance participants. Male also generate higher income compared to female. In terms of herding, participants with better skills in maths, self-monitoring and prone to risk-loving choose to follow the leaders significantly less. In contrast, non-finance students choose to follow the leaders significantly more compared to finance students. The results are beneficial in the sense that having educated participants in the markets would reduce decision bias. Also, information transparency should be improved so that market participants can choose the right ones to follow, which improve the stability and efficiency of the markets.

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APPENDIX 1.1 - Bubble measures in the three treatment

This table reports the magnitude of price bubbles in the three treatments using different measures. The table also includes the level of trading volume (turnover).

Treatment	Group	Amplitude	AB	TD	PD	ND	Boom	Burst	Turnover
1	1	2.84	100.80	2758	2135	623	10	5	1.61
1	2	1.93	0.50	1799.5	903.5	896	7	8	2.83
1	3	1.97	43.13	2021	1334	687	10	5	2.22
1	4	1.15	-40.77	1144.5	266.5	878	6	9	3.36
1	5	2.00	50.23	1660.5	1207	453.5	8	7	2.58
1	6	1.34	-10.00	1102	476	626	10	5	2.69
Average		**1.87**	**23.98**	**1747.58**	**1053.67**	**693.92**	**8.50**	**6.50**	**2.55**
2	1	0.98	-25.77	971.5	292.5	679	6	9	5.78
2	2	1.95	63.73	2118	1537	581	10	5	2.22
2	3	1.13	-23.53	1165	406	759	8	7	4.00
2	4	1.52	14.27	1483	848.5	634.5	8	7	4.00
2	5	1.26	53.47	1386	1094	292	12	3	5.86
2	6	1.88	98.40	2394	1935	459	12	3	2.31
Average		**1.45**	**30.09**	**1586.25**	**1018.83**	**567.42**	**9.33**	**5.67**	**4.03**
3	1	1.24	19.80	1047	672	375	10	5	2.67
3	2	1.30	-63.83	1623.5	333	1290.5	4	11	2.67
3	3	0.95	-27.03	864.5	229.5	635	9	6	3.03
3	4	1.28	-21.27	761	221	540	6	8	1.92
3	5	0.88	-46.67	796	48	748	4	11	1.86
3	6	0.94	-20.73	888	288.5	599.5	8	7	2.78
Average		**1.10**	**-26.62**	**996.67**	**298.67**	**698.00**	**6.83**	**8.00**	**2.49**
p-value (T12)		0.109	0.748	0.748	0.872	0.336	0.509	0.509	0.126
p-value (T13)		**0.016****	**0.054***	**0.010****	**0.025****	0.631	0.219	0.286	0.872
p-value (T23)		0.109	**0.078***	**0.037****	**0.016****	0.631	0.143	0.168	0.108

AB indicates Average Bias, TD is Total Dispersion, PD is Positive Dispersion,
ND is Negative Dispersion, Boom and Burst is Boom duration and Burst Duration
p-values are taken from Mann Whitney U-test *** p<0.01, ** p<0.05, * p<0.1

Average Bias is the average deviation of median price from the fundamental value.

$$Average\ Bias = \sum \frac{P_t - FV_t}{15}$$

where Pt and FVt are the median price and fundamental value in period t, respectively.

Total dispersion is the sum, over all 15 periods, of absolute deviation of median period price from the fundamental value. Correspondently, a low Total dispersion indicates close deviations of prices from fundamentals.

$$Total\ Dispersion = |P_t - FV_t|)$$

Positive (Negative) Deviation as the sum, over all 15 periods, of the absolute per period deviation of the median price from the fundamental value if prices are above (below) fundamental value.

$$Positive\ deviation = \sum |P_t - FV_t| \qquad where\ P_t > FV_t$$

$$Negative\ deviation = \sum |P_t - FV_t| \qquad where\ P_t < FV_t$$

Boom Duration (Burst Duration) is the greatest number of consecutive periods above (below) fundamental value.

Turnover is the standardised measure of trading activity and defined as the sum of all transactions divided by the number of shares in the market. High Turnover is related to high trading activity and is associated with mispricing (Eckel and Fullbrunn, 2015)

$$Turnover = \frac{\sum Q_t}{36}$$

The amplitude of a bubble, which gives an indication of the magnitude of peak-to-trough deviations of market prices from the fundamental value (Kirchler, Huber and Stöckl, 2012)

$$Price\ amplitude = \max \frac{(\overline{P}_p - FV_p)}{FV_1} - min \frac{(\overline{P}_p - FV_p)}{FV_1}$$

APPENDIX 1.2

Table A1.1 - Bubble measures of the three treatments (Phase 1)

This table reports the bubble measures in Phase 1, starting from period 1 to period 5.

Treatment	Group	RAD	RD	Amplitude	AB	TD	PD	ND	Boom	Burst	Turnover
1	1	1.02	-1.02	0.77	-124.60	623	0	623	0	5	0.86
1	2	1.35	-1.35	0.53	-175.60	878	0	878	0	5	1.67
1	3	0.88	-0.83	0.93	-110.20	599	24	575	1	4	1.28
1	4	1.15	-1.15	0.50	-145.00	725	0	725	0	5	1.06
1	5	0.84	-0.44	1.43	-57.00	533	124	409	1	4	1.08
1	6	1.14	-0.69	1.34	-84.00	764	172	592	2	3	0.83
Average		**1.06**	**-0.91**	**0.92**	**-116.07**	**687.00**	**53.33**	**633.67**	**0.67**	**4.33**	**1.13**
2	1	0.85	-0.85	0.34	-108.00	540	0	540	0	5	2.06
2	2	0.73	-0.73	0.99	-85.80	477	24	453	1	4	1.28
2	3	0.89	-0.89	0.62	-140.00	700	0	700	0	5	2.5
2	4	0.92	-0.92	0.36	-113.10	565.5	0	565.5	0	5	1.58
2	5	0.56	-0.33	0.98	-43.00	369	77	292	2	3	2.67
2	6	0.97	-0.52	1.45	-65.30	591.5	132.5	459	2	3	0.89
Average		**0.82**	**-0.71**	**0.79**	**-92.53**	**540.50**	**38.92**	**501.58**	**0.83**	**4.17**	**1.83**
3	1	0.70	-0.58	0.93	-68.00	384	22	362	2	3	1.17
3	2	1.40	-1.40	0.33	-175.70	878.5	0	878.5	0	5	1.44
3	3	1.03	-1.03	0.41	-124.90	624.5	0	624.5	0	5	0.83
3	4	0.74	-0.36	1.28	-50.80	488	117	371	2	3	0.58
3	5	0.95	-0.95	0.69	-129.00	645	0	645	0	5	1.03
3	6	0.93	-0.93	0.42	-116.10	580.5	0	580.5	0	5	1.00
Average		**0.96**	**-0.88**	**0.68**	**-110.75**	**600.08**	**23.17**	**576.92**	**0.67**	**4.33**	**1.01**
p-value (T12)		**0.078***	0.336	0.748	0.336	**0.054***	0.864	0.109	0.794	0.794	**0.065***
p-value (T13)		0.423	0.872	0.172	1.000	0.423	0.372	0.748	0.856	0.856	0.470
p-value (T23)		0.262	0.149	0.631	0.336	0.423	0.475	0.423	0.715	0.715	**0.037****

RAD and RD are a relative absolute deviation and relative deviation.
AB indicates Average Bias, TD is Total Dispersion, PD is Positive Dispersion, ND is Negative Dispersion, Boom and Burst is Boom duration and Burst Duration
p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

Table A1.2 - Bubble measures of the three treatments (Phase 2)

This table reports the bubble measures in Phase 2, starting from period 6 to period 10.

Treatment	Group	RAD	RD	Amplitude	AB	TD	PD	ND	Boom	Burst	Turnover
1	1	1.28	1.28	1.19	166.00	830	830	0	5	0	0.28
1	2	1.23	1.23	0.91	163.50	817.5	817.5	0	5	0	0.64
1	3	1.37	1.02	1.59	141.60	932	820	112	4	1	0.31
1	4	0.27	-0.22	0.34	-27.80	167	14	153	1	4	1.31
1	5	1.68	1.68	0.37	211.70	1058.5	1058.5	0	5	0	0.58
1	6	0.47	0.47	0.28	56.00	280	280	0	5	0	0.92
Average		**1.05**	**0.91**	**0.78**	**118.50**	**680.83**	**636.67**	**44.17**	**4.17**	**0.83**	**0.67**
2	1	0.24	-0.22	0.29	-26.00	148	9	139	1	4	2.08
2	2	1.01	0.61	1.28	85.60	684	556	128	4	1	0.72
2	3	0.29	0.18	0.38	11.00	173	114	59	3	2	0.81
2	4	0.28	0.06	0.47	8.40	180	111	69	3	2	1.00
2	5	0.71	0.71	0.13	91.20	456	456	0	5	0	1.67
2	6	1.38	1.38	0.88	180.50	902.5	902.5	0	5	0	0.75
Average		**0.65**	**0.46**	**0.57**	**58.45**	**423.92**	**358.08**	**65.83**	**3.50**	**1.50**	**1.17**
3	1	0.69	0.69	0.21	82.80	414	414	0	5	0	0.78
3	2	0.61	-0.61	0.43	-76.80	384	0	384	0	5	0.83
3	3	0.11	-0.04	0.17	12.30	82.5	72	10.5	4	1	1.28
3	4	0.40	-0.14	0.95	-15.60	258	90	168	1	4	0.50
3	5	0.15	-0.15	0.15	-20.00	100	0	100	0	5	0.42
3	6	0.20	0.14	0.30	22.50	132.5	122.5	10	4	1	0.97
Average		**0.36**	**-0.02**	**0.37**	**0.87**	**228.50**	**116.42**	**112.08**	**2.33**	**2.67**	**0.80**
p-value (T12)		0.262	0.297	0.631	0.336	0.200	0.262	0.494	0.302	0.302	**0.078***
p-value (T13)		**0.037****	**0.054***	0.109	**0.054***	**0.037****	**0.037****	0.184	**0.077***	**0.077***	0.521
p-value (T23)		0.149	0.149	0.423	0.262	0.149	0.108	0.628	0.369	0.369	0.336

RAD and RD are a relative absolute deviation and relative deviation.
AB indicates Average Bias, TD is Total Dispersion, PD is Positive Dispersion, ND is Negative Dispersion, Boom and Burst is Boom duration and Burst Duration
p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

Table A1.3 - Bubble measures of the three treatments (Phase 3)

This table reports the bubble measures in Phase 3, starting from period 11 to period 15.

Treatment	Group	RAD	RD	Amplitude	AB	TD	PD	ND	Boom	Burst	Turnover
1	1	2.02	2.02	1.64	261.00	1305	1305	0	5	0	0.47
1	2	0.20	0.15	0.33	13.60	104	86	18	2	3	0.53
1	3	0.78	0.78	0.76	98.00	490	490	0	5	0	0.64
1	4	0.39	0.39	0.14	50.50	252.5	252.5	0	5	0	1.00
1	5	0.12	-0.01	0.22	-4.00	69	24.5	44.5	2	3	0.92
1	6	0.08	-0.02	0.13	-2.00	58	24	34	3	2	0.94
Average		**0.60**	**0.55**	**0.53**	**69.52**	**379.75**	**363.67**	**16.08**	**3.67**	**1.33**	**0.75**
2	1	0.43	0.43	0.23	56.70	283.5	283.5	0	5	0	1.64
2	2	1.50	1.50	0.52	191.40	957	957	0	5	0	0.22
2	3	0.43	0.43	0.16	58.40	292	292	0	5	0	0.69
2	4	1.10	1.10	0.64	147.50	737.5	737.5	0	5	0	1.42
2	5	0.86	0.86	0.27	112.20	561	561	0	5	0	1.53
2	6	1.36	1.36	0.65	180.00	900	900	0	5	0	0.67
Average		**0.95**	**0.95**	**0.41**	**124.37**	**621.83**	**621.83**	**0.00**	**5.00**	**0.00**	**1.03**
3	1	0.38	0.36	0.45	44.60	249	236	13	3	2	0.72
3	2	0.52	0.45	0.49	61.00	361	333	28	4	1	0.39
3	3	0.22	0.22	0.15	31.50	157.5	157.5	0	5	0	0.92
3	4	0.04	0.03	0.04	2.60	15	14	1	3	1	0.83
3	5	0.04	0.03	0.04	9.00	51	48	3	4	1	0.42
3	6	0.25	0.23	0.23	31.40	175	166	9	4	1	0.81
Average		**0.24**	**0.22**	**0.23**	**30.02**	**168.08**	**159.08**	**9.00**	**3.83**	**1.00**	**0.68**
p-value (T12)		0.108	0.108	0.748	0.109	0.109	0.109	**0.058***	**0.057***	**0.057***	0.336
p-value (T13)		0.422	0.872	0.422	0.872	0.423	0.631	0.935	0.934	0.867	0.377
p-value (T23)		**0.010****	**0.010****	**0.091***	**0.010****	**0.010****	**0.010****	**0.007*****	**0.006*****	**0.006*****	0.521

RAD and RD are a relative absolute deviation and relative deviation.
AB indicates Average Bias, TD is Total Dispersion, PD is Positive Dispersion, ND is Negative Dispersion, Boom and Burst is Boom duration and Burst Duration
p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 1.3

Table A1.4 - Herding the average prices (executed offers only)

The following tables report herding decisions to the average prices and average prices with 5% interval (executed offers).

(A) Exact average prices

Market	F (Executed)	Percentage	FAverage (Executed)	Percentage
1	8.13	59%	0.13	1%
2	1.39	26%	0.53	10%
3	2.46	26%	0.00	0%
4	2.72	28%	0.26	3%
5	6.05	43%	1.2	9%
6	0.79	14%	0.00	0%
7	2.13	30%	0.00	0%
8	1.05	11%	0.13	1%
9	2.13	25%	0.13	2%
10	1.4	26%	0.26	5%
11	1.79	31%	0.40	7%
12	0.92	15%	0.26	4%
Mean	**2.58**	**28%**	**0.28**	**3%**
p-value F(Executed) vs. Faverage (Executed)				**0.000*** **

F (Executed) is the number of times participants follow the exact prices offered by the first, second and third-ranked leaders and the offers are traded; FAverage is following the average executed price in the market. p-values are taken from Wilcoxon signed-rank test (*** p<0.01, ** p<0.05, * p<0.1)

(B) Average prices with 5% interval

Market	FIn (Executed)	Percentage	FAverageIn (Executed)	Percentage
1	10.92	79%	11.2	81%
2	1.79	34%	1.46	27%
3	3.12	33%	1.06	11%
4	4.92	51%	2.26	24%
5	9.66	69%	8.8	63%
6	1.53	28%	1.06	19%
7	2.53	36%	2.4	34%
8	1.52	16%	.66	7%
9	3.79	44%	2.13	25%
10	2.93	54%	3.6	66%
11	1.86	32%	1.2	20%
12	1.8	28%	3.33	53%
Mean	**3.86**	**42%**	**3.26**	**36%**
p-value F-In (Executed) vs. FaverageIn (Executed)				**0.002*** **

Fin (Executed) is the number of times participants follow the exact prices with 5% interval offered by the first, second and third-ranked leaders and the offers are traded; FAverageIn is following the average executed price with 5% interval in the market. p-values are taken from Wilcoxon signed-rank test (*** p<0.01, ** p<0.05, * p<0.1)

Table A1.5 - Herding the average prices (All offers)

The following tables report herding decisions to the average prices and average prices with 5% interval (all offers).

(A) Exact average prices

Market	F (All)	Percentage	FAverage (All)	Percentage
1	18.98	39%	0.66	1%
2	5.06	11%	1.46	3%
3	21.85	24%	0.00	0%
4	7.39	21%	0.60	2%
5	12.59	30%	1.33	3%
6	4.33	16%	0.00	0%
7	5.13	15%	0.00	0%
8	8.52	16%	0.66	1%
9	7.59	20%	0.40	1%
10	3.79	12%	0.46	1%
11	10.25	21%	1.06	2%
12	7.19	20%	1.40	4%
Mean	**9.39**	**20%**	**0.67**	**2%**
p-value F(All) vs. Faverage (All)				**0.000*****

F (All) is the number of times participants follow the exact prices offered by the first, second and third-ranked leaders; FAverage (All) is following the average prices in the market.
p-values are taken from Wilcoxon signed-rank test (*** p<0.01, ** p<0.05, * p<0.1)

(B) Average prices with 5% interval

Market	FIn (All)	Percentage	FAverageIn (All)	Percentage
1	29.99	61%	16.40	33%
2	10.19	23%	7.00	16%
3	29.65	32%	5.46	6%
4	13.86	39%	6.20	17%
5	23.32	55%	14.46	34%
6	7.66	28%	3.20	12%
7	8.19	24%	3.93	11%
8	11.19	21%	3.33	6%
9	13.19	36%	5.00	13%
10	12.92	41%	7.73	25%
11	11.19	23%	3.06	6%
12	11.92	33%	9.00	25%
Mean	**15.27**	**35%**	**7.06**	**17%**
p-value FIn(All) vs. FaverageIn (All)				**0.002*****

FIn (All) is the number of times participants follow the exact prices with 5% interval offered by the first, second and third-ranked leaders; FAverageIn (All) is following the average prices with 5% interval in the market.
p-values are taken from Wilcoxon signed-rank test (*** p<0.01, ** p<0.05, * p<0.1)

APPENDIX 1.4

Table A1.6 - Characteristics of the subject pool

This table reports the characteristics of the subject pool. Different measures are used including overconfidence (miscalibration and better than average), maths skill, self-monitoring ability, risk preference, gender and nationality.

Characteristics/ Personalities	Value/ Percentage
Miscalibration	2.00
Maths skill	3.92
Self-monitor	8.66
Risk (Holt and Laury, 2002)	6.38
Better than average	26.07%
Men	44.55%
Western students	33.18%

Table A1.7 - Characteristics of finance and non-finance students

This table compares the characteristics of finance and non-finance students. The characteristics include overconfidence (miscalibration and better than average), maths skill, self-monitoring ability, risk preference, gender and nationality.

Characteristics/ Personalities	Non-Finance	Finance	p-value
Miscalibration	1.85	2.59	0.100
Math skill	3.86	4.12	**0.049****
Self-monitor	8.68	8.35	0.679
Risk (Holt and Laury, 2002)	6.56	5.71	0.135
Better than average	21.43%	47%	**0.000*****
Men	45.24%	51%	0.492
Western students	37.30%	16%	**0.007*****

p-values are taken from Mann–Whitney U test
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 1.5

Table A1.8 - Treatment effect and individual differences on wealth

This table reports the regression results on the impact of treatment effect and individual differences on wealth. The dependent variable in the OLS regression is the average wealth per participant in a particular market while the fixed effect and random effect regressions are conducted with participants' wealth in a particular period using panel data.

	OLS1	OLS2	FE	RE1	RE2
Leaderboard	0.050	0.077		0.066	0.074
	(0.108)	(0.104)		(0.081)	(0.083)
Costly-information	**-0.230***	**-0.287****		**0.382*****	**0.377*****
	(0.124)	(0.099)		(0.093)	(0.093)
Period			0.002	0.002	0.002
			(0.006)	(0.006)	(0.006)
Period x Leaderboard			-0.001	-0.001	0.001
			(0.008)	(0.008)	(0.008)
Period x costly-information			**-0.041*****	**-0.041*****	**-0.041*****
			(0.009)	(0.009)	(0.009)
Miscalibration		-0.141			0.003
		(0.084)			(0.012)
Maths		-0.083			0.020
		(0.076)			(0.018)
Self-monitoring ability		-0.022			0.006
		(0.037)			(0.006)
Risk preference		-0.027			0.009
		(0.058)			(0.010)
Better-than-average		0.004			-0.016
		(0.003)			(0.050)
Gender		0.002			**0.078***
		(0.002)			(0.044)
Major		0.003			**0.145*****
		(0.002)			(0.048)
Nationality		-0.000			0.066
		(0.003)			(0.049)
Age		**-0.069***			-0.003
		(0.038)			(0.008)
Constant	7.197***	9.372***	6.957***	6.829***	6.593***
	(0.088)	(1.203)	(0.029)	(0.066)	(0.226)
Observations	24	24	216	216	211
R - squared	0.2482	0.7783	0.0127	0.0120	0.0301

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 1.6

Table A1.9 - Individual differences on herding decisions

This table reports the impacts of individual differences on **herding decisions** (exact price and 5% interval) using panel data with the number of time participants follow the exact prices and prices with 5% interval offered by the first-ranked leaders and the top three leaders as the dependent variable. The results are taken from random effect regression with panel data.

Individual difference	F1times	Ftimes	F1timesin	Ftimesin
Miscalibration	0.024	0.002	0.051	0.036
	(0.037)	(0.057)	(0.066)	(0.083)
Maths	**-0.158****	-0.138	-0.136	-0.098
	(0.065)	(0.098)	(0.114)	(0.144)
Self-monitoring ability	-0.015	**-0.049***	-0.034	**-0.076***
	(0.020)	(0.030)	(0.035)	(0.044)
Risk preference	**-0.068****	-0.044	-0.060	-0.048
	(0.032)	(0.048)	(0.056)	(0.070)
Better-than -average	-0.044	0.063	0.201	0.333
	(0.143)	(0.216)	(0.250)	(0.317)
Gender	0.157	0.322	**0.561****	**0.612***
	(0.143)	(0.217)	(0.251)	(0.318)
Major	-0.253	**-0.582****	**-0.612****	**-0.957****
	(0.178)	(0.269)	(0.312)	(0.395)
Nationality	**-0.432*****	**-0.717*****	**-0.642****	**-0.942****
	(0.165)	(0.250)	(0.290)	(0.367)
Age	-0.041	-0.050	-0.061	-0.104
	(0.032)	(0.048)	(0.056)	(0.071)
Constant	2.847***	3.735***	3.783***	5.602***
	(0.806)	(1.220)	(1.415)	(1.791)
Observations	1545	1545	1545	1545
R – squared	0.0303	0.0405	0.0329	0.0555

F1times is the number of time participants follow the exact prices offered by the first-ranked leaders; Ftimes is the number of times participants follow the exact prices offered by the first three leaders. F1timesin refers the number of times participant follow the prices with 5% interval offered by the first-ranked leaders while Ftimesin refers the number of times participants follow the prices with 5% interval offered by the top three leaders.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 1.7

Table A1.10 - Impact of herd behaviour on wealth

This table reports the impact of herding decisions on wealth.

Herd behaviour	Wealth
Follow the 1st leaders	0.025
Follow the 2nd leaders	-0.028
Follow the 3rd leaders	-0.010
Follow the leaders	-0.015
Follow the 1st leaders (5% interval)	**0.053****
Follow the 2nd leaders (5% interval)	**-0.062****
Follow the 3rd leaders (5% interval)	**-0.047***
Follow the leaders (5% interval)	-0.008

The correlations are taken from Spearman rho correlations
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

APPENDIX 1.8

THE INSTRUCTION OF THE EXPERIMENT

WELCOME TO CENTRE FOR RESEARCH IN BEHAVIOURAL SCIENCES (CRIBS).

Dear Participants! We welcome you to this experimental session and ask you to refrain from talking to each other for the duration of the experiment. If you face any difficulty, contact one of the experimenters.

This is an experiment in the economics of market decision making. If you follow the instructions and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. Money in these experiments is expressed in ECU (Experimental Currency Unit). The exchange rate between ECU and GBP will be presented in every case.

TREATMENT 1: THE BASE

The experiment will consist of a sequence of 15 trading periods in which you will have the opportunity to buy and sell stocks. Each period will last for 120 seconds.

At the beginning of period 1, you will be assigned to a group of 9 people. Every person in the groups will be given the same amount of money (280 ECU) and the same number of assets (4 assets), which is called as stocks or shares in this context.

You can use your money to buy stocks. By owning stocks, you will receive dividends at the end of each period. The probability of dividend payment is described as follows:

- 25% the dividend will be 40 ECU;
- 25% the dividend will be 16 ECU;
- 25% the dividend will be 8 ECU;
- 25% the dividend will be 0 ECU;

The dividend payment is randomly drawn and is announced at the end of each period. Therefore, you will receive the dividend for 15 times if you hold an asset during 15 periods. After paying the dividend at the end of period 15, the asset value will be 0.

When you buy a stock, your Money decreases by the price of the purchase and your stocks increase by one. When you sell a stock, your Money increases by the price of the sale and your stocks decrease by one.

The number of stocks you get at the end of each period will be the start stock for the next period, which is calculated by the following formula:

Stock = Start Stock + Number of Buying Stocks – Number of Selling Stocks.

The money you get at the end of each period will be the start money for the next period, which is calculated by the following formula:

Money = Start Money + Selling Price*Number of Selling Stocks – Buying Price*Number of Buying Stocks + Dividend Payment*Number of remaining Stocks.

Your wealth in a period is calculated as follows:

Your wealth = Money + Number of Asset*16*(15-Period)

Your profit in a period is calculated as follows:

Profit = Your wealth in the current period – Your wealth in the previous period

For example, your initial money at the beginning of period 1 is 280 ECU; your initial number of stocks is 4. During period 1, you buy one stock at the price of 20 ECU and sell one stock at the price of 30 ECU, the dividend payment at the end of this period is 40 ECU per stock.

Your remaining Stock will be:

Stock = 4 + 1 – 1 = 4 (Stock);

Your money will be:

Money = 280 + 30*1 – 20*1 + 40*4 = 450 (ECU);

Your wealth after period 1 is:

Wealth = 450 + 4*16*14 = 1346 (ECU);

Your initial wealth is 1240.

That means your profit is:

Profit = 1346 – 1240 = 106 (ECU);

In this example, four stocks and 450 ECU will be the number of Stocks and the amount of money you have in period 2.

Trading procedure:

On the left-hand side of your trading screen, you can see the amount of Money and the number of Stocks you have.

If you would like to offer to sell a stock, use the text area entitled **"Submit offers to sell"**. In that text area, you can enter the price at which you are offering to sell a stock, and then select **"Confirm"**. All the offering prices will appear in the **"Selling prices"** column. The **lowest ask price** will always be on the top of that column. If you are interested in any offer on the list, you can select the price at which you are willing to buy a stock and press **"BUY"**.

Similarly, if you would like to bid to buy a stock, use the text area entitled **"Submit bids to buy"**. In that text area, you can enter the price at which you are bidding to buy a stock, and then select **"Confirm"**. All the bidding prices will appear in the **"Buying prices"** column. The **highest bid price** will always be on the top of that column. If you are interested in any bid in the list, you can select the price at which you are willing to sell and press **"SELL"**.

The "Trading prices" column present all the successful selling and buying transactions.

After each period, you will receive the information on your performance including the amount of money you have before dividend, dividend per share in the previous period, the number of shares you have, your total dividend income, your total amount of money after dividend and your total number of stocks.

Payment

Your payment will be calculated based on your total wealth at the end of Period 15. The exchange rate will be:

124 ECU = 1 GBP

TREATMENT 2: THE *LEADERBOARD*

The experiment will consist of a sequence of 15 trading periods in which you will have the opportunity to buy and sell stocks. Each period will last for 120 seconds.

At the beginning of period 1, you will be assigned to a group of 9 people. Every person in the groups will be given the same amount of money (280 ECU) and the same number of assets (4 assets), which is called as stocks or shares in this context.

You can use your money to buy stocks. By owning stocks, you will receive dividends at the end of each period. The probability of dividend payment is described as follows:

- 25% the dividend will be 40 ECU;
- 25% the dividend will be 16 ECU;
- 25% the dividend will be 8 ECU;
- 25% the dividend will be 0 ECU;

The dividend payment is randomly drawn and is announced at the end of each period. Therefore, you will receive the dividend for 15 times if you hold an asset during 15 periods. After paying the dividend at the end of period 15, the asset value will be 0.

When you buy a stock, your Money decreases by the price of the purchase and your stocks increase by one. When you sell a stock, your Money increases by the price of the sale and your stocks decrease by one.

The number of stocks you get at the end of each period will be the start stock for the next period, which is calculated by the following formula:

Stock = Start Stock + Number of Buying Stocks – Number of Selling Stocks.

The money you get at the end of each period will be the start money for the next period, which is calculated by the following formula:

Money = Start Money + Selling Price*Number of Selling Stocks – Buying Price*Number of Buying Stocks+ Dividend Payment*Number of remaining Stocks.

Your wealth in a period is calculated as follows:

Your wealth = Money + Number of Asset*16*(15-Period)

Your profit in a period is calculated as follows:

Profit = Your wealth in the current period – Your wealth in the previous period

For example, your initial money at the beginning of period 1 is 280 ECU; your initial number of stocks is 4. During period 1, you buy one stock at a price 20 ECU and sell one stock at the price of 30 ECU, the dividend payment at the end of this period is 40 ECU per stock.

Your remaining Stock will be:

Stock = 4 + 1 – 1 = 4 (Stock)

Your money will be:

Money = 280 + 30*1 – 20*1 + 40*4 = 450 (ECU);

Your wealth after period 1 is:

Wealth = 450 + 4*16*14 = 1346 (ECU);

Your initial wealth is 1240.

That means your profit is:

Profit = 1346 – 1240 = 106;

In this example, four stocks and 450 ECU will be the number of Stocks and the amount of money you have in period 2.

Trading procedure:

On the left-hand side of your trading screen, you can see the available Money you have to buy Stocks and the number of Stocks you have.

If you would like to offer to sell a stock, use the text area entitled **"Submit offers to sell"**. In that text area, you can enter the price at which you are offering to sell a stock, and then select **"Confirm"**. All the offering prices will appear in the **"Selling prices"** column. The **lowest ask price** will always be on the top of that column. If you are interested in any offer on the list, you can select the price at which you are willing to buy a stock and press **"BUY"**.

Similarly, if you would like to bid to buy a stock, use the text area entitled **"Submit bids to buy"**. In that text area, you can enter the price at which you are bidding to buy a stock, and then select **"Confirm"**. All the bidding prices will appear in the **"Buying prices"** column. The **highest bid price** will always be on the top of that column. If you are interested in any bid in the list, you can select the price at which you are willing to sell and press **"SELL"**.

The "Trading prices" column presents all the successful selling and buying transactions.

After each period, you will receive the information on your performance including the amount of money you have before dividend, dividend per share in the previous period, the number of shares you have, your total dividend income, your total amount of money after dividend and your total number of shares.

Leaderboard

After each period, you can see a leaderboard which expresses how all participants in your group performed in the previous period. The leaderboard shows the ranks and profits of all participants in the same group. Also, the leaderboard shows the trading prices and ID of the participants who make offers and/or bids in the previous period.

For example, you can see a picture of leaderboard below. From the upper table, participant 6 is the best performer with a profit of 140 ECU; the second position belongs to participant 7 with 120 ECU, so on and so forth. The lower table shows that the current participant is participant 9. During the last period, participant 1 sold 1 Stock to Participant 6 at the price of 100 ECU; participant 2 sold 1 Stock to Participant 7 at the price of 120 ECU; participant 4 sold 1 Stock to Participant 8 at the price of 140 ECU; and participant 5 sold 1 Stock to participant 9 at the price of 160 ECU. As you are participant 9 in this case, you rank fourth in the leaderboard, and you bought 1 Asset at the price of 160 ECU.

Payment

Your payment will be calculated based on your total wealth at the end of Period 15. The exchange rate will be:

124 ECU = 1 GBP

TREATMENT 3: THE COSTLY-INFORMATION

The experiment will consist of a sequence of 15 trading periods in which you will have the opportunity to buy and sell stocks. Each period will last for 120 seconds.

At the beginning of period 1, you will be assigned to a group of 9 people. Every person in the groups will be given the same amount of money (280 ECU) and the same number of assets (4 assets), which is called as stocks or shares in this context.

You can use your money to buy stocks. By owning stocks, you will receive dividends at the end of each period. The probability of dividend payment is described as follows:

- 25% the dividend will be 40 ECU;
- 25% the dividend will be 16 ECU;
- 25% the dividend will be 8 ECU;
- 25% the dividend will be 0 ECU;

The dividend payment is randomly drawn and is announced at the end of each period. Therefore, you will receive the dividend for 15 times if you hold an asset during 15 periods. After paying the dividend at the end of period 15, the asset value will be 0.

When you buy a stock, your Money decreases by the price of the purchase and your stocks increase by one. When you sell a stock, your Money increases by the price of the sale and your stocks decrease by one.

The number of stocks you get at the end of each period will be the start stock for the next period, which is calculated by the following formula:

Stock = Start Stock + Number of Buying Stocks – Number of Selling Stocks.

The money you get at the end of each period will be the start money for the next period, which is calculated by the following formula:

Money = Start Money + Selling Price*Number of Selling Stocks – Buying Price*Number of Buying Stocks+ Dividend Payment*Number of remaining Stocks.

Your wealth in a period is calculated as follows:

Your wealth = Money + Number of Asset*16*(15-Period)

Your profit in a period is calculated as follows:

Profit = Your wealth in the current period – Your wealth in the previous period

For example, your initial money at the beginning of period 1 is 280 ECU; your initial number of stocks is 4. During period 1, you buy one stock at a price 20 ECU and sell one stock at the price of 30 ECU, the dividend payment at the end of this period is 40 ECU per stock.

Your remaining Stock will be:

Stock = 4 + 1 – 1 = 4 (Stock)

Your money will be:

Money = 280 + 30*1 – 20*1 + 40*4 = 450 (ECU);

Your wealth after period 1 is:

Wealth = 450 + 4*16*14 = 1346 (ECU);

Your initial wealth is 1240.

That means your profit is:

Profit = 1346 – 1240 = 106;

In this example, four stocks and 450 ECU will be the number of Stocks and the amount of money you have in period 2.

Trading procedure:

On the left-hand side of your trading screen, you can see the available Money you have to buy Stocks and the number of Stocks you have.

If you would like to offer to sell a stock, use the text area entitled **"Submit offers to sell"**. In that text area, you can enter the price at which you are offering to sell a stock, and then select **"Confirm"**. All the offering prices will appear in the **"Selling prices"** column. The **lowest ask price** will always be on the top of that column. If you are interested in any offer on the list, you can select the price at which you are willing to buy a stock and press **"BUY"**.

Similarly, if you would like to bid to buy a stock, use the text area entitled **"Submit bids to buy"**. In that text area, you can enter the price at which you are bidding to buy a stock, and then select **"Confirm"**. All the bidding prices will appear in the **"Buying prices"** column. The **highest bid price** will always be on the top of that column. If you are interested in any bid in the list, you can select the price at which you are willing to sell and press **"SELL"**.

The "Trading prices" column present all the successful selling and buying transactions.

After each period, you will receive the information on your performance including the amount of money you have before dividend, dividend per share in the previous period, the number of shares you have, your total dividend income, your total amount of money after dividend and your total number of shares.

Costly-information

In this treatment, you have the right to buy the information on leaderboard and trading activities. The leaderboard includes the ranks of all participants and their payoffs during the last period. The trading activities include the price at which participants buy and sell their stocks. This information is very useful for you in the next period. The cost of this information is 20 ECU.

The figures below show the screen that you are asked to buy information or not. If you choose "No", you will be processed directly to the next period. If you choose "Yes", you will be transferred to another screen.

The following screen shows that participant 6 is the participant with the highest profit in the previous period, which is 140 ECU. The second position belongs to participant 7 with 120 ECU. The table on the right-hand side shows that during the previous period, participant 1 sold 1 Stock to participant 6 at the price of 100 ECU; participant 2 sold 1 Stock at the price of 120 ECU to participant 7; participant 3 sold 1 Stock at the price of 140 ECU to participant 8; and participant 4 sold 1 Stock at the price of 160 ECU to Participant 9. As you are participant 9 in this case, you rank fourth in the leaderboard, and you bought 1 Stock at the price of 160 ECU in the previous period.

Payment

Your payment will be calculated based on your total wealth at the end of Period 15. The exchange rate will be:

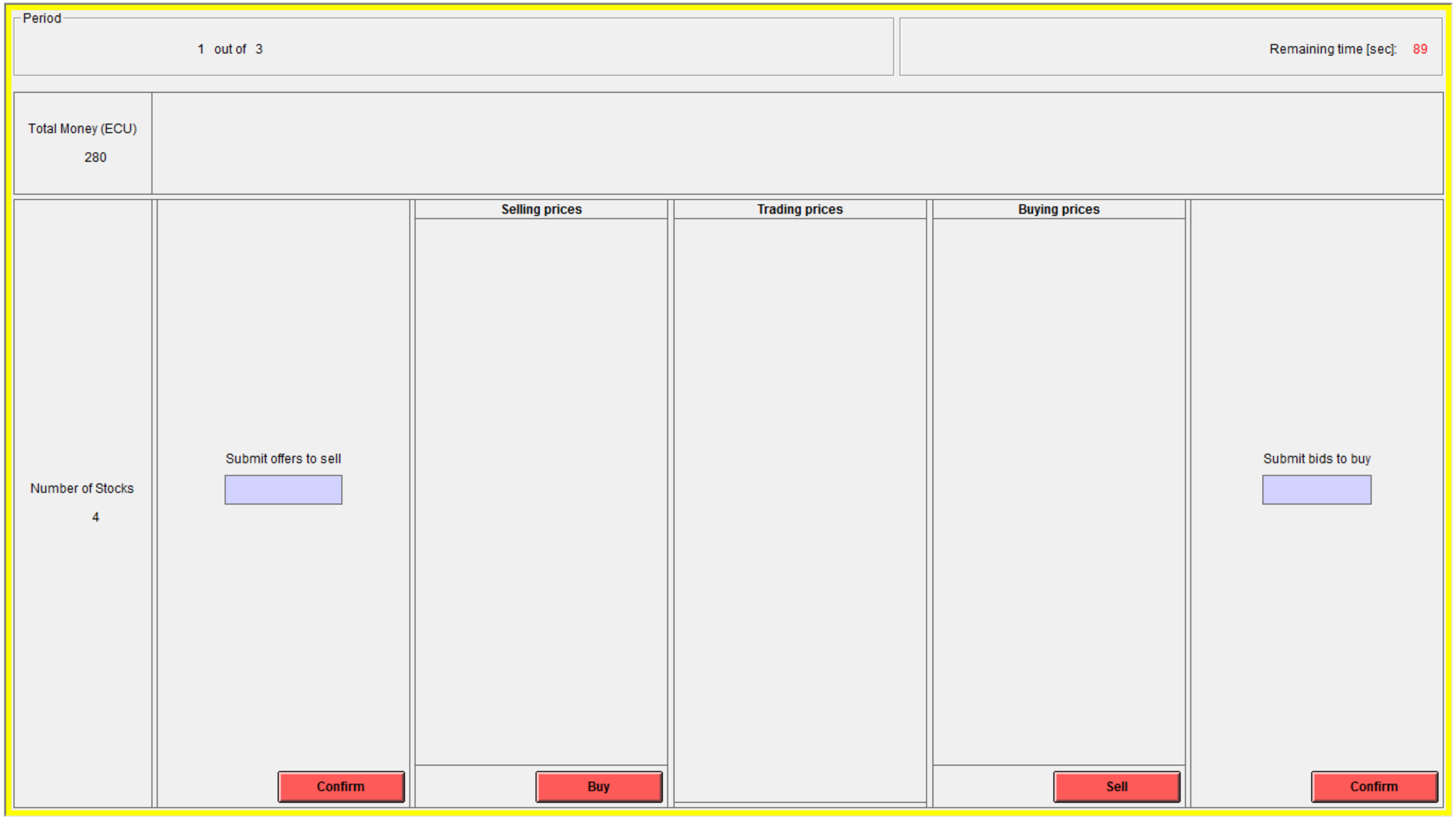
124 ECU = 1GBP

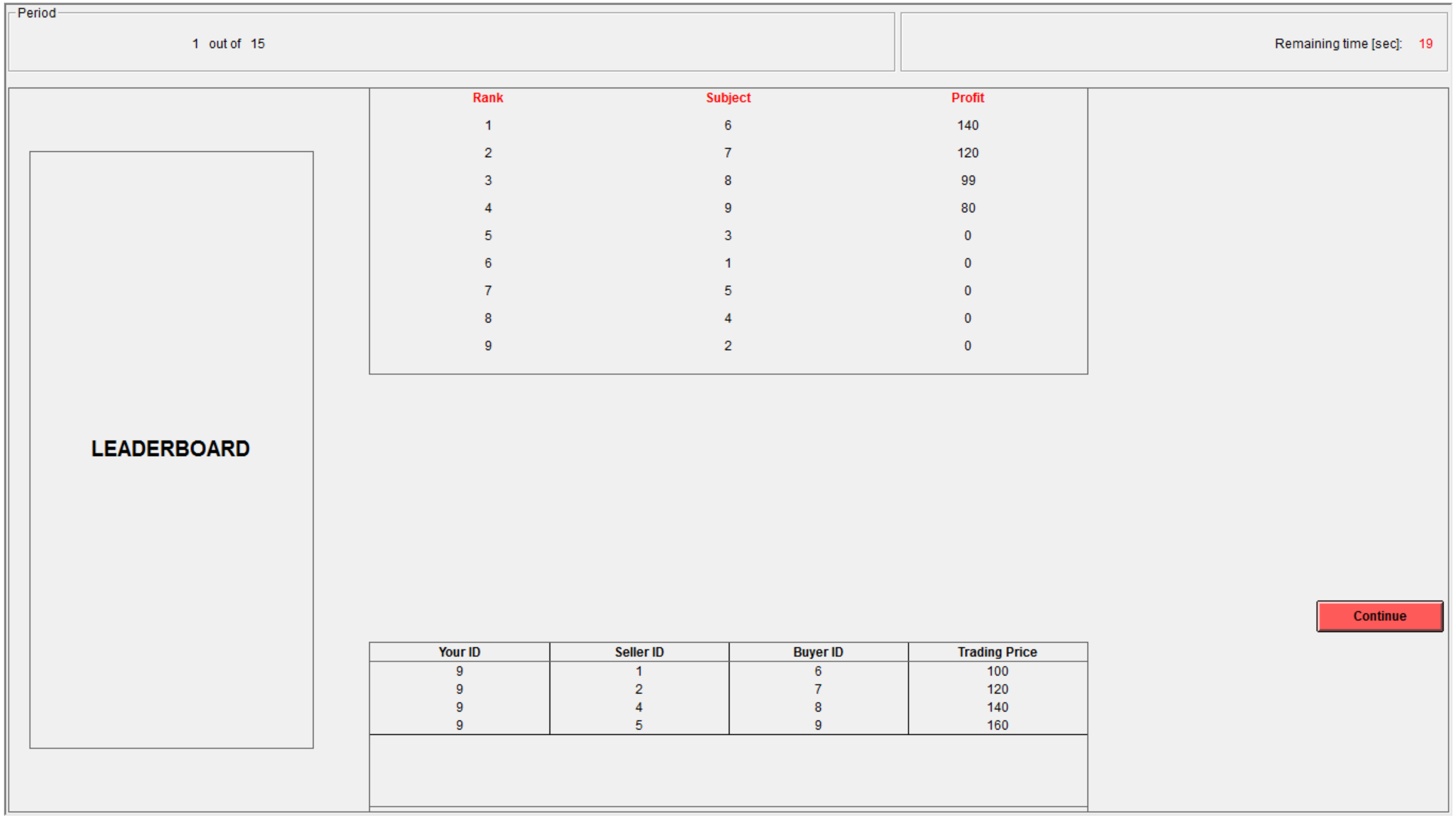
APPENDIX 1.9 - SCREENSHOTS OF THE EXPERIMENT

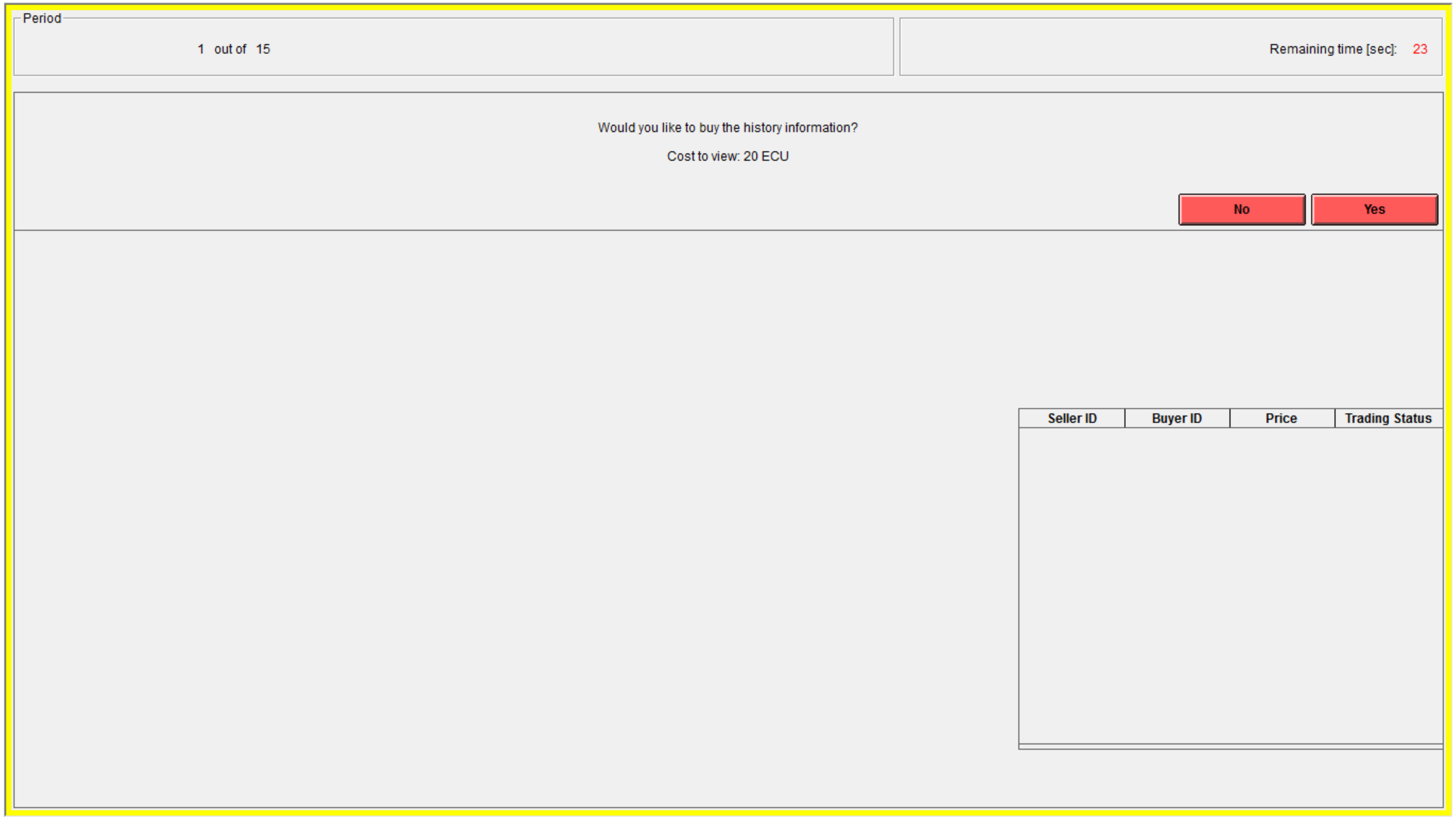
(1) THE BASE

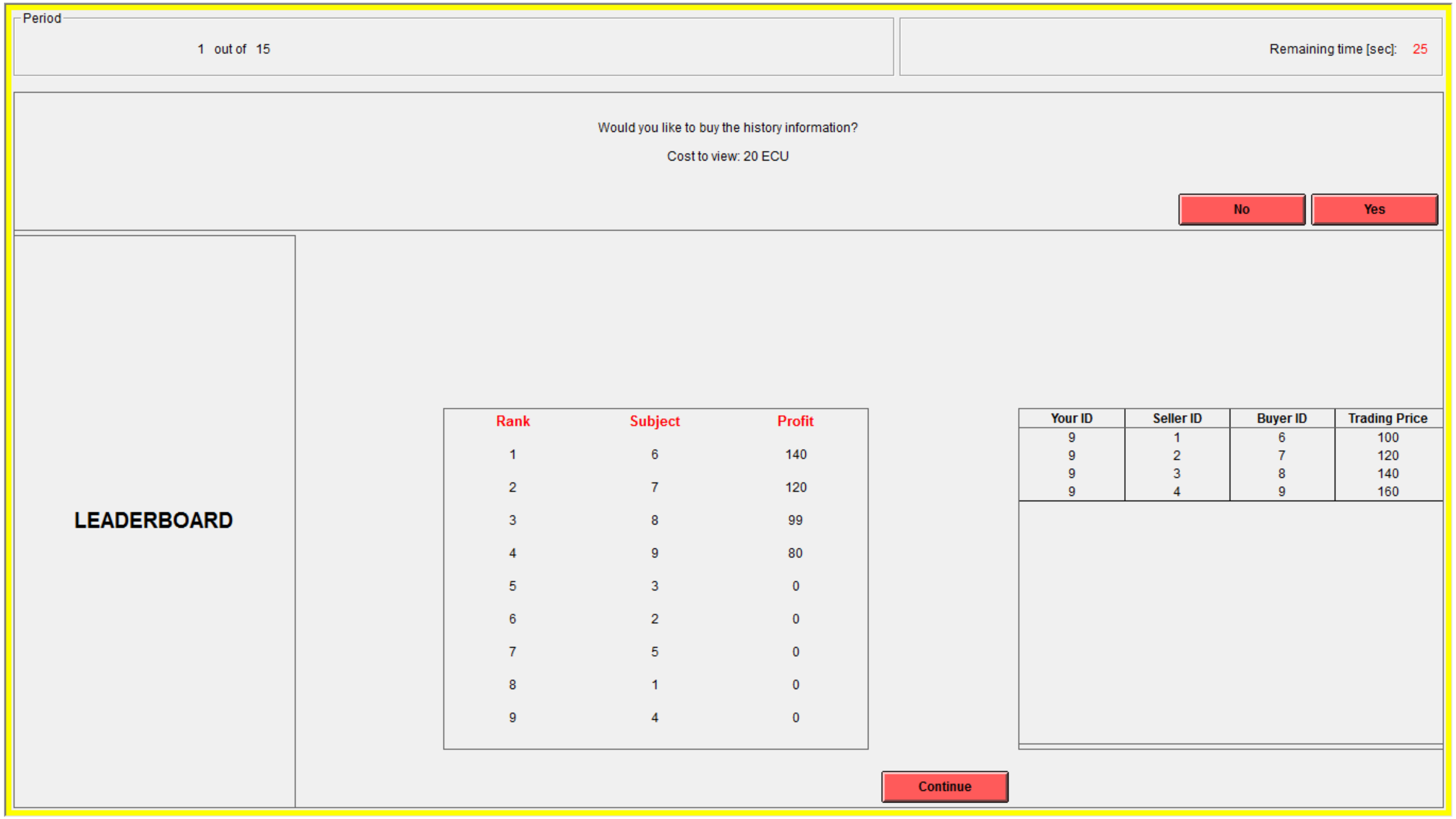
(2) THE LEADERBOARD

(3) THE COSTLY-INFORMATION


Period
1 out of 3
Remaining time [sec]: 89
Total Money (ECU)
280
Selling prices
Trading prices
Buying prices
Number of Stocks
4
Submit offers to sell
Submit bids to buy
Confirm
Buy
Sell
Confirm


Period
1 out of 15
Remaining time [sec]: 19
LEADERBOARD
Rank Subject Profit
1 6 140
2 7 120
3 8 99
4 9 80
5 3 0
6 1 0
7 5 0
8 4 0
9 2 0
Continue
Your ID Seller ID Buyer ID Trading Price
9 1 6 100
9 2 7 120
9 4 8 140
9 5 9 160


Period
1 out of 15
Remaining time [sec]: 23
Would you like to buy the history information?
Cost to view: 20 ECU
No
Yes
Seller ID
Buyer ID
Price
Trading Status


Period
1 out of 15
Remaining time [sec]: 25
Would you like to buy the history information?
Cost to view: 20 ECU
No
Yes
LEADERBOARD
Rank
Subject
Profit
1 6 140
2 7 120
3 8 99
4 9 80
5 3 0
6 2 0
7 5 0
8 1 0
9 4 0
Your ID
Seller ID
Buyer ID
Trading Price
9 1 6 100
9 2 7 120
9 3 8 140
9 4 9 160
Continue

ESSAY 2: HERD BEHAVIOUR IN FINANCIAL MARKETS: AN EXPERIMENTAL APPROACH WITH INFORMATION CASCADE EXPERIMENT

Abstract

This research applies the concept of information cascade to examine herd behaviour in a market with and without a price mechanism. Herd behaviour due to information externality is found to exist at a relatively low level compared to the literature. This behaviour decreases when there is more information released on the market. In such a situation, participants choose to follow their signals or make irrational decisions. We have a treatment where participants receive the information on the decisions of the best performers in a previous session. We do not find any evidence for the presence of herd behaviour due to reputational effect. The result is confirmed in the market with and without a price mechanism. In the price treatment, we separate between participants' beliefs and their purchasing decisions. The results show that while participants herd following their beliefs, they gamble on their purchasing decisions by buying an asset which they do not believe in the potentials. This decision is against the efficient market hypothesis in financial markets. Overconfidence and risk preferences express significant effect on herding decisions.

JEL Classification: C91, D81, G41

Keywords: information cascade, price mechanism, reputational effect, efficient market hypothesis

2.1. Introduction

In the era of information technology, it is easy to look for information online. The available information may lead people to join a crowd of many others who follow the same information. For example, a person travels to a new town knowing nothing about where to go for food. She can easily search for reviews on the consumer-generated contents such as TripAdvisor and make decisions. The results from many studies (see, e.g. Miguéns, Baggio and Costa, 2008; Casaló, Flavián and Guinalíu, 2011) indicate that travellers prefer relying on the recommendations of the peers and follow the advice. This tendency happens with other decisions such as booking a hotel, buying a new house or even applying for a university. We make such a decision since we trust the "wisdom of the crowd" and believe others have more information, which is the root of herd behaviour due to information externality (information cascade). Banerjee (1992) identify that information cascade is the situation people choose to follow others regardless of their private information. Celen and Kariv (2004) argue that the concept of herd behaviour is broader, which is the situation people make identical decisions. In this paper, we use information cascade and herd behaviour interchangeably, with the meaning of herd behaviour due to informational externality.

Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) independently construct a model for herd behaviour. In the model, people make decisions in sequence. Participants update their beliefs after observing the decisions of others using conditional probability (Bayes' rule). Based on the theoretical model, Anderson and Holt (1997) (hereafter AH) conduct the information cascade experiment to examine the existence of herd behaviour due to information cascade. This approach is a novelty at the time since studies claim that market data is too noisy for testing herd behaviour (Fama, 1998; Cipriani and Guarino, 2005). AH confirm the presence of information cascade in their experiment and use Bayesian updating rule to explain this behaviour. Accordingly, people update the probability of occurrence not only based on private information but also on public data. Other studies have used the experiment since then and reveal similar results (Nöth and Weber, 2002; Alevy, Haigh and List, 2007; Ziegelmeyer et al., 2010). However, the magnitude of herd behaviour decreases recently. More importantly, the following decisions are found to occur due to heuristics, but not Bayesian updating (Huck and Oechssler, 2000). The results play as a challenge for the robustness of the information cascade experiment to examine herd behaviour.

Also, the design of the information cascade experiment is not appropriate to study herd behaviour in financial markets because participants do not pay for their decisions. In other words, there is a lack of a price mechanism. Avery and Zemsky (1998) state that information cascade disappears when the participants pay for the assets. In such situations, they choose to make decisions based on the offered price but not the predecessors. The results from Cipriani and Guarino (2005) and Drehmann, Oechssler and Roider (2005) are in line with this finding.

The presence of herd behaviour in financial markets could be a threat to financial stability (see, e.g. Demirer and Kutan, 2006) or prevent investors from reducing their risk exposure via diversification (see, e.g. Chang et al., 2000, Chiang and Zheng, 2010, Morelli, 2010). Due to the need of finding the presence of herd behaviour in financial markets and the characteristics of this behaviour, we develop a modified design of the information cascade experiment, which allows us to examine the existence of herd behaviour in a market with a price mechanism. Also, we could identify the determinants of herding decisions, which are information externality, reputational effects and individual differences.

This paper adds to the literature in many strands. Firstly, we revisit the presence of herd behaviour due to informational externality by conducting the standard experiment. Secondly, we add to the setting a reputational feature where people know the decisions of the one who earn the highest payoff. We expect to find the presence of herd behaviour due to reputational externality. Bikhchandani and Sharma (2000) indicate that reputation plays a vital role in market decision-making. This design helps us to explain why people make identical decisions and whom the market is following.

Additionally, one of the contributions of this paper is that we attach a price mechanism in the standard design to replicate the behaviour in financial markets. The results taken from this treatment (the *price* treatment) are more applicable in the markets. The price is constructed based on the availability of information. More specifically, participants choose which asset between the two (Asset A and Asset B)

they believe in the success possibility and which one they want to invest in given the price of each asset. The available information supporting the success of an asset determines the price. For example, if the available information supports the success of Asset *A*, the price of this asset will increase. This mechanism addresses the features of the efficient market hypothesis. The price mechanism allows us to test for the existence of herd behaviour and the validity of the efficient market hypothesis. More specifically, people face a decision puzzle in which they choose to follow their private information or public decisions and buy an asset depending on its price or the supporting information. The price mechanism is a new feature, which is the main contribution of this paper.

The results show that people still engage in information cascade; however, the magnitude of information cascade is lower than being suggested by AH (1997). Interestingly, reputation does not play a significant impact on the level of information cascade. Instead, participants tend to make irrational decisions when there is more information revealed. In the *price* treatment, a proportion of participants purchase an asset based on its offered price, although they do not believe in the success of the asset. This finding is against the fundamental analysis in investment. Finally, individual differences, including overconfidence and risk preference, play a significant role in herding and investing decisions.

This paper makes two main contributions to the existing literature on herd behaviour and its characteristics. Firstly, this paper is one of the few studies examining herd behaviour due to reputational externality, especially in the context of an experimental financial market. Secondly, the price mechanism design is unique, which allows testing the existence of herd behaviour in financial markets and efficient market hypothesis.

The introduction is followed by a literature review (section 2), experimental design (section 3), results and discussions (section 4) and a conclusion (section 5).

2.2. Related Literature

AH (1997), in their seminal paper, construct an experiment to examine the existence of information cascade according to the model of BHW. They use the Urn game to detect information cascade. In particular, there are two Urns with the same probability to be chosen (Ω = {A, B}). Participants were asked to choose between Urn A and Urn B. Before making this decision; they receive a private signal $s_i \epsilon \{a, b\}$ about the chosen probability, in which Pr ($A|a$) > Pr ($B|a$) and Pr ($B|b$) > Pr($A|b$). The probability of signal precision is identical to all participants $Pr\ (s = \omega|\omega)$. If the choice of a participant (c) is correct ($c_i = \omega$), she receives a payoff of 1; otherwise, she receives 0. Before making a decision, the participant can observe the decisions of other participants who make decisions before her $H_i = \{c_{1,}c_{2,\ldots,}c_{n-1}\}$. If $Pr\ (\omega = A)$ and $Pr\ (\omega = B)$ are common knowledge and the participant updates her belief according to Bayesian's rule, the probability of selecting the right Urn ($Pr\ (\omega|H_i, s_i)$ can be easily calculated. Information cascade may presence whenever an imbalanced event occurs. Imbalanced events indicate the situation that it is optimal to follow others regardless of the private information. For example, if a participant receives a signal "a" while knowing the first two participants chose Urn B, it is optimal to choose Urn B regardless the private signal "a" (Pr($B|b$,b,a)). AH (1997) confirm the presence of information cascade in most of the imbalanced events (73% of the imbalanced events). However, Huck and Oechssler (2000) argue that there is little support for rational updating while heuristics play as a better explanation for participants' decisions. In their setup, participants are asked to explain "why they made information cascade decisions". Although participants are students from economics and business administration who have just finished a microeconomics module covering Bayesian decision making, they could not explain why they made such cascade decisions.

Despite the doubt of employing Bayesian updating to explain information cascade, many following studies apply the concept of information cascade experiment to examine information cascade and herd behaviour. Alevy, Haigh and List (2007) designed a 2x2x2 facial across Urn types including symmetric and asymmetric treatments with gain and loss domains and two subject pools with students and financial professionals. The purpose of this study is to make a comparison between students and professionals in decision making, cascade formation and behaviour during gain and loss domains. The results show that market professionals and students behave differently. In particular, market professionals are better in recognising the quality of signals and are not affected by the domain of earnings (gain and loss). Nöth and Weber (2002) add to the information cascade experiment the qualities of information, which is a strong or weak signal. By observing how participants update their information, the authors can identify how many times the participants deviate Bayesian rule. The authors explain that this deviation happens since participants are too overconfident about the quality of their private signals and irrationally follow their information. Ziegelmeyer et al. (2010) modify the Urn design with low-informed and high-informed participants. They reveal that high informed participants still follow despite their advantage information. They confirm the existence of information cascade and argue that cascades are not fragile. Other features of information cascade are examined by employing this experiment including payoff externalities and reputation (Drehmann, Oechssler and Roider, 2007); majority rule of group effect (Hung and Plott, 2001); depth of reasoning (Kübler and Weizsäcker, 2004); group size and group effect (Fahr and Irlenbusch, 2011).

Despite the popularity of this experiment, Cipriani and Guarino (2005) state that information cascade cannot be directly applied to examine herd behaviour in financial markets where there is a price mechanism. In other words, participants do not pay for choosing an Urn while they pay to get an asset in the financial markets. By employing the model of Glosten and Milgrom (1985), Cipriani and Guarino (2005) construct an experiment to examine herd behaviour in financial markets. In particular, there is market makers and traders in a market where traders have to pay for their assets. In this context, traders do not care about the decisions of other people and focus on the offered price only. The result is consistent with the theory suggested by Avery and Zemsky (1998) in the disappearance of herd behaviour where there is a price mechanism. Drehmann, Oechssler and Roider (2005) add the price mechanism in the information cascade experiment by letting the price move in line with participants' decisions. They conclude that information cascade does not only disappear in the treatment where a price mechanism exists; participants also make contrarian decisions. In other words, participants made decisions to go against the market, which is considered as contrarian behaviour. Drehmann, Oechssler and Roider (2005) suggest that contrarian behaviour occurs since participants are sceptical about the rationality of their peers. Although Avery and Zemsky (1998) concern about the presence of herd behaviour in financial markets with a price mechanism, they argue that other externalities except price can be the motivation for herding such as reputational and compensational externality.

2.3. Experimental design

Information cascade (AH) is a standard experiment which is used to examine herd behaviour due to information externality. This paper applies the concept of AH with modifications to examine the existence of herd behaviour due to informational and reputational effect. Also, a price mechanism will be added to the standard design to investigate the presence of herding in a market where participants pay for their decisions. In particular, participants are asked to choose between two assets (A and B) based on public and private information. The chosen asset is the one the participants think it would be successful. After choosing the assets, participants are asked to make decisions which asset (A or B) they would like to buy. The price of asset A and B depends on the available information supporting the success of asset A and B.

The experiment includes four treatments, which are the *base*, the *info*, the *price* and the *info&price*. The *base* treatment follows the concept of AH and acts as a base case. In the *info* treatment, participants receive information about the choices and payoffs of a person who get the highest payoff in a previous session. This design is used to test for herd behaviour due to the reputational effect. A price mechanism, which is determined by the available information in the market, will be introduced in the *price* treatment, in which participants pay to get the asset. Finally, the *info&price* treatment combines two features of the *info* treatment and the *price* treatment.

Treatment 1: *base* (without information on the best performance and without a price mechanism).

This treatment is the base case, which replicates the symmetric design of AH. Specifically, six participants play the information cascade for ten times (10 periods). The task is choosing the successful asset between Asset A and Asset B. The probability of success is equal to the two assets, which is:

$$P(A) = P(B) = 50\%$$

Before making the decision, participants receive a signal from a computerised investment banker, which is signal "a" or signal "b". The investment banker is an expert, but he cannot make a perfect prediction. Therefore, the precise probability of the signal is:

$$P(A/a) = P(B/b) = 2/3\ (66.67\%)$$

Participants make decisions in sequence. Apart from the private signal, they are informed about the decisions of their predecessors. Based on this information, participants are expected to update their beliefs on the successful asset according to Bayesian rule. If participants choose the right asset, they earn 10 ECU (experimental currency unit); otherwise, they receive zero ECU. We expect information cascade occurs wherever there is an imbalanced event. Imbalanced events indicate the situation where it is optimal to follow the predecessors rather than participants' private information. For example, a participant makes decisions in the fourth order of the sequence. Her private signal is "b" while the decisions of the three participants making decisions before him are Asset A, Asset A and Asset A. Those choices infer the prior private signals should be "a", "a" and "a". In this situation, it is optimal for the fourth participant to choose Asset A since the Bayesian probability of success is higher for Asset A (80%). In other words, she should disregard his private information to follow the market.

Hypothesis 1: The imbalance of the previously inferred signals causes information cascade.

Treatment 2: *info* (with information on the performance of the best performer and without a price mechanism)

In this treatment, besides the signal from the investment banker and decisions from previous investors, participants also receive the decisions of the one who gets the highest payoff in the *base* treatment. Although this extra information is irrelevant, we expect the participants to take this information into account. The one who gets the highest payoff has a better reputation. Therefore, the participants may make more herding decisions due to reputational externality (Scharfstein and Stein, 1990).

Hypothesis 2: Information cascade increases due to reputational externality.

Treatment 3: ***price*** (without information on the performance of the best performers and with a price mechanism)

The main drawback of AH experiment is that participants do not pay for their decisions. In other words, there is no price mechanism, which is one of the main features of financial markets, in the information cascade experiment. Following the suggestion of Avery and Zemsky (1998), we add a price mechanism to the experiment.

Similar to the last two treatments, there are two assets in the market (asset A and asset B) which have an equally successful probability:

$$\mathrm{P}(A) = \mathrm{P}(B) = 50\%$$

To determine which asset will be successful, a computerised investment banker gives two types of signals to investors, which are a or b with the precise probability as follows:

$$\mathrm{P}(A/a) = \mathrm{P}(B/b) = 2/3\ (66.67\%)$$

Again, six participants play the ten independent periods. Different to the two previous treatments, participants make two decisions this in treatment: (i) which asset they think is successful (Asset A or Asset B); (ii) which asset they want to purchase (Asset A or Asset B) given the prices of the two assets. If they choose to purchase the successful asset, their payoff is calculated by taking the fundamental value of the asset (10 ECU) minus the purchasing price. Otherwise, the purchasing price will be their loss (the fundamental value of the asset is 0).

$$\text{Payoff} = \text{asset value (10 or 0)} - \text{purchasing price}$$

The asset price is set to move according to the Bayesian rule, which is presented in AH:

$$P(A|n, m) = \frac{2^n}{2^{n+}2^m}$$

Where n is the number of times the investment bankers provide “a” signal and m is the number of times the investment bankers provide “b” signal[6].

[6] The price of asset A and asset B can be found in Appendix 2.2 in case that the signals six participants sequentially receive are a, a, b, b, b, b, respectively.

The price of Asset *A* and Asset *B* are the successful probability of each asset. With this design, the price of an asset is determined by the available information in the market, which is in line with the efficient market hypothesis (EMH) (Fama, 1970). Avery and Zemsky (1998) argue that information cascade disappears wherever there is a price mechanism since participants make decisions based on the offered prices and do not follow others. This result is experimentally confirmed by Cipriani and Guarino (2005) and Drehmann, Oechssler and Roider (2005). While Cipriani and Guarino (2005) design an experiment following the concept of Glosten and Milgrom (1985) model, Drehmann, Oechssler and Roider (2005) employ the information cascade experiment. In the price mechanism treatment introduced by Drehmann, Oechssler and Roider (2005), the price of an asset is determined based on the number of offers for an asset. This setup helps to illustrate the correlation between trading volume and price. However, this does not focus on the impact of fundamental value on decision making. In this paper, we set the price using a different approach. More specifically, the price is formed based on the successful probability of an asset. Using the Bayesian rule, we can infer the fundamental value of the asset. Participants should buy an asset which offers a higher probability of success. Also, before asking participants to make decisions on which asset they would like to buy, we ask them which asset they think would be successful. Using these two questions, we can distinguish between participants' beliefs and their decisions. In other words, we would like to examine whether participants would invest in the asset they think will be successful. This decision may not be the case because the successful asset should have a higher price; therefore, participants may think one asset will be successful but make decisions to buy another asset due to the price difference.

This treatment can be used to test for the two following hypotheses:

> *Hypothesis 3.1: Information cascading disappears in the information cascade with a price mechanism.*
>
> *Hypothesis 3.2:* Participant*s purchase an asset against their beliefs due to the price difference.*

Treatment 4: price&info (with information on the performance of the best performers and with a price mechanism)

This treatment is a combination of the *info* treatment and *price* treatment. Accordingly, participants receive information on the decisions of the participants who had the highest payoff in a previous session and make decisions in the information cascade experiment with a price mechanism. The historical information is not relevant to the decisions. However, we expect that participants will follow the decisions of the best performer. Indeed, we expect there is a discrepancy in participants' beliefs and the purchasing decisions due to the price difference.

There are two hypotheses in this treatment:

> *Hypothesis 4.1: Information cascade due to reputational externality exists in the information cascade experiment with a price mechanism.*
>
> *Hypothesis 4.2: Participants make decisions against their beliefs due to the price difference.*

We also examine the participants' personalities and characteristics and correlate with their decisions. We are interested in overconfidence, risk reference, math skills, self-monitoring ability, gender, nationality, income and major of study. Overconfidence is estimated using two measures, which are miscalibration and better than average. For miscalibration, we adopt the questionnaire introduced by Biais et al. (2005). Participants provide an interval that they are 90% sure the correct answers will fall inside. For example, participants are asked to give their estimation for Martin Luther King's age at death. A well-calibrated participant should provide a wide interval if they do not know the answer. A miscalibrated participant, who is too overconfident about his judgemental ability, provide a narrow interval which leaves the correct answer out. The second measure for overconfidence is better than average. For this measure, we ask participants to evaluate their performance in comparison with their peers. A participant who overestimates her performance is considered as overconfidence. Risk preference is measured by using the Holt and Laury (2002) experiment. More specifically, participants are asked to choose from which point they would like to switch from a risk-free asset to a risky asset. The lower switching points indicate a high risk-loving preference. As a robustness test for the impacts of the risk preferences, we include the Balloon Analogue Risk Task (BART) to measure risk preference (Lejuez et al., 2002)[7]. For maths skill and self-monitoring ability, we include 6 mathematical questions (Eckel and Füllbrunn, 2015) and 18 situations in which participants apply their self-monitoring ability (Biais et al., 2005) to solve. Other demographic characteristics included in the questionnaire are gender, nationality, income, discipline and age. The questionnaire and Holt and Laury (2002) experiment are conducted after the main experiment[8].

[7] The computer screen showed a small simulated balloon accompanied by a balloon pump. Each click on the pump inflated the balloon 1°. With each pump, a certain amount of Money will be accrued in a temporary bank. When a balloon was pumped past its individual explosion point, the balloon will explode. When a balloon exploded, all Money in the temporary bank was lost, and the next uninflated balloon appeared on the screen. At any point during each balloon trial, the participant can stop pumping the balloon and click the "Collect Rewards" button. By clicking this button, the participant transfers all Money from the temporary bank to the permanent bank. Each participant will have 15 balloons, and the final amount of Money in the permanent bank is the final payoff of that participant. Risk preferences (BART) are measured by the adjusted number of pumps across balloons excluding balloons that exploded.

[8] The description of these variables could be found in the Appendix 2.1.

2.4. Results and Discussions

2.4.1. Sample description

We conduct the experiment with 162 students studying at The University of Nottingham. The experiment is run at The Centre for Research in the Behavioural Sciences (CRIBS) of The Nottingham University Business School. We conduct six sessions for each treatment except the *info* treatment, which we have nine sessions.

The characteristics of the subject pool are shown in Table 2.1. Participants express a relatively high level of overconfidence. For the miscalibration measure particularly, only 18.2% of answers stay inside the 90% correct interval, which is relatively low compared to the literature. For instance, this value is 42% to 62% in Russo and Schoemaker (1992) with business managers, 43% in Klayman et al. (1999) and 36% in Biais et al. (2005). For better-than-average measure, there are 19.75% of participants overestimate their performance during the experiment. Participants show a modest rate of self-control (48.67%). They are prone to risk-averse (the average switching point is 6.59) and get 3.86/ 6 mathematical questions. Out of 162 participants, 42.59% of participants are male, 37.65% study natural sciences, 38.27% come from Western countries, and 61.73% have lived in a foreign country for more than six months. The average age of our subject pool is 20.58 with the average living allowance (income) of £1044.

Table 2. 1 - Characteristics of the subject pool

This table reports the results collected from the questionnaire and Holt and Laury (2002) experiment, which is used to measure risk-preference. Different characteristics are measured, including overconfidence (miscalibration and better-than-average), self-monitoring ability, risk preference, maths skill, gender, major, nationality, age and income. The data also indicates whether the participants live in a foreign country before.

Overconfidence (Miscalibration)	1.82
Overconfidence (Better than average) (1: Overconfidence; 0: Non-Overconfidence)	19.75%
Self-Monitoring Ability	8.76
Risk preference (Holt and Laury, 2002)	6.59
Maths skill	3.86
Gender (Male over Female)	42.59%
Major (Natural Science over Social Science)	37.65%
Nationality (Western over Asian)	38.27%
Living abroad (Yes)	61.73%
Average age	20.58
Average Income	1044
N	**162**

2.4.2. Information cascade and irrational decisions

Information cascade occurs where cascade decision is possible. For example, the decisions received from the predecessors are A and A, which infers their signals are a, a. If a participant receives signal b in this situation, she should choose A as the successful asset since the probability of success of A is higher (P($A|a,a,b$)=67%). AH (1997) named this as an imbalanced event. Accordingly, an imbalanced event of the previously inferred signals indicates the situation that it is optimal for a participant to follow the predecessors regardless of her private information. AH (1997) shows that the proportion of information cascade in the imbalanced event is relatively high, which accounts for 73% of the total imbalanced events (41 cascades over 56 imbalanced events). Ten years later, Alevy, Haigh and List (2007) conduct a similar experiment and conclude that the proportion of information cascade significantly decreases, which is 56% (245 cascades over 441 imbalanced events).

The number of imbalanced events, features and cascade behaviour in the four treatments are shown in Table 2.2. Specifically, there are 263 imbalanced events in the four treatments, in which 65% is the normal cascade[9]. The number of normal cascades is significantly higher the reverse cascades[10], indicating that it is optimal to follow the predecessors in the imbalanced events. However, the herding rate is relatively low in this experiment, which is 49.43% (Figure 2.1). After 20 years since the first information cascade experiment conducted by AH (1997), the herding decisions due to information cascade significantly decreases. Compared to the *base*, the cascade behaviour declines when there are price and (or) information released to the market. More interestingly, the regression in Appendix 2.3 shows that the order where participants make decision significantly affect cascade decisions (1% level of significance). Accordingly, when participants are allocated in the later positions in the sequence, they express higher cascade behaviour. The results can be explained since in later positions more imbalanced events take place.

[9] Normal cascade is the situation that following the cascade will lead participants to a successful asset.
10 Reverse cascade is opposite to the normal cascade, in which following the cascade will lead participants to a wrong asset.

Table 2. 2 - Imbalanced events and cascade behaviour in imbalanced events

Table 2.2 (A) reports the number of imbalance events in the four treatments and the characteristics of the imbalanced events while table 2.2 (B) indicates the cascade behaviour in the imbalanced events.

(A) Imbalanced events

Treatment	IB (Total)	IB (Mean)	Reverse cascade	Normal cascade	p-value
Base	56	1.56	25%	75%	**0.001*****
Info	95	1.76	35%	65%	**0.008*****
Price	59	1.64	38%	61%	0.233
Info & price	53	1.47	42%	58%	0.284
Total	**263**	**1.62**	**35%**	**65%**	**0.000*****

IB means imbalanced events
p-values are taken from Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

(B) Cascade behaviour in imbalanced events

Treatment	IB (Mean)	Follow (FIB)	Own	p-value
Base	1.56	55%	45%	0.685
Info	1.76	48%	52%	0.785
Price	1.64	46%	55%	0.658
Info & price	1.47	49%	51%	0.967
Total	**1.62**	**49%**	**51%**	**0.860**

IB means imbalanced events; FIB means herd behaviour in the imbalanced events
p-values are taken from Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

Unlike imbalanced events, there are situations where it is indifferent to the participants to choose a particular asset, which we call balanced events. Interestingly, many participants choose to follow predecessors in such events. An example of herding in a balanced event taken from the experiment is shown in Table 2.3 (A). More specifically, the participant in position 4 (participant 3) got an "*a* signal" as her private information. She knows that the predecessors' decisions are *B, A, B*, which implies the previous signals are *b, a, b*. Given the "a signal" she received, the successful probability of asset *A* and asset *B* is identical, which is 50%. In this case, participant 3 decided to go against her private signal and follow the market, creating an information cascade in a balanced event. The models of Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) consider this situation as a tie-breaking rule. Accordingly, the model assumes that whenever the participants are indifferent between two options, they will randomise with an equal probability. In AH (1997), decisions are found to be consistent with private information whenever the posterior probability of each Urn is ½. However, Koessler and Ziegelmeyer (2000) state that such a pattern is not common knowledge. They propose a non-confident tie-breaking rule, in which participants follow predecessors in the balanced events. The re-examination of updated tie-breaking rule shows that the proportions of decisions which are consistent with AH tie-breaking rule are just 83%, 75% and 86%, respectively in AH (1997) with symmetric design, Willinger and Ziegelmeyer's (1998), and Hung and Plott (2001). The presence of non-confident tie-breaking rule is considerably high in this research, especially in the last three treatments. Twenty-five per cent of participants chooses to follow the market in balanced events, shown in Table 2.4 (A). Interestingly, this number is significantly high in the case there is information/ price in the market (Figure 2.2). The herding rate moves from 15% in the *base* to 33% in the *info*, 21% in the *price* and 28% in the *info&price*. The regression results show that the cascade behaviour in balanced events in the *info* treatment is significantly higher compared to the *base* (5% level of significance, Appendix 2.3). In other words, participants tend to follow the predecessors more when they handle more information, even it is not optimal to do so.

Herding others in a balanced event is still understandable since participants face a situation of indifference. Unexplainably, there are situations participants do not follow both private information and public information, which is considered as irrational decisions. An example taking from the experiment, in which participants make irrational decisions, are shown in Table 2.3 (B). Accordingly, the first three participants chose Asset *A*, which implies that their signals were "*a*". The private signal the participant in the fourth position (Participant 2) receives is also "*a*". Rationally, Asset *A* should be the optimal choice. However, this participant chose Asset *B*, which is inconsistent with the prediction of the market and her private signal.

Similarly, the participant in the fifth position (Participant 3) also chose Asset *B*, although her private signal is "*a*". There are 104 irrational decisions made in the experiment, which means 6.4% of all decisions are irrational decisions, shown in Table 2.4 (B). Noticeably, the number of irrational decisions in the treatments where the price mechanism is available is higher than the *base* treatment (Figure 2.3). The number of irrational decisions is significantly high in *price* treatment and *info&price* treatment (1% and 10% level of significance, respectively), shown in Table A2.6 (Appendix 2.3). Again, when participants deal with a complicated decision, they tend to follow the heuristics. Heuristics could be used to explain the irrational decisions in this context. Huck and Oechssler (2000) argue that herd behaviour due to Bayesian updating suggested by AH (1997) is inappropriate. In particular, they conducted the same experiment; in which, participants are students who have just finished the microeconomics module covering Bayesian rule. Although participants have a prior understanding of the Bayesian rule, they could not explain the reason why they make identical decisions. As a result, the heuristic of "follow the majority" is a more convincing explanation for herding. Back to irrational decisions, participants choose not to follow the market nor their private signals. This decision increases when there is more information/ price released in the market. Participants may stick to the heuristic of "go against the market and signals" when making decisions. We can also use the concept of contrarian behaviour in this context. Drehmann, Oechssler and Roider (2005) suggest that people may make decisions against the market since they are sceptical about the rationality of others. We believe both heuristic and contrarian behaviour can be used to explain participants' irrational decisions in this context.

Table 2. 3 - Examples of imbalanced events and irrational decisions

Table 2.3 (A) shows an example of an information cascade formed in a balanced event while table 2.3 (B) shows an example of an irrational decision. The examples are taken from the experiment's results.

(A) An example of the information cascade formed in a balanced event.

Period	Successful Asset	1st	2nd	3rd	4th	5th	6th
2	B	S6: B (b)	S1: A (a)	S2: B (b)	S3: B** (a)	**S4: B (a)**	S5: B (b)

Bold infers information cascade in an imbalanced; ** infers information cascade in a balanced event.

(B) An example of the irrational decisions

Period	Successful Asset	1st	2nd	3rd	4th	5th	6th
3	A	S5: A (a)	S6: A (a)	**S1: A (b)**	S2: B*** (a)	S3: B*** (a)	S4: A (a)

This example is taken from the experiment' results; Bold infers information cascade in an imbalanced; *** infers irrational decisions

Table 2. 4 - Information cascades in balanced events and Irrational decisions

Table 2.4 (A) reports the number of balanced events as well as participants' behaviour in the balanced events while Table 2.4 (B) indicates the irrational decisions in the experiment.

(A) Information cascades in balanced events

Treatment	**Balance (Total)**	**Balance (Mean)**	**Follow (FB)**	**Own (B)**	**p-value**
Base	53	1.47	15%	85%	
Info	83	1.54	33%	67%	**0.043****
Price	47	1.31	21%	79%	0.773
Info & price	57	1.58	28%	72%	0.152
Total	**240**	**1.48**	**25%**	**75%**	

p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

(B) Irrational decisions

Treatment	**Irrational (Total)**	**Irrational (Mean)**	**p-value**
Base	16	0.44	
Info	19	0.35	0.813
Price	41	1.14	**0.021****
Info & price	28	0.78	0.183
Total	**104**	**0.64**	

p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

Figure 2. 1 - Herd behaviour in imbalanced events

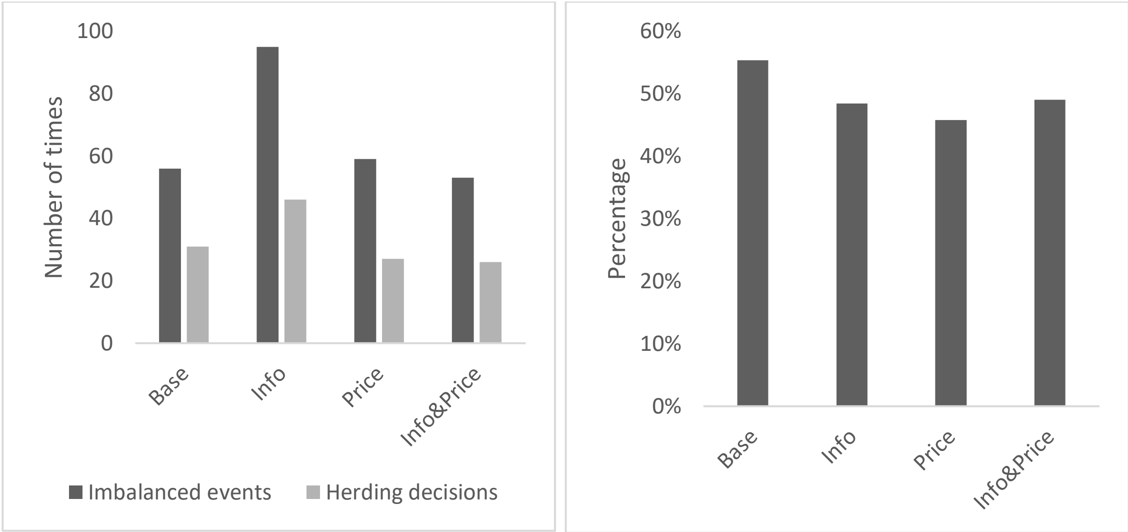


Figure 2. 2 - Herd behaviour in balanced events

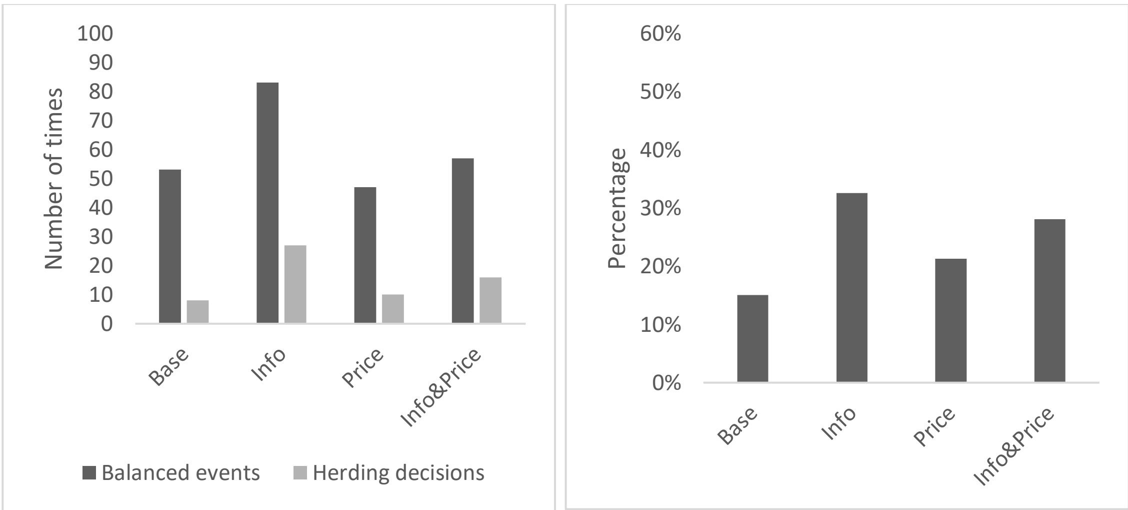


Figure 2. 3 - Irrational decisions

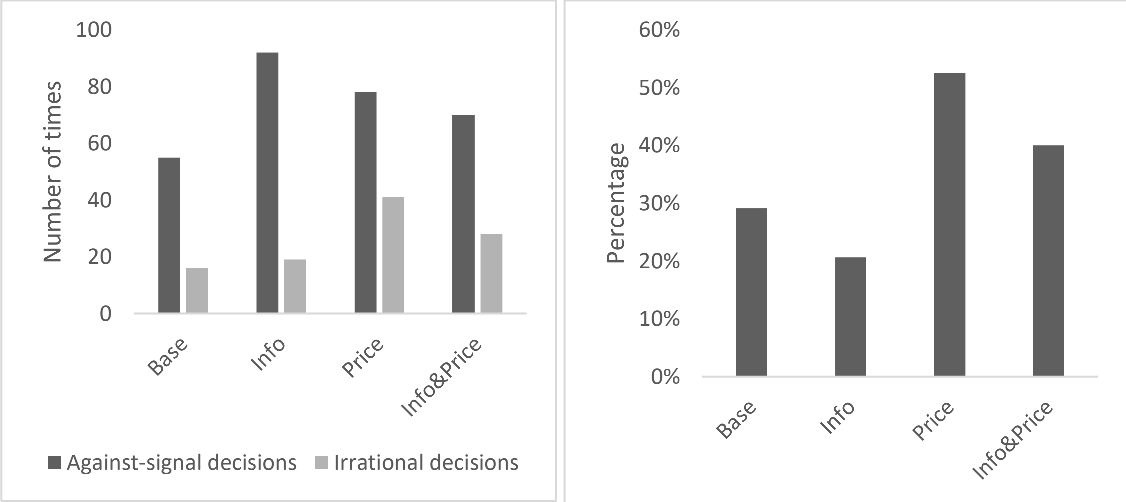
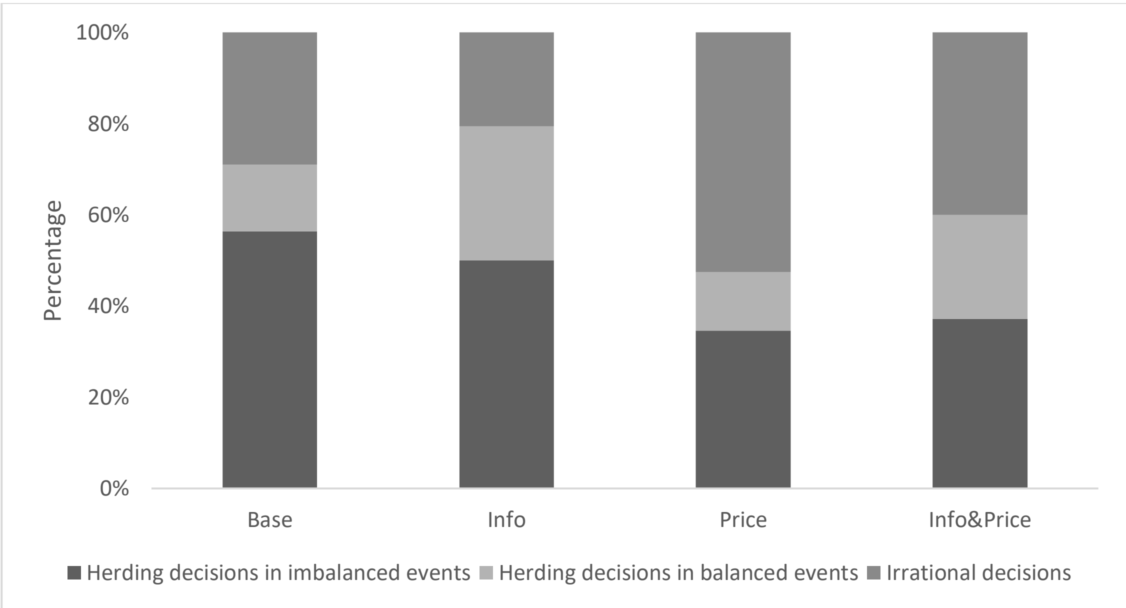


Figure 2. 4 - The proportion of cascade behaviour in imbalanced, balanced events and irrational decisions over the total against-signal decisions



2.4.3. Reputational effect

In treatments where historical information is available, participants know the decisions of the predecessors, the private signals and the decisions of the participant who gets the highest payoff. We expect that participants take this information into account before making their decisions. The participant with the highest payoff is the one who gets a better reputation, which can be an externality for herding. We examine all situations where participants make decisions against their signals, including cascades in imbalanced events, cascades in balanced events and irrational decisions. Participants make 1.53 decisions against their signals on average in the *base* case, shown in Table 2.5. This number is 1.70 and 1.94 in the *info* and *info&price*, respectively. Although the number of times participants make decisions against their signals is higher in the case historical information available, the difference is not significant. The proportion of against-signal decisions and be consistent with historical information is only half of the case. The results indicate that there is no reputational effect in this experiment.

Table 2. 5 - Impact of historical information

This table reports the number of times participants make decisions against their beliefs and whether the decisions are consistent with the informed historical information.

Treatment	Against-signal decisions	p-value	Consistent with historical information
Base	1.53		
Info	1.70	0.410	52%
Info & price	1.94	0.435	57%

p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

2.4.4. The effect of a price mechanism

The price mechanism allows us to distinguish between participants' beliefs and decisions. Participants provide their beliefs on the successful asset before they make decisions to buy. The price of an asset is estimated based on the number of signals supporting the success of that asset. In other words, the price of an asset is higher in the case that the success probability of that asset is high. The price is calculated based on the Bayesian rule. This design follows the concept of the efficient market hypothesis, which suggests the price of an asset already included all available information in the market. In this context, participants should pay to purchase an asset at a higher price since that asset is more likely successful. The fact that participants reveal their beliefs before making purchasing decisions allows us to compare their beliefs and their purchasing decisions. A rational participant should purchase the asset, which he believes in its potential.

Thirty per cent of participants purchases an asset against their belief, shown in Table 2.6. Interestingly, 69% of participants make such decision to get a lower price (Figure 2.5 and Figure 2.6). The participants may think a particular asset is successful, but they gamble on their own purchasing decisions with the hope that they can get an abnormally higher payoff. This decision can be easily observed in the financial markets. Some investors are interested in high-yield securities such as junk bonds or stocks of small, unlisted companies. The information in the markets does not support the success of these securities; however, investors still gamble on their investment decisions. The "crazy" securitised market, one of the leading causes of the financial crisis in 2007-2008 is strong evidence for this tendency. The obsession of abnormal gain forces investors to make decisions against their beliefs. This type of decision is threatening financial stability.

Cipriani and Guarino (2005) and Drehmann, Oechssler and Roider (2005), who include a price mechanism in their setup, conclude that information cascade disappears in the market with a price mechanism. This design helps us to separate between participants' beliefs and decisions; therefore, we find that participants are still engaged in information cascade decisions. However, they change their purchasing behaviours to capture the market price. The number of information cascade in the price treatment is not significantly different from the number in the *base* case. The participants change their purchasing decisions to look for the abnormal return. The regression results from Table A2.7 (Appendix 2.3) show that men are more likely to make against-belief purchasing decisions (5% level of significance).

In the *price* treatment, we recruit another 24 finance students who study master and PhD in Finance at the Nottingham University Business School. We want to examine whether finance students make different decisions compared to non-finance students. Alevy, Haigh and List (2007) conduct the information cascade experiment with students and market professionals and conclude market professionals are better at recognising the right signal. Venezia, Nashikkar and Shapira (2011) also indicate that professional investors are involved in less herding decisions compared to amateur investors. In this context, we consider finance students as market professionals since they have a high level of financial literacy. A comparison between finance and non-finance students is shown in Table A2.8 (Appendix 2.4). In general, the two subject pools are homogeneous except the fact that finance participants are better in maths.

The results are in line with our previous expectation (Appendix 2.5). More specifically, finance students make fewer decisions against their signals, including information cascades in imbalanced (Figure 2.7), balanced events and irrational decisions. More interestingly, finance students make significantly fewer decisions against their beliefs. In other words, they are less likely to purchase an asset that they do not believe in its success possibility. This result is noticeable in the context of examining the impact of financial literacy on decision making. In fact, with better knowledge of financial markets, finance students can make better decisions, which help to improve financial stability.

Table 2. 6 - Buy an asset against a participant's belief

This table reports the number of times participants buy an asset against their prior beliefs. The table also shows the motivation behind these decisions, which are purchasing against belief to get a cheaper price, a higher price and the same price.

Treatment	AB	B-cheaper	B-higher	B-same	p-value
Price	120 (33.33%)	71%	19%	10%	**0.001*** **
Info & Price	93 (25.83%)	66%	24%	11%	**0.010** **
Total	**213 (30%)**	**69%**	**21%**	**10%**	**0.000*** **

AB means purchasing an asset against a participant's belief. B-cheaper, B-higher and B-same indicate that the against belief purchasing behaviour is done by a participant to get a lower price, a higher price and the same price, respectively.
p-values are taken from Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

Figure 2. 5 - Proportion of against-belief purchasing behaviour over the number of purchasing decisions

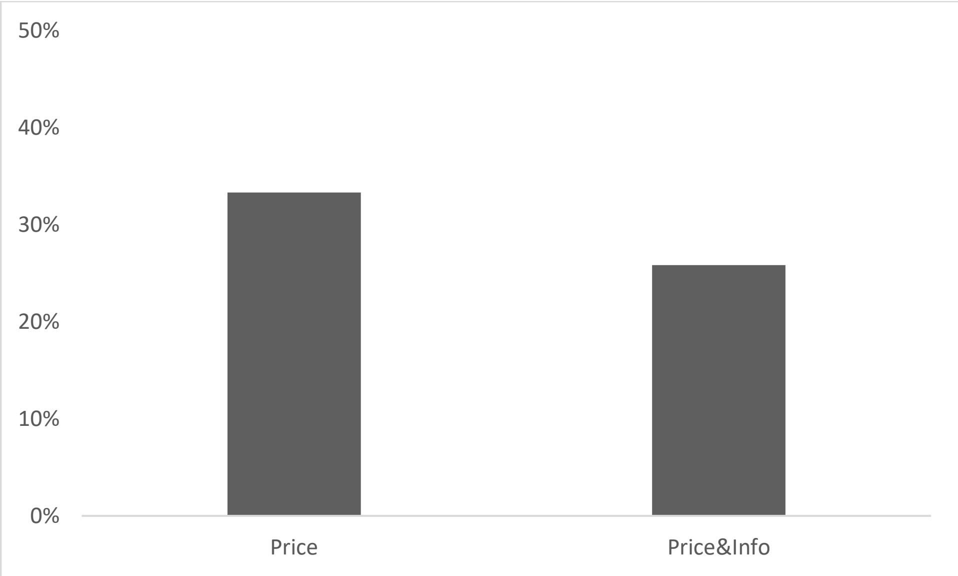


Figure 2. 6 - Proportion of against-belief purchasing behaviour to get cheaper price, higher price and same price over the number of against-belief purchasing behaviour

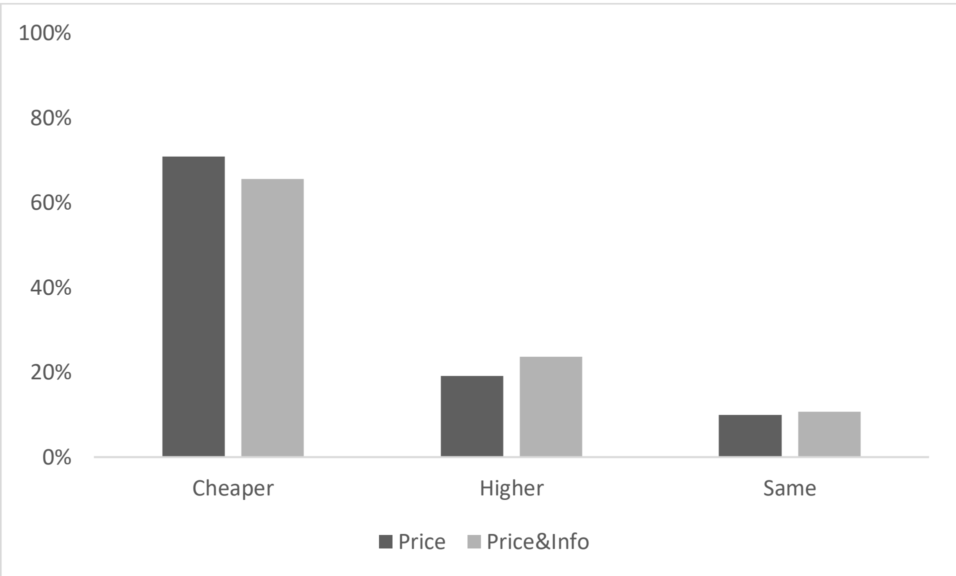
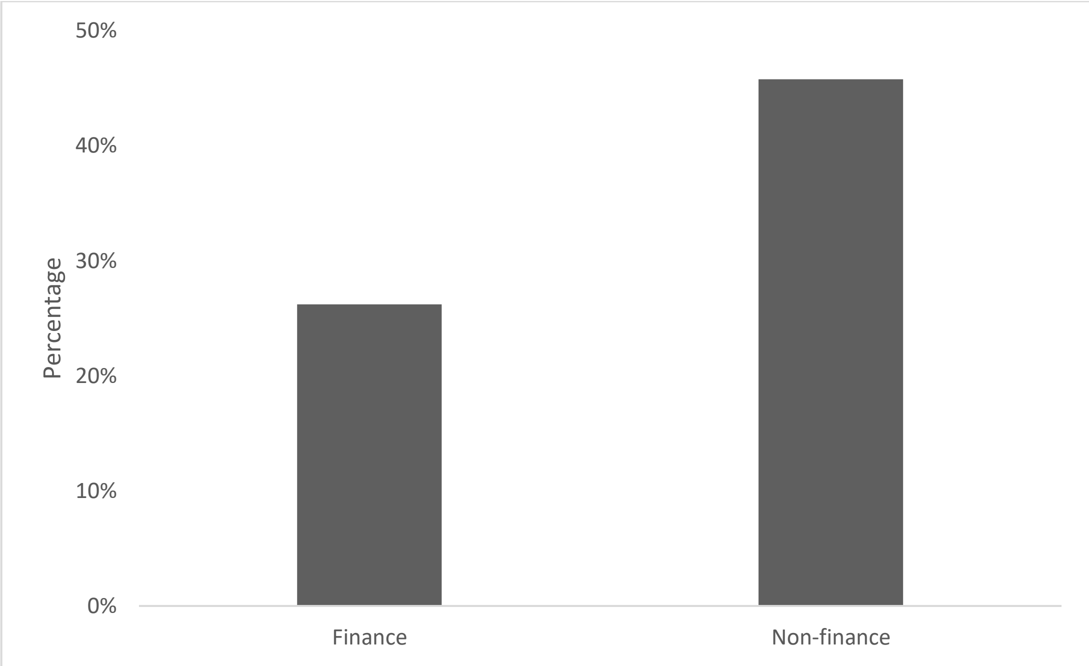


Figure 2. 7 - Comparison of herding decisions in imbalanced events between finance and non-finance students



2.4.5. The determinants of individual differences in decision making

The impacts of individual characteristics on herding decisions are examined in this section. We include overconfidence (miscalibration and better than average), risk preference, self-monitoring ability, maths skill, major, nationality, number of years living abroad, age and income in the analysis. The description of these variables can be found in Appendix 2.1.

The correlation between participants' characteristics and their payoff is shown in Table A2.10 (Appendix 2.6). The results indicate that the risk-loving participants earn significantly more in comparison to the others (5% level of significance). This correlation is the same in the case of the risk measure using the balloon game. Individual differences also affect herding decisions (Table 2.7). Specifically, risk-loving participants tend to make decisions against their signals at a higher degree; in which, the dominant decisions are herding others in the balanced events and irrational decisions (5% level of significance).

In contrast, overconfident participants are less likely to make against-signal decisions and cascade decisions in balanced events (Table A2.5). Overconfident participants, who strongly believe in their abilities, choose to follow their information. Bernardo & Welch (2001) show that overconfident people prefer to lead the herd rather than follow it. Nöth and Weber (2002) conduct the information cascade with two different qualities of the signals (strong and weak) and indicate that overconfident participants avoid aggregating information and follow their signals. This result is interesting since risk-loving and overconfidence are found to be positively correlated (Menkhoff, Schmidt and Brozynski, 2006; Barber and Odean, 2001). In the context of this research; however, overconfident participants do not follow others while risk-loving participants do.

Age is negatively correlated with cascade behaviour in imbalanced events while living allowances increase the level of cascade decisions in balanced events and against-signal decisions. The result of age is in line with the literature. Lamont (2002) shows that the American forecasters stop herding when they become older. In the psychological literature, Visser & Krosnick (1998) conclude that younger individuals are easily influenced compared to the ones who are in their 40s, 50s.

The unexpected results are found with self-monitor and nationality. While the literature confirms the positive relationship between self-monitoring and conformity (Scher and Thompson, 2007; Snyder, 1974), we do not find a significant correlation. Similarly, while it is found that Asian people are more likely to make conformity decisions[11], the nationality factor is insignificant in this study.

In the questionnaire, we ask about risk tolerance in different contexts as well as trust behaviour, return/ revenge behaviour and satisfaction. The result of the risk is in line with the other measures. Specifically, the participants who are prone to risk-taking in general issues and financial issues make more against-belief decisions. Participants expressing higher levels of trust, surprisingly, make less herd-like decisions while this tendency occurs with participants who are likely to take revenge/ return-difficulty decisions. Participants who are likely to return the favour and are satisfied with their health are more likely to make against-belief decision and cascade decisions in imbalanced events.

Finally, we examine the impact of individual differences on against-belief behaviour. The results in Table 2.8 show that men are more likely to purchase the asset which they do not believe in its success. Trust behaviour is negatively correlated with against-belief decisions. Accordingly, participants do not buy an asset against their belief if they express a high level of trust. The opposite result is found with return offend/ difficulty/ revenge behaviour.

[11] The conformity is more likely in hierarchical cultures such as East Asian, where people live in a small town and know each other. Bond and Smith (1996) analyse the results of 133 research which use Asch's line-judging taken from 17 countries and conclude that conformity is greater in collectivistic countries than in individualistic ones. Kim and Markus (1999) show that while the ads in the U.S focus on uniqueness, e.g. "Choose your own view!"; "Individualize", the ads in Korea focus more on conformity, e.g. "Seven out of 10 people use this product"; "Our company is working toward building a harmonious society".

Table 2. 7 - Individual differences and decision-making

Correlation between individual differences and against-signal decisions, cascade decisions in imbalanced and balanced events and irrational decisions.

Characteristics	AS	FIB	FB	IRR
Overconfidence (Miscalibration)	0.095	0.041	0.127	0.070
Overconfidence (Better-than-average)	0.001	0.030	-0.090	-0.044
Maths skill	0.025	0.012	0.037	0.036
Self-control	0.011	-0.008	0.025	0.038
Risk (H&L 2002)	**-0.159****	-0.048	**-0.167****	-0.119
Risk General (Questionnaire)	**0.143***	-0.027	0.102	**0.185****
Risk Finance (Questionnaire)	**0.143***	-0.076	**0.189****	0.068
Risk (Balloon Game)	0.004	-0.014	-0.022	0.001
Gender	0.113	0.073	0.031	0.071
Major	0.064	0.033	0.085	0.033
Nationality	-0.104	-0.008	-0.115	-0.055
Age	0.018	**-0.146***	0.104	0.066
Living abroad	0.045	-0.030	**0.132***	0.054
Income	**0.153***	0.086	**0.147***	0.056
Trust Accountants	**0.130***	**0.140***	0.044	0.058
Trust Press	-0.056	**-0.061**	**-0.155****	0.048
Trust Insurance Company	-0.068	**-0.004**	**-0.155****	0.021
Return Favour	**0.147***	**0.137***	0.097	0.046
Revenge	**-0.136***	**-0.177****	-0.065	0.087
Return Difficulty	**-0.147***	-0.129	-0.043	-0.001
Health Satisfaction	0.124	**0.141***	-0.014	0.007
Study Satisfaction	0.026	0.025	**-0.149***	0.063

The results are taken from The Spearman's Correlations
*** p<0.01, ** p<0.05, * p<0.1

Table 2. 8 - Individual differences and purchasing behaviour

Correlation between individual differences and against-belief purchasing behaviour.

Characteristics	AB
Overconfidence (Miscalibration)	0.077
Overconfidence (Better-than-average)	-0.180
Maths skill	-0.038
Self-control	0.108
Risk (H&L 2002)	-0.046
Risk General (Questionnaire)	0.170
Risk Finance (Questionnaire)	0.066
Risk Drive (Questionnaire)	**0.214***
Risk (Balloon Game)	0.106
Gender	**0.344*****
Major	0.171
Nationality	0.051
Age	-0.016
Living abroad	0.074
Income	0.089
Trust Parliament	**-0.236****
Trust EU	**-0.226***
Trust Education	**-0.254****
Trust Police	**-0.264****
Trust Family	**-0.219***
Trust Churches	**-0.197***
Revenge	**0.431*****
Return Difficulty	**0.233****
Return Offends	**0.451*****

The results are taken from The Spearman's Correlations
*** p<0.01, ** p<0.05, * p<0.1

2.5. Conclusion

The pioneering experiment introduced by AH (1997) indicates the significant presence of herd behaviour due to information externality (73% decisions in imbalanced events are cascade decisions). Ten years later, a similar experiment conducted by Alevy, Haigh and List (2007) show that the rate decreases to 56%, which is similar to the results in the *base* case of this experiment (55%). After twenty years, the number of cascade formation in imbalanced events has dramatically declined. However, information cascade still exists in approximately 50% of imbalance events. The participants even follow others in the balanced events where it is indifferent to follow the market or the private information. This result is inconsistent with the AH's tie-breaking rule while confirming the non-confident tie-breaking rule suggested by Koessler and Ziegelmeyer (2000). Indeed, participants make irrational decisions which do not comply with their private signals and the available information in the market. Noticeably, the number of irrational decisions significantly increases when there is more information released in the market. In other words, whenever there is too much information in the market, participants choose to follow their heuristics.

The reputation does not play a significant effect on promoting information cascade while a price mechanism does not dissolve this behaviour. Participants do not follow the one who gets the highest payoff while they still follow in their beliefs where a price mechanism exists. However, they make decisions based on the offered price. By distinguishing between beliefs and purchasing behaviour, we find that participants make decisions against their beliefs more than 30% and in most of the case to get a lower price. Since the price supports the successful probability of an asset, a lower price means the asset has a low probability of being successful. This result has various implications in the financial markets. Efficient Market Hypothesis suggests that the price in the market already includes all available information; therefore, a higher price expresses better prospects of an asset. However, most of the financial crises are caused by contradicting behaviour. A portion of investors is more interested in high-yield, risky assets, which is the root of market instability. For instance, the subprime mortgage market and securitisation process are claimed to be the leading causes of the recent financial crisis in 2007-2008. This research confirms the fact that participants are interested in low-price assets, although they already know their fundamental value. This behaviour is a challenge to market stability and should be regulated. Individual characterisations are found to play a significant role in determining the participant's decision making and payoff. Most importantly, finance students with better financial literacy tend to make a significantly less against-belief purchasing decision. This result is essential to the policymakers who would like to enhance the stability of the financial markets.

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APPENDIX 2.1

Table A2.1: Variable descriptions

This table reports the measures of individuals used in the papers

Variables	Measures	References
Overconfidence (Miscalibration)	Questionnaire (10 questions) Participants are asked to give the low and high values which they are 90% sure that the true value will fall inside the interval. Overconfident participants will get a less correct answer.	Biais et al., (2005)
Overconfidence (Better-than-average)	Asset market experiment After participants play asset market experiment, we ask participants to rank their performance with the other participants in the groups. Overconfident participants are the ones who overestimate their performance.	Glaser and Weber (2007); Deaves, Luders and Luo (2008)
Maths skill	Questionnaire (6 questions)	Eckel and Füllbrunn (2015)
Self-monitor ability	Questionnaire (18 questions)	Biais et al., (2005)
Risk reference (Holt and Laury, 2002)	Experiment	Holt and Laury (2002)
Gender	Male/ Female	
Major	Natural science/ Social science	
Nationality	Western/ Asian	
Income	Living Allowance	

APPENDIX 2.2

Table A2.2 - Price mechanism for Asset A and Asset B

This table shows the price of Asset A and Asset B according to the given signals.

Subject	Signal	Price of asset A	Price of asset B
1	a	6.7	3.3
2	a	8.0	2.0
3	b	6.7	3.3
4	b	5.0	5.0
5	b	3.3	6.7
6	b	2.0	8.0

APPENDIX 2.3

Table A2.3 - Treatment effect on against-signal behaviour

This table reports the treatment effect on against-signal behaviour using cross-sectional data and panel data. The main characteristics of participants are also included in the regressions. We conduct OLS regression with cross-sectional data and random effect regression with panel data.

VARIABLES	(1) AS (OLS)	(2) AS (OLS)	(3) AS (RE)	(4) AS (RE)	(5) AS (RE)
Info	0.176	0.140	0.018	-0.014	-0.017
	(0.372)	(0.379)	(0.037)	(0.060)	(0.060)
Price	0.639	0.483	0.064	0.056	0.040
	(0.408)	(0.415)	(0.041)	(0.066)	(0.066)
Info&price	0.417	0.117	0.042	0.067	0.037
	(0.408)	(0.425)	(0.041)	(0.066)	(0.067)
Period				0.003	0.003
				(0.007)	(0.007)
Period * Info				0.006	0.006
				(0.009)	(0.009)
Period * Price				0.002	0.002
				(0.009)	(0.009)
Period * Info&Price				-0.005	-0.005
				(0.009)	(0.009)
Order					**0.032***
					(0.005)
Miscalibration		**0.166***			**0.017***
		(0.092)			(0.009)
Better-than-average		-0.367			-0.039
		(0.354)			(0.036)
Maths skill		-0.023			-0.002
		(0.130)			(0.013)
Self-monitoring		0.012			0.001
		(0.039)			(0.004)
Risk (Holt&Laury, 2002)		**-0.190****			**-0.019****
		(0.073)			(0.007)
Gender		0.367			0.038
		(0.297)			(0.030)
Major		0.206			0.021
		(0.304)			(0.031)
Nationality		-0.437			-0.041
		(0.319)			(0.032)
Age		-0.071			-0.007
		(0.058)			(0.006)
Constant	1.528***	4.046**	0.153***	0.137***	0.265
	(0.288)	(1.659)	(0.029)	(0.047)	(0.172)
Observations	162	162	1620	1620	1620
R – squared	0.0180	0.1118	0.0036	0.0053	0.0441

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.4 - Treatment effect on cascade behaviour in imbalanced events

This table reports the treatment effect on cascade behaviour in imbalanced events using cross-sectional data and panel data. The main characteristics of participants are also included in the regressions. We conduct OLS regression with cross-sectional data and random effect regression with panel data.

VARIABLES	(1) FIB (OLS)	(2) FIB (OLS)	(3) FIB (RE)	(4) FIB (RE)	(5) FIB (RE)
Info	-0.009	0.040	-0.001	-0.028	-0.023
	(0.209)	(0.220)	(0.021)	(0.041)	(0.040)
Price	-0.111	-0.115	-0.011	0.017	0.016
	(0.229)	(0.240)	(0.023)	(0.045)	(0.044)
Info&price	-0.139	-0.171	-0.014	-0.007	-0.011
	(0.229)	(0.246)	(0.023)	(0.045)	(0.045)
Period				-0.000	-0.000
				(0.005)	(0.005)
Period * Info				0.005	0.005
				(0.006)	(0.006)
Period * Price				-0.005	-0.005
				(0.007)	(0.007)
Period * Info&Price				-0.001	-0.001
				(0.007)	(0.007)
Order					**0.035***
					(0.004)
Miscalibration		0.036			0.004
		(0.054)			(0.005)
Better-than-average		0.019			-0.001
		(0.205)			(0.021)
Maths skill		-0.002			-0.000
		(0.075)			(0.008)
Self-monitoring		-0.015			-0.001
		(0.023)			(0.002)
Risk (Holt&Laury, 2002)		-0.022			-0.002
		(0.043)			(0.004)
Gender		0.248			0.026
		(0.172)			(0.017)
Major		0.001			0.000
		(0.176)			(0.018)
Nationality		-0.084			-0.006
		(0.185)			(0.019)
Age		-0.055			-0.005
		(0.034)			(0.003)
Constant	0.861***	2.123**	0.086***	0.087***	0.079
	(0.162)	(0.961)	(0.016)	(0.032)	(0.101)
Observations	162	162	1620	1620	1620
R – squared	0.0039	0.0398	0.0005	0.0020	0.0549

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.5 - Treatment effect on cascade behaviour in balanced events

This table reports the treatment effect on cascade behaviour in balanced events using cross-sectional data and panel data. The main characteristics of participants are also included in the regressions. We conduct OLS regression with cross-sectional data and random effect regression with panel data.

VARIABLES	(1) FB (OLS)	(2) FB (OLS)	(3) FB (RE)	(4) FB (RE)	(5) FB (RE)
Info	**0.278**** (0.137)	**0.238*** (0.137)	**0.028**** (0.014)	-0.004 (0.028)	-0.008 (0.028)
Price	0.056 (0.150)	-0.022 (0.150)	0.006 (0.015)	0.007 (0.031)	-0.000 (0.031)
Info&price	0.222 (0.150)	0.091 (0.154)	0.022 (0.015)	-0.000 (0.031)	-0.013 (0.031)
Period				0.000 (0.003)	0.000 (0.003)
Period * Info				0.006 (0.004)	0.006 (0.004)
Period * Price				-0.000 (0.005)	-0.000 (0.005)
Period * Info&Price				0.004 (0.005)	0.004 (0.005)
Order					0.002 (0.003)
Miscalibration		**0.081**** (0.033)			**0.008**** (0.003)
Better-than-average		**-0.238*** (0.128)			**-0.024*** (0.013)
Maths skill		-0.051 (0.047)			-0.005 (0.005)
Self-monitoring		0.011 (0.014)			0.001 (0.001)
Risk (Holt&Laury, 2002)		**-0.079***** (0.027)			**-0.008***** (0.003)
Gender		0.010 (0.107)			0.001 (0.011)
Major		0.161 (0.110)			0.016 (0.011)
Nationality		**-0.222*** (0.115)			**-0.022*** (0.012)
Age		-0.012 (0.021)			-0.001 (0.002)
Constant	0.222** (0.106)	1.085* (0.599)	0.022** (0.011)	0.020 (0.022)	0.099 (0.064)
Observations	162	162	1620	1620	1620
R – squared	0.0333	0.1538	0.0037	0.0076	0.0215

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A2.6 - Treatment effect on irrational decisions

This table reports the treatment effect on irrational decisions using cross-sectional data and panel data. The main characteristics of participants are also included in the regressions. We conduct OLS regression with cross-sectional data and random effect regression with panel data.

VARIABLES	(1) IRR (OLS)	(2) IRR (OLS)	(3) IRR (RE)	(4) IRR (RE)	(5) IRR (RE)
Info	-0.093	-0.138	-0.009	0.019	0.014
	(0.227)	(0.237)	(0.023)	(0.038)	(0.038)
Price	**0.694******	**0.620****	**0.069******	0.031	0.024
	(0.249)	(0.260)	(0.025)	(0.041)	(0.042)
Info&price	0.333	0.197	0.033	**0.074***	0.061
	(0.249)	(0.266)	(0.025)	(0.041)	(0.042)
Period				0.003	0.003
				(0.004)	(0.004)
Period * Info				-0.005	-0.005
				(0.005)	(0.005)
Period * Price				0.007	0.007
				(0.006)	(0.006)
Period * Info&Price				-0.007	-0.007
				(0.006)	(0.006)
Order					-0.005
					(0.003)
Miscalibration		0.049			0.005
		(0.058)			(0.006)
Better-than-average		-0.149			-0.014
		(0.222)			(0.022)
Maths skill		0.030			0.003
		(0.081)			(0.008)
Self-monitoring		0.016			0.002
		(0.025)			(0.002)
Risk (Holt&Laury, 2002)		**-0.089***			**-0.009***
		(0.046)			(0.005)
Gender		0.108			0.011
		(0.186)			(0.019)
Major		0.043			0.004
		(0.190)			(0.019)
Nationality		-0.131			-0.013
		(0.200)			(0.020)
Age		-0.004			-0.000
		(0.036)			(0.004)
Constant	0.444**	0.838	0.044**	0.030	0.088
	(0.176)	(1.039)	(0.018)	(0.029)	(0.108)
Observations	162	162	1620	1620	1620
R – squared	0.0811	0.1226	0.0159	0.0199	0.0292

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.7 - Treatment effect on against-belief purchasing decisions

This table reports the treatment effect on against-belief purchasing decisions using cross-sectional data and panel data. The main characteristics of participants are also included in the regressions. We conduct OLS regression with cross-sectional data and random effect regression with panel data.

VARIABLES	(1) AB (OLS)	(2) AB (OLS)	(3) AB (RE)	(4) AB (RE)	(5) AB (RE)
Info&price	-0.750	-0.688	-0.075	-0.104	-0.097
	(0.487)	(0.518)	(0.049)	(0.078)	(0.080)
Period				0.003	0.003
				(0.008)	(0.008)
Period * Info&Price				0.005	0.005
				(0.011)	(0.011)
Order					**0.036*****
					(0.009)
Miscalibration		0.091			0.009
		(0.160)			(0.016)
Better-than-average		-1.133			**-0.120***
		(0.700)			(0.070)
Maths skill		-0.320			-0.031
		(0.237)			(0.024)
Self-monitoring		0.117			**0.012***
		(0.074)			(0.007)
Risk (Holt&Laury, 2002)		-0.076			-0.008
		(0.149)			(0.015)
Gender		**1.218****			**0.123****
		(0.566)			(0.057)
Major		0.322			0.032
		(0.550)			(0.055)
Nationality		-0.241			-0.021
		(0.607)			(0.061)
Age		-0.020			-0.001
		(0.125)			(0.013)
Constant	3.333***	3.759	0.333***	0.315***	0.199
	(0.344)	(3.184)	(0.034)	(0.055)	(0.326)
Observations	72	72	720	720	720
R – squared	0.0328	0.2051	0.0068	0.0084	0.0607

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 2.4

Table A2.8 - Finance and non-finance students who play the PRICE treatment

This table compares the individual differences of the two subject pools, finance students and non-finance students. There are 21 finance participants who play the PRICE treatment while the number of non-finance participants who play this treatment is 36 participants (We exclude 3 finance students who do not finish the questionnaire)

Personalities and Characteristics	**Non-Finance**	**Finance**	**p-value**
Overconfidence (Miscalibration)	1.72	2.33	0.541
Overconfidence (Better than average)	19.44%	33.33%	0.244
Self-Monitoring Ability	8.39	7.90	0.790
Risk preference	6.58	6.80	0.172
Maths skill	3.78	4.52	**0.005*** **
Male	58.33%	61.90%	0.793
Western	36.11%	23.81%	0.339
Living abroad	69.44%	38.10%	**0.021** **
Age	21.14	24.67	**0.000*** **
N	36	21	

p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 2.5

Table A2.9 - A comparison in decision-making between finance and non-finance students

This table reports the decisions made by finance students and non-finance students. The decisions include information cascade (IC), following private information in imbalanced events; IC, following the private information in balanced events and purchasing against belief and its motivations.

	Non-Finance	**Finance**	**p-value**
Cascade possible	59	39	
Follow (Imbalanced events)	27 (45%)	10 (26%)	0.264
Own (Imbalanced events)	33 (55%)	29 (74%)	0.146
Balanced events	47	30	
Follow (Balanced events)	10 (21%)	5 (17%)	0.555
Own (Balanced events)	37 (79%)	25 (83)	0.362
Irrational Decisions	41 (11%)	17 (8%)	0.499
Against Belief	120 33%)	45 (21%)	**0.067***
Buy Cheaper	85 (71%)	35 (78%)	
Buy Higher	23 (19%)	6 (13%)	
Buy Same	12 (10%)	4 (9%)	
N	**36**	**21**	

p-values are taken from Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 2.6

Table A2.10 - Individual differences and payoff

This table reports the correlation between individual differences and participant's payoff.

Characteristics	Payoff
Overconfidence (Miscalibration)	0.040
Overconfidence (Better-than-average)	0.004
Maths skill	-0.063
Self-control	-0.021
Risk (H&L 2002)	**-0.155****
Gender	0.110
Major	-0.024
Nationality	-0.083
Age	0.023
Living abroad	0.106
Income	0.071
Risk (Balloon game)	**-0.233*****

The results are taken from The Spearman's Correlations
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 2.7 - THE INSTRUCTION OF THE EXPERIMENT

WELCOME TO CENTRE FOR RESEARCH IN BEHAVIOURAL SCIENCES (CRIBS).

Dear Participants! We welcome you to this experimental session and ask you to refrain from talking to each other for the duration of the experiment. If you face any difficulty, contact one of the experimenters.

This is an experiment in the economics of market decision making. If you follow the instructions and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. Money in these experiments is expressed in ECU (Experimental Currency Unit). The exchange rate between ECU and GBP will be presented in every case

TREATMENT 1: THE BASE

In this experiment, you are asked to choose between Asset A and Asset B to invest. Before making this decision, you will be consulted by your agent (investment banker) on which asset should you choose. Also, if there are other participants making decisions before you, you will be informed about their decisions. You will get profit if you choose the right asset; otherwise, you will end up with nothing.

There are six participants in your group, including you. Participants will make decisions in sequence, i.e. participant 1 makes the decision first, then participant 2 makes the decision, and so on. By this design, participant 2 will be informed about the decision of participant 1; participant 3 will be informed about the decisions of participant 1 and participant 2, and so on. In the end, participants will be announced the successful asset and their payoffs. There will be ten periods in this experiment, which means participants will make the same decision ten times. The order of making the decision will change every period.

You are asked to choose between Asset A and Asset B. The successful probability of asset A and asset B is the same, which is 50%.

P (A) = P (B) = 50%.

Before making the decision, you will receive advice from your investment banker, which is "*a*" or "*b*". The investment banker is experienced but cannot make the perfect predictions. If you receive signal "*a*", then 67% (2/3) probability that Asset *A* will be successful and only 33% probability that Asset *B* will be successful. In contrast, if you receive signal "*b*", then 67% (2/3) probability that Asset *B* will be successful and only 33% probability that Asset *A* will be successful.

P $(A|a)$ = P $(B|b)$ = 67%;

Or

P $(A|b)$ = P $(B|a)$ = 33%;

As additional information, you can observe the decisions of the predecessors in your group (If you are the first participant in the group, you do not have this information).

After each period, you will be announced the successful asset. If your choice is correct, you will receive 10 ECU. Otherwise, you will receive nothing.

The payments will be accumulated after each period, which will be considered as your payoff. Therefore, if you make the right choice for ten times, your payoff will be 100 ECU.

The exchange rate for this treatment is **10 ECU = 1 GBP**

TREATMENT 2: THE INFO

In this experiment, you are asked to choose between Asset *A* and Asset *B* to invest. Before making the decision, you will receive the decisions of a participant who gets the highest payoff in a previous experiment. In addition, you will be consulted by your agent (investment banker) on which asset should you choose. Also, if there are other participants making decisions before you, you will be informed about their decisions. You will get profit if you choose the right asset; otherwise, you will end up with nothing.

There are six participants in your group, including you. Participants will make decisions in sequence, i.e. participant 1 makes the decision first, then participant 2 makes the decision, and so on. By this design, participant 2 will be informed about the decision of participant 1; participant 3 will be informed about the decisions of participant 1 and participant 2, and so on. In the end, participants will be announced the successful asset and their payoffs. There will be ten periods in this experiment, which means participants will make the same decision ten times. The order of making the decision will change every period.

You are asked to choose between Asset A and Asset B. The successful probability of asset A and asset B is the same, which is 50%.

P (A) = P (B) = 50%.

Before making the decision, you will receive the decisions of a participant who get the highest payoff in a previous experiment. In addition, you will receive advice from your investment banker, which is "a" or "b". The investment banker is experienced but cannot make the perfect predictions. If you receive signal "a", then 67% (2/3) probability that Asset A will be successful and only 33% probability that Asset B will be successful. In contrast, if you receive signal "b", then 67% (2/3) probability that Asset B will be successful and only 33% probability that Asset A will be successful.

P ($A|a$) = P ($B|b$) = 67%;

Or

P ($A|b$) = P ($B|a$) = 33%;

As additional information, you can observe the decisions of the predecessors in your group (If you are the first participant in the group, you do not have this information).

After each period, you will be announced the successful asset. If your choice is correct, you will receive 10 ECU. Otherwise, you will receive nothing.

The payments will be accumulated after each period, which will be considered as your payoff. Therefore, if you make the right choice for ten times, your payoff will be 100 ECU.

The exchange rate for this treatment is **10 ECU = 1 GBP**

TREATMENT 3: THE PRICE

In this experiment, you are asked to make two decisions. The first decision is to choose which asset you think will be successful between Asset *A* and Asset *B*. Before making the decision; you will receive advice from an investment banker. You will also know about the decisions of the predecessors (if any) in your group. Then, you are asked to choose which asset you want to buy after getting the quoted price. You will be given 10 ECU, and you can buy **one asset** (Asset *A* or Asset *B*). The price of each asset will depend on the advice the investment bankers provide to all participants. For example, the price of asset A will increase if the advice you get from the investment banker is "*a*" while the price of asset B will decrease in this case. In other words, the asset price is correlated with the available information in the market. In the end, you will get profit if you buy the right asset. Otherwise, you will experience a loss.

There are six participants in your group, including you. Participants will make decisions in sequence, i.e. participant 1 makes the decision first, then participant 2 makes the decision, and so on. By this design, participant 2 will be informed about the decision of participant 1; participant 3 will be informed about the decisions of participant 1 and participant 2, and so on. In the end, participants will be announced the successful asset and their payoffs. There will be ten periods in this experiment, which means participants will make the same decisions ten times. The order of making the decision will change every period.

In this game, you are asked to choose between Asset *A* and Asset *B*. The successful probability of asset *A* and asset *B* is the same, which is 50%.

P (*A*) = P (*B*) = 50%.

Before making the decision, you will receive advice from your investment banker, which is "*a*" or "*b*". The investment banker is experienced but cannot make the perfect predictions. If you receive signal "a", then 67% Asset *A* will be successful, and only 33% Asset *B* will be successful. In contrast, if you receive signal "*b*", then 67% per cent Asset *B* will be successful, and only 33% Asset *A* will be successful.

P (*A*|*a*) = P (*B*|*b*) = 67%;

Or

P ($A|b$) = P ($B|a$) = 33%;

As additional information, you can observe the decisions of the predecessors in your group (If you are the first participant in the group, you do not have this information).

After making this decision, you will be asked which asset you want to buy between Asset *A* and Asset *B*. The price of each asset will be quoted based on the advice the investment banker release to the market. Your payment in this period depends on which asset you choose to buy, which will be calculated as follows:

Payment = 10 – Price of asset + Value of asset

For example, if you buy Asset *A* at the price of 6.7 ECU and Asset *A* is the correct asset, your payment will equal to:

Payment = 10 - 6.7 + 10= 13.3 ECU.

There are ten periods in this treatment. The payments will be accumulated after each period.

The exchange rate for this treatment is **10 ECU = 1 GBP**

TREATMENT 4: THE INFO AND THE PRICE

In this experiment, you are asked to make two decisions. The first decision is to choose which asset you think will be successful between Asset *A* and Asset *B*. Before making the decision; you are given the choices of a participant who got the highest payoff in a selected treatment. In addition, you will receive advice from an investment banker. You will also know about the decisions of the predecessors (if any) in your group. Then, you are asked to choose which asset you want to buy after getting the quoted price. You will be given 10 ECU, and you can buy **one asset** (Asset *A* or Asset *B*). The price of each asset will depend on the advice the investment bankers provide to all participants. For example, the price of Asset *A* will increase if the advice you get from the investment banker is "*a*" while the price of Asset *B* will decrease in this case. In other words, the asset price is correlated with the available information in the market. In the end, you will get profit if you buy the right asset. Otherwise, you will experience a loss.

There are six participants in your group, including you. Participants will make decisions in sequence, i.e. participant 1 makes the decision first, then participant 2 makes the decision, and so on. By this design, participant 2 will be informed about the decision of participant 1; participant 3 will be informed about the decisions of participant 1 and participant 2, and so on. In the end, participants will be announced the successful asset and their payoffs. There will be ten periods in this experiment, which means participants will make the same decision ten times. The order of making the decision will change every period.

In this game, you are asked to choose between Asset A and Asset B. The successful probability of Asset A and Asset B is the same, which is 50%.

P (A) = P (B) = 50%.

Before making the decision, you are given the choices of a participant who got the highest payoff in a selected treatment. In addition, you will receive advice from your investment banker, which is "a" or "b". The investment banker is experienced but cannot make the perfect predictions. If you receive signal "a", then 67% Asset A will be successful, and only 33% Asset B will be successful. In contrast, if you receive signal "b", then 67% Asset B will be successful, and only 33% Asset A will be successful.

P ($A|a$) = P ($B|b$) = 67%;

Or

P ($A|b$) = P ($B|a$) = 33%;

As additional information, you can observe the decisions of the predecessors in your group (If you are the first participant in the group, you do not have this information).

After making this decision, you will be asked which asset you want to buy between Asset A and Asset B. The price of each asset will be quoted based on the advice the investment banker release to the market. Your payment in this period depends on which asset you choose to buy, which will be calculated as follows:

Payment = 10 – Price of asset + Value of asset

For example, if you buy Asset *A* at the price of 6.7 ECU and Asset *A* is the correct asset, your payment will equal to:

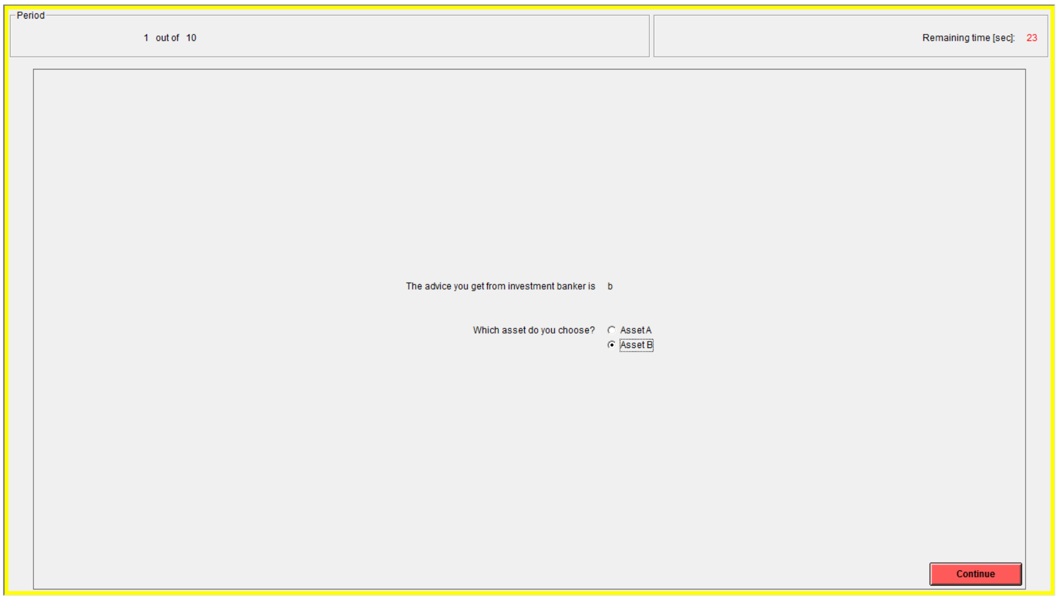
Payment = 10 - 6.7 + 10= 13.3 ECU.

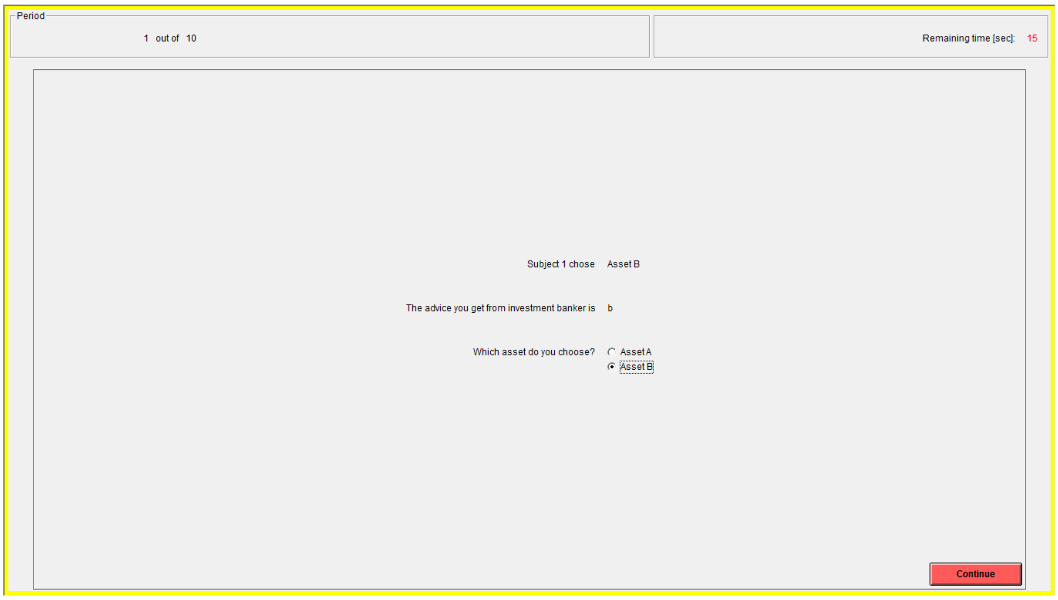
There are ten periods in this treatment. The payments will be accumulated after each period.

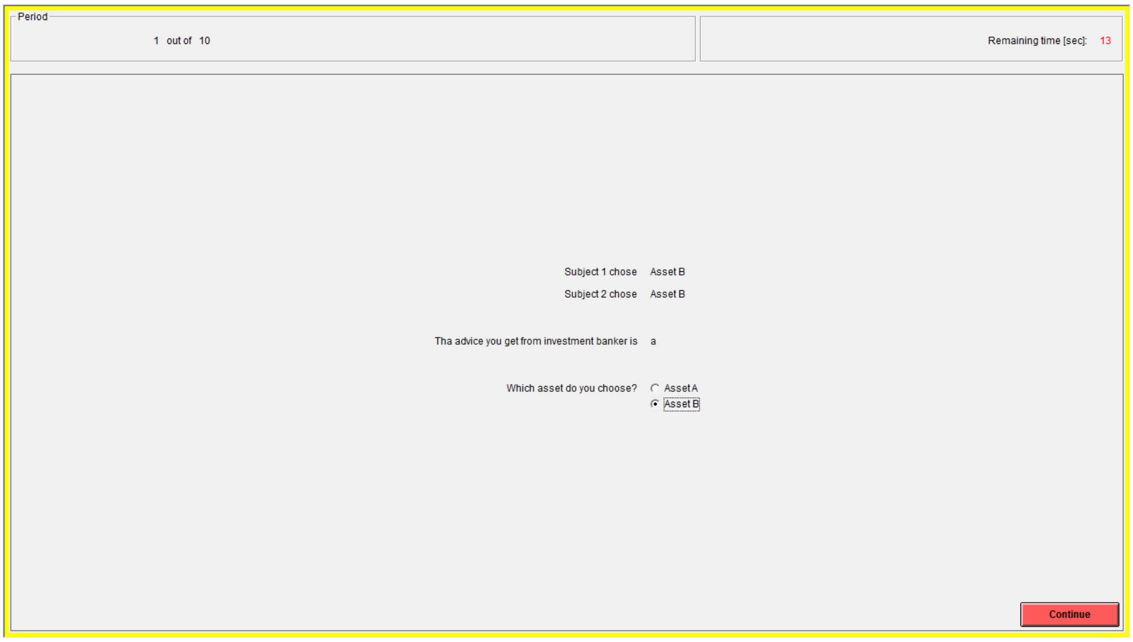
The exchange rate for this treatment is **10 ECU = 1 GBP.**

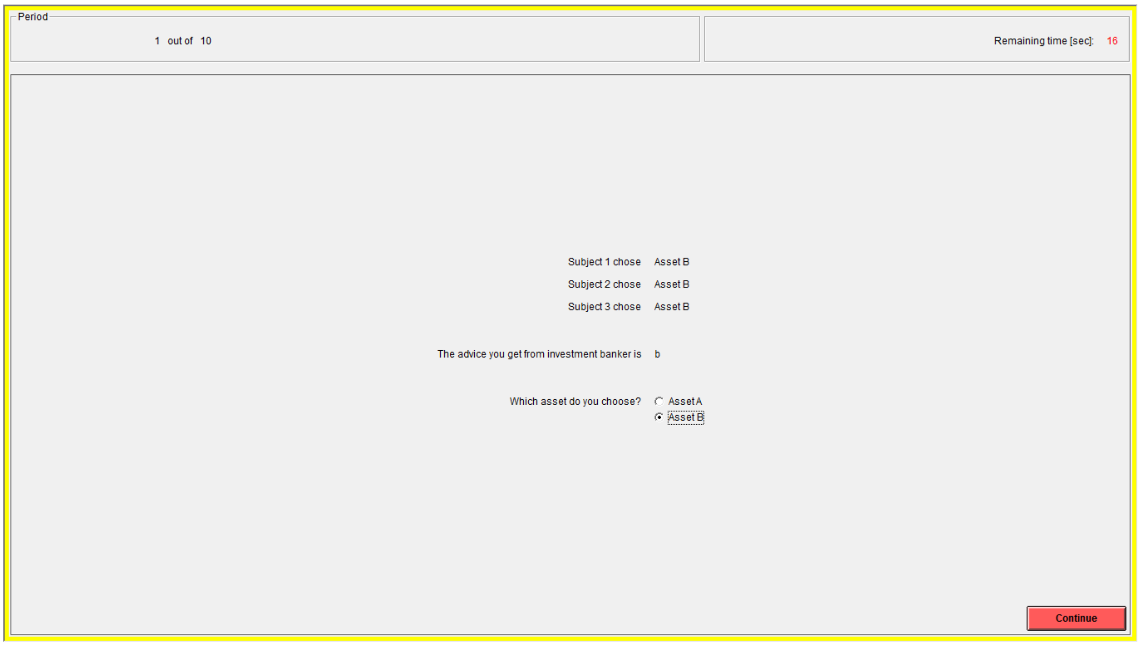
APPENDIX 2.8 - SCREENSHOTS OF THE EXPERIMENT

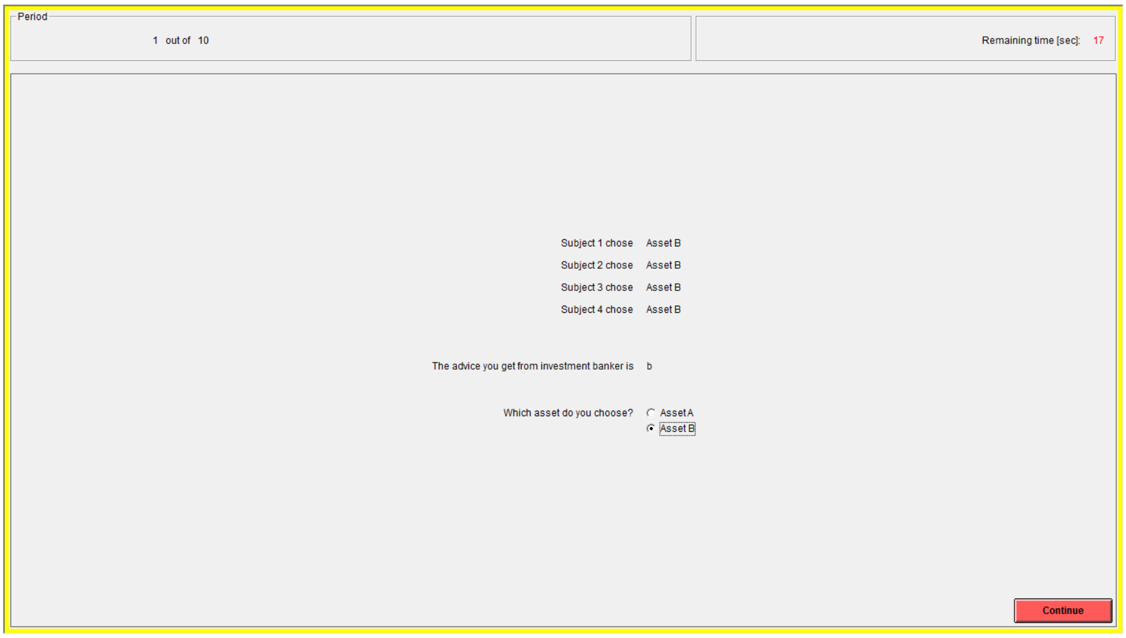
TREATMENT 1: THE BASE

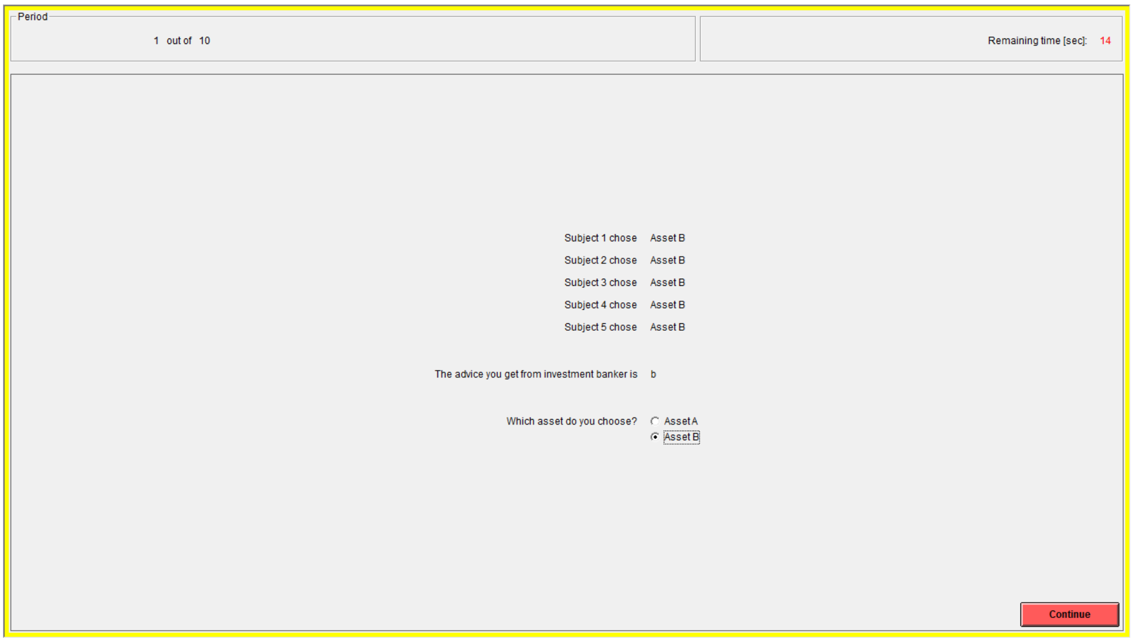




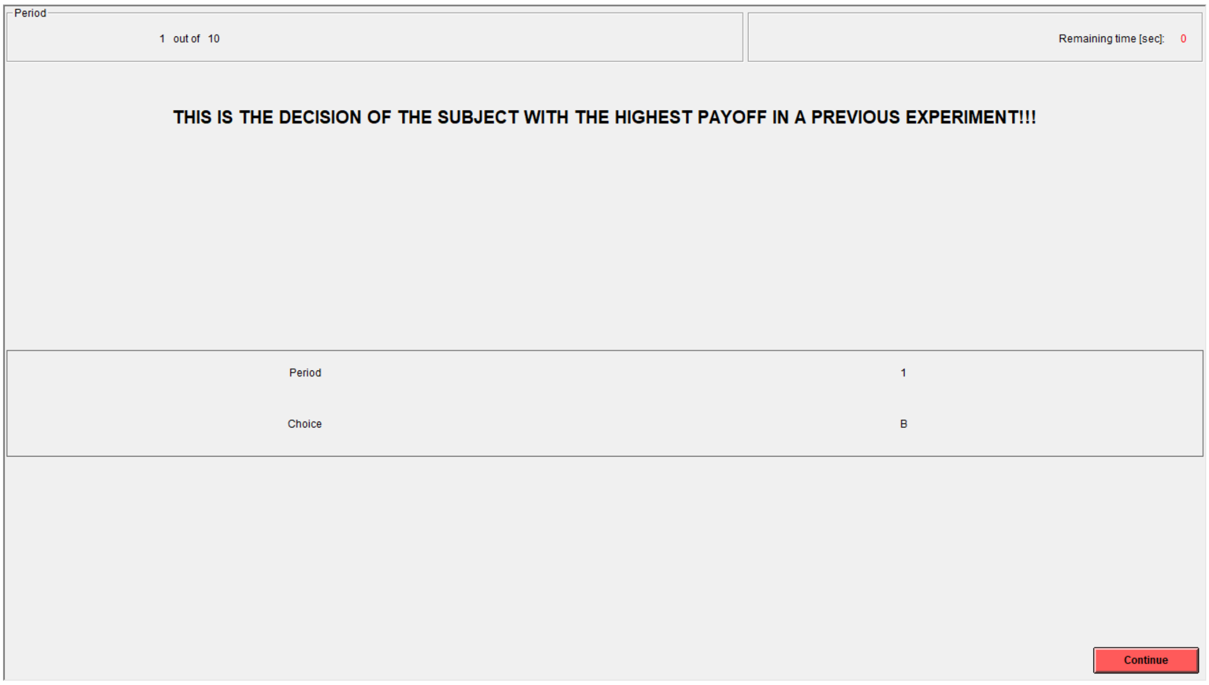

Period
1 out of 10
Remaining time [sec]: 13
Subject 1 chose Asset B
Subject 2 chose Asset B
Tha advice you get from investment banker is a
Which asset do you choose? Asset A
Asset B
Continue

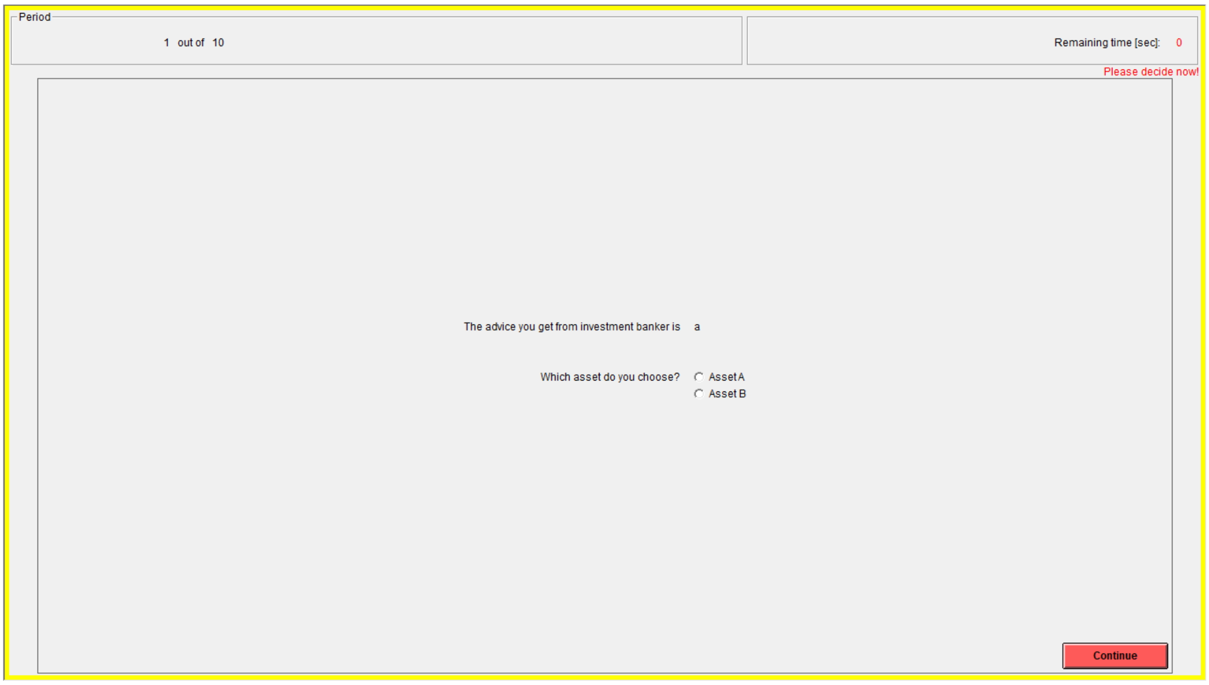

Period
1 out of 10
Remaining time [sec]: 16
Subject 1 chose Asset B
Subject 2 chose Asset B
Subject 3 chose Asset B
The advice you get from investment banker is b
Which asset do you choose? Asset A
Asset B
Continue


Period
1 out of 10
Remaining time [sec]: 17
Subject 1 chose Asset B
Subject 2 chose Asset B
Subject 3 chose Asset B
Subject 4 chose Asset B
The advice you get from investment banker is b
Which asset do you choose?
Asset A
Asset B
Continue

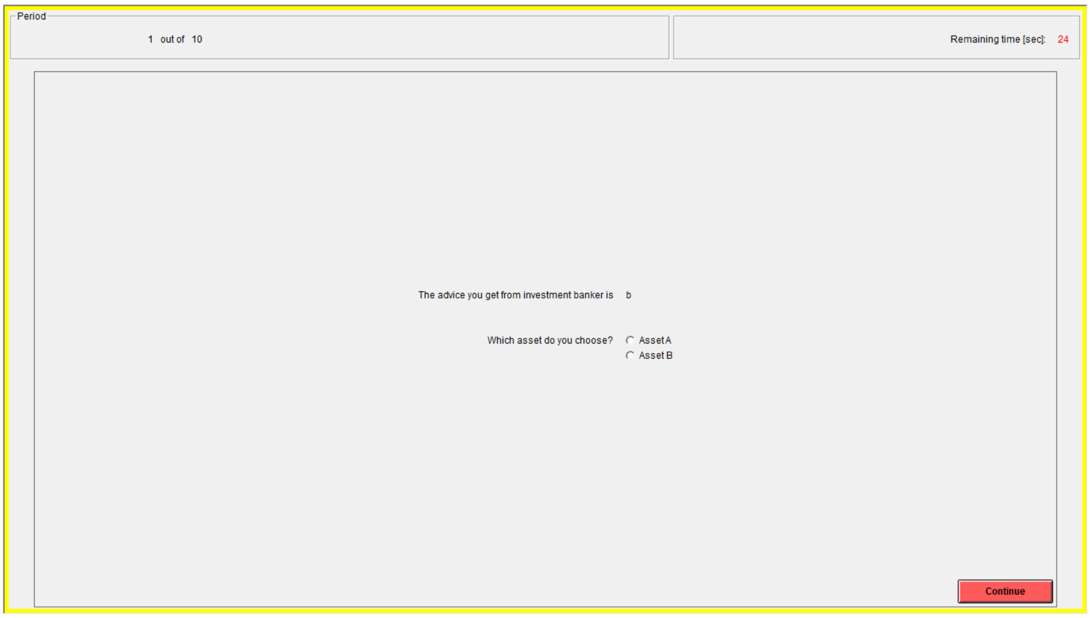

Period
1 out of 10
Remaining time [sec]: 14
Subject 1 chose Asset B
Subject 2 chose Asset B
Subject 3 chose Asset B
Subject 4 chose Asset B
Subject 5 chose Asset B
The advice you get from investment banker is b
Which asset do you choose?
Asset A
Asset B
Continue

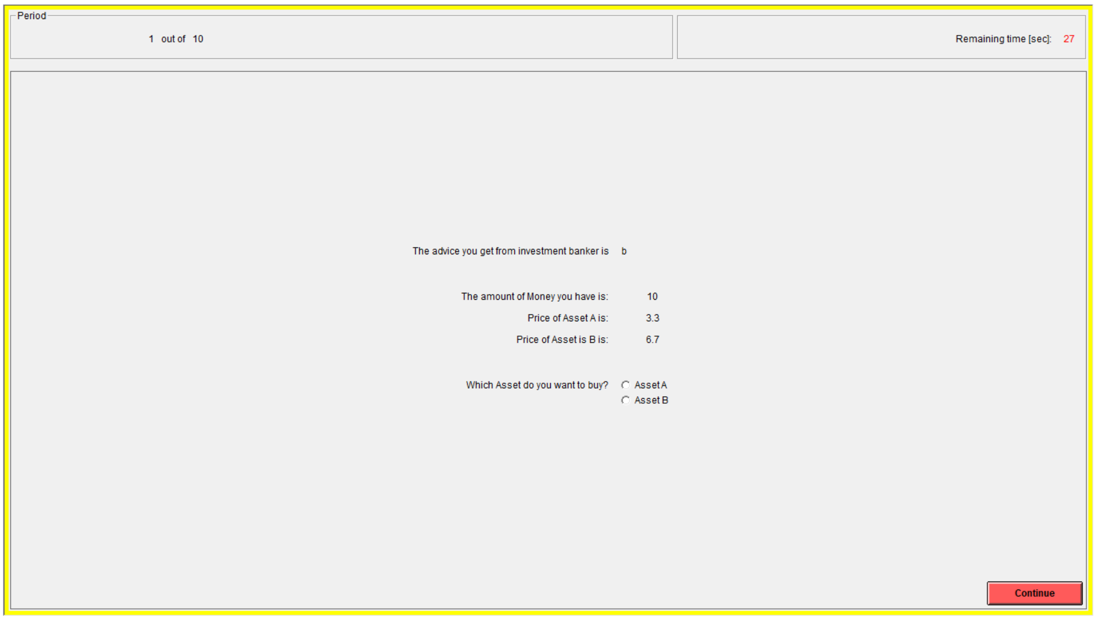
TREATMENT 2: THE INFO

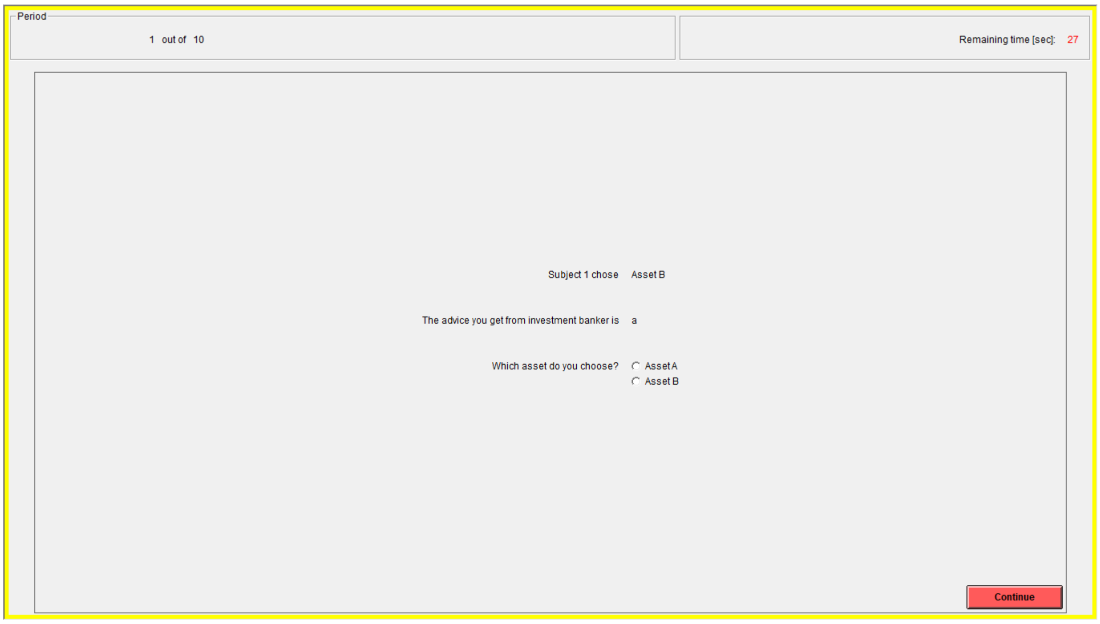


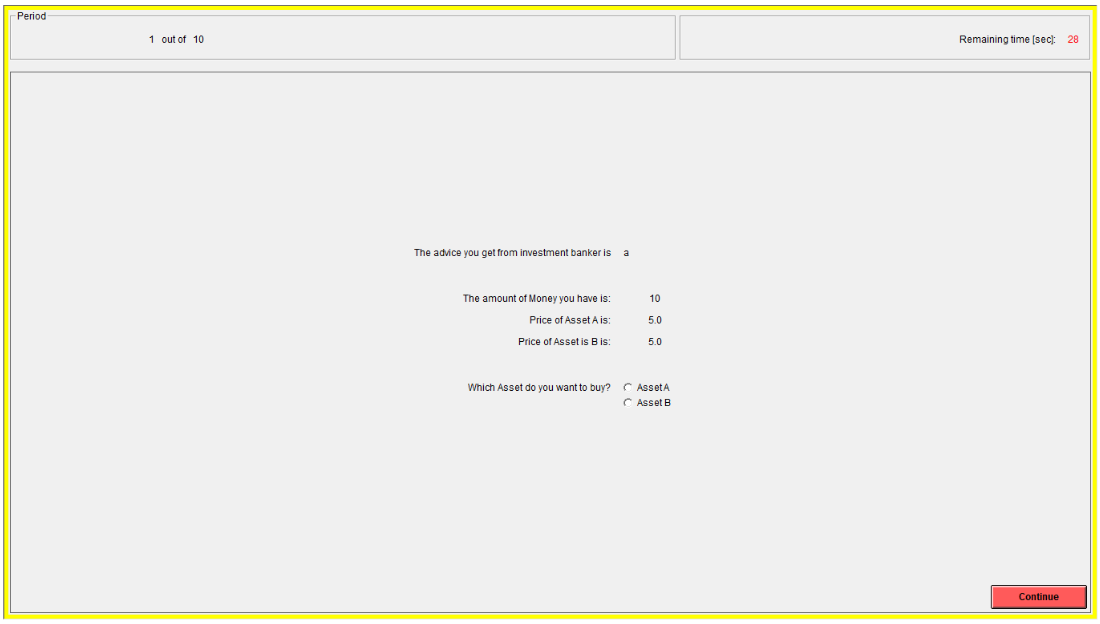


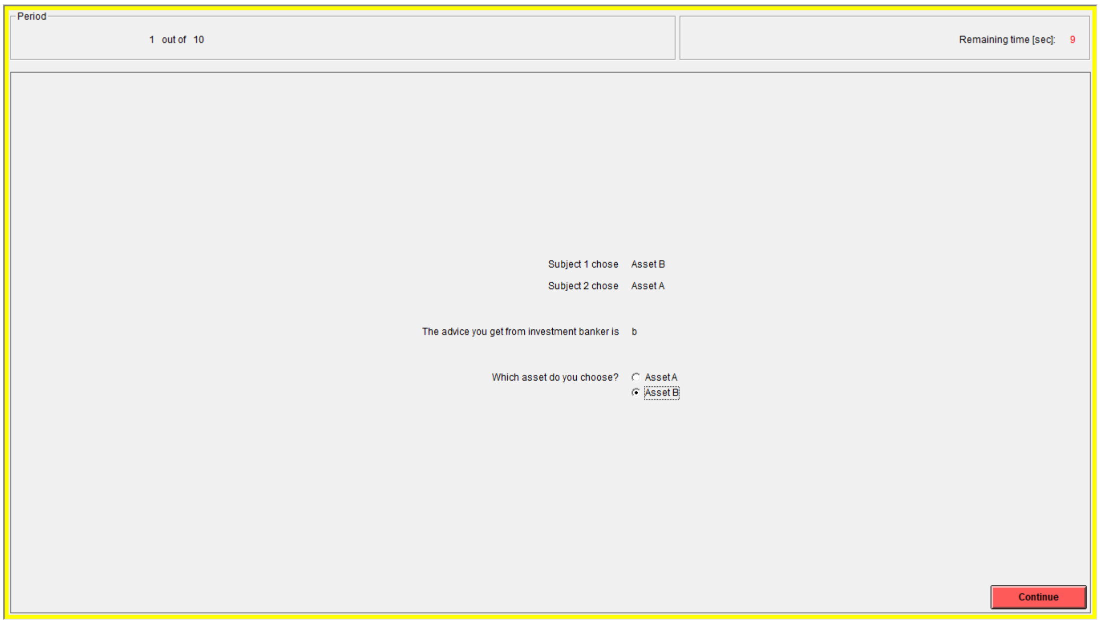
TREATMENT 3: THE PRICE

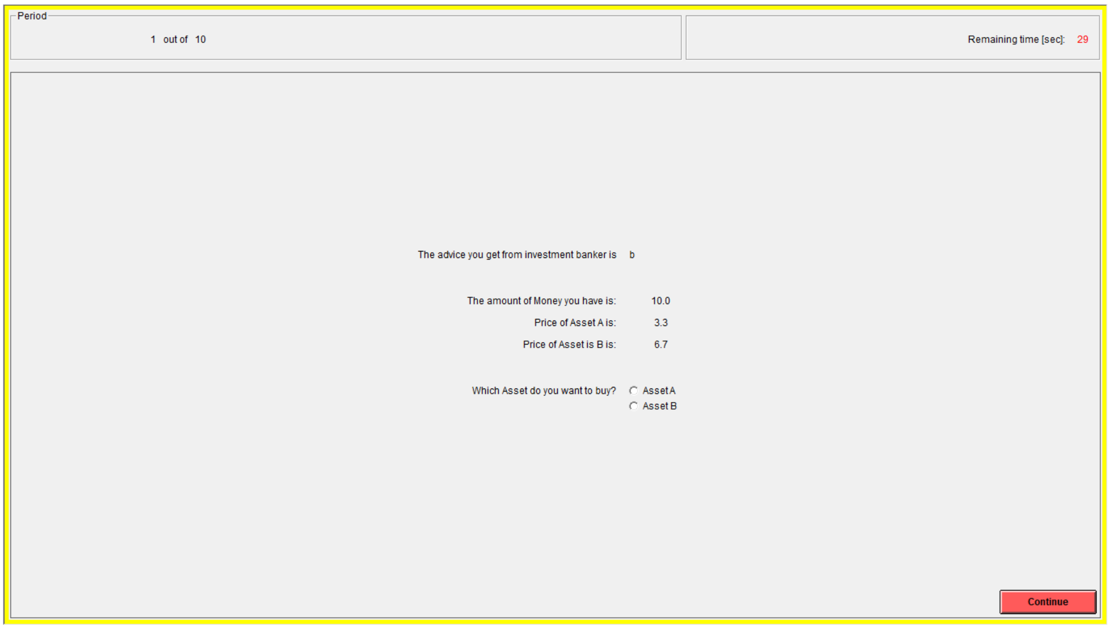




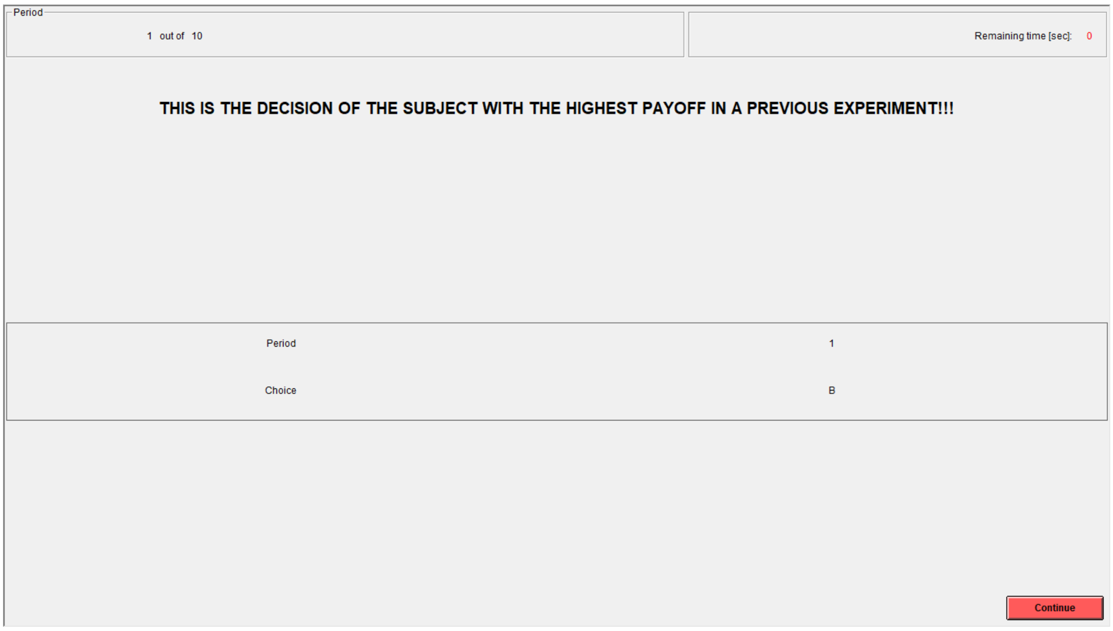

Period
1 out of 10
Remaining time [sec]: 27
Subject 1 chose Asset B
The advice you get from investment banker is a
Which asset do you choose?
Asset A
Asset B
Continue

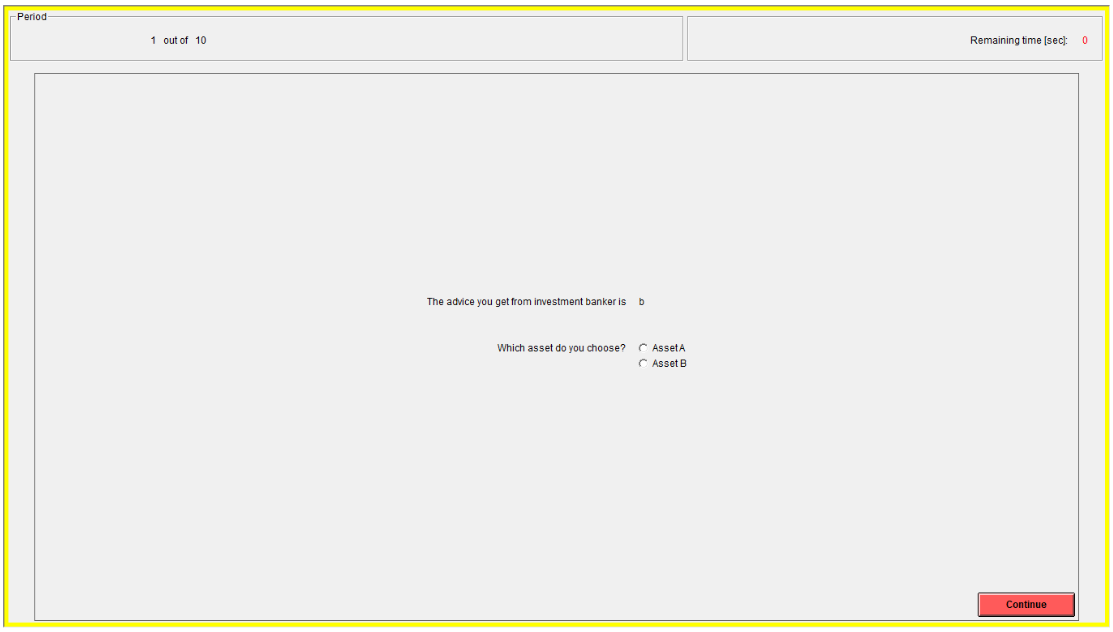

Period
1 out of 10
Remaining time [sec]: 28
The advice you get from investment banker is a
The amount of Money you have is: 10
Price of Asset A is: 5.0
Price of Asset is B is: 5.0
Which Asset do you want to buy?
Asset A
Asset B
Continue

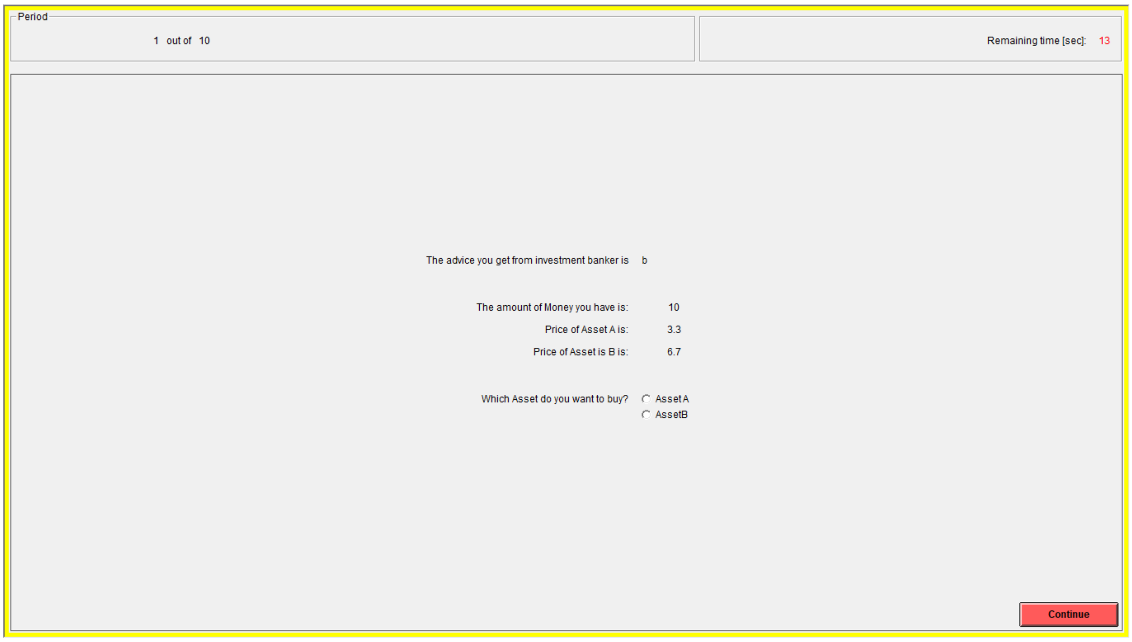

Period
1 out of 10
Remaining time [sec]: 9
Subject 1 chose Asset B
Subject 2 chose Asset A
The advice you get from investment banker is b
Which asset do you choose?
Asset A
Asset B
Continue


Period
1 out of 10
Remaining time [sec]: 29
The advice you get from investment banker is b
The amount of Money you have is: 10.0
Price of Asset A is: 3.3
Price of Asset is B is: 6.7
Which Asset do you want to buy?
Asset A
Asset B
Continue

TREATMENT 4: THE INFO&PRICE






Period
1 out of 10
Remaining time [sec]: 13
The advice you get from investment banker is b
The amount of Money you have is: 10
Price of Asset A is: 3.3
Price of Asset is B is: 6.7
Which Asset do you want to buy?
Asset A
AssetB
Continue

ESSAY 3: RISK PREFERENCE SHIFTING

DO DECISIONS OF OTHERS MATTER?

Abstract

Are individual risk preferences shifted by the information on risk preferences of the peers? We conduct an experiment introduced by Holt and Laury (2002) to examine individual risk preferences to answer this question. The participants make decisions that reflect their individual risk preferences, and after they have been informed about average group decisions of their peers. The results show that participant*s update their beliefs after knowing the risk preferences of others and shift their risk preferences in the direction of their peers. More importantly, when we ask the participants from which stage they would like to get their payoff, most of them choose the stage after they already shifted their risk preferences. This decision shows that risk preference shifting in this context is a robust and long-run phenomenon. Individual differences are found to have a significant impact on risk preference shifting.*

JEL Classification: C91, D81, G41

Keywords: Risk-preference shifting, herd behaviour, contrarian behaviour, reference-dependent utility.

3.1. Introduction

Hurricane Harvey is one of the most expensive hurricanes in America. According to the National Hurricane Center (NOAA), the total damage of the hurricane is 40 billion dollars. Nevertheless, approximately 80% of hurricane victims do not have flood insurance (Washington Post, 2017). Interestingly, this issue occurred in the U.S. before. When Hurricane Katrina ended in 2005, Americans started to buy the flood insurance after watching the tragedy of this hurricane. However, the demand for flood insurance had fallen back to the pre-Katrina levels within three years (Harford, 2017). Browne and Hoyt (2000) reveal that risk perception and the Bayesian learning model significantly influence flood insurance purchasing behaviour in the U.S. In particular, they show that the number of flood insurance policies sold is positively correlated with the flood losses during the prior period. Indeed, the demand for additional insurance policies is relatively price-inelastic. In other words, the risk preference for such disaster has changed after the hurricane.

The extraordinary performance of the bitcoin market has impressed the investors and attracted the attention of many authors. However, the results are against the efficiency of the market. For example, Katsiampa (2017) indicate that the bitcoin market is highly speculative. Cheah and Fry (2015) and Corbet et al. (2018) indicate the existence of speculative bubbles in the Bitcoin market, while Wei (2018) show the weak efficiency of cryptocurrencies. Interestingly, a number of studies confirm the presence of herd behaviour in the cryptocurrency market. Vidal-Tomás, Ibáñez & Farinós (2018) find that herd behaviour presents in the down markets and smallest digital currencies are herding with the largest ones. Therefore, the investment decisions of traders are based on the performance of the leading cryptocurrencies. Also, Feng et al. (2018) and Vidal-Tomás and Ibañez (2018) indicate that investors trading in cryptocurrencies respond quickly to bad news. The existence of herd behaviour in the market is robust with different models (see, e.g. Stavroyiannis and Babalos, 2019; Da Gama Silva et al., 2019; Ferreira and Pereira; 2019).

The last two examples demonstrate the instability of individual risk preferences. Risk preference, which may change due to external factors, is not a permanent phenomenon. Collin-Dufesne, Johannes and Lochstaer (2016) constructed a learning model in which large shocks can shift long-run risk. Malmendier and Nagel (2011) support the model by showing that macroeconomic shocks shape the risk preference of private household investors. In the first example, Hurricane Katrina was the external shock which shifted the risk preference of Americans. On the other hand, risk sensitivity, which is explained by the model of reference-dependent utility (Kőszegi and Rabin, 2006) demonstrates that people tend to make decisions based on a reference point. Back to the cryptocurrency example, the performance of leading bitcoins and the bad news in the market are the references for decisions of traders.

Apart from external shocks and reference-dependent utility, other factors could cause risk-shifting. For instance, Cohn et al. (2015) showed that personal experience determines the risk attitude of financial professionals. Gagliardini, Porchia, and Trojani (2008) and Boyarchenko (2012) argue that risk shifting may be caused by the uncertainty about the state of the economy while Drechsler (2013) claims model misspecification for creating risk-shifting. Indeed, time and group effect can also be the sources of risk-shifting. Weber, Weber and Nosić (2012) surveyed U.K. online-brokerage customers and concluded that risk-taking considerably changes over time, which correlates with changes in subjective expectations of market portfolios and returns. Masclet et al. (2009) examined group and individual risk preferences and concluded that their participants were more risk-averse when they made decisions as a group. Similarly, He, Martinsson and Sutter (2012) showed that risk attitude changed when their participants made decisions as a couple compared to individual decisions. This result serves as evidence of group effect on risk-preference shifting when the individuum is part of the group.

This paper applies the concept of the reference-dependent utility, which is introduced by Kőszegi and Rabin (2006), to examine risk preference shifting of the individual. More specifically, we measure changes in risk preferences when people know about the risk preference of their peers. We make two main contributions to the literature. Firstly, the experimental approach allows us to examine the presence and the magnitude of risk-shifting behaviour. Also, we could indicate the determinants of this behaviour by investigating the peer effect and individual differences. Secondly, we could measure whether risk-shifting is a long-run phenomenon by asking the participants to choose between getting the payoff from their decisions before and after knowing the risk preferences of their peers. If the participants are more confident with the decisions made after knowing the decisions of others, we consider risk-shiting is a long-run phenomenon, which is one of the significant findings in this area.

We employ the experiment introduced by Holt and Laury (2002) to measure risk preference before and after participants are informed about the risk preferences of the peers. We conduct the experiment at the Centre for Research in Behavioural Sciences (CRIBS), Nottingham University Business School. The results show that participants shift their risk preferences according to the information they received. More importantly, this tendency is found to be a long-run phenomenon. We run the experiments with finance and non-finance students to investigate the impact of financial literacy on risk-shifting. The results show that students with better financial literacy shift their risk preferences to a lesser magnitude. We also examine the correlations between individual differences and risk preference shifting.

This paper is followed by the relevant literature and experimental design (section 2), results and discussions (section 3) and a conclusion (section 4).

3.2. Relevant Literature

Kőszegi and Rabin (2006) construct a model of reference-dependent preference, which indicates that the utility from an outcome is dependent on comparisons to appropriate reference levels or reference points. Social preferences are among the explanations for the reference points, which is considered as a central theme in psychology and economics literature. For example, Camerer et al. (1997) examined the labour supply of New York cab drivers and concluded that the working hours are negatively correlated with the wages. More specifically, drivers set up their daily income targets as a reference point and stop working when they reach their goals.

Banerjee (1992) develop a simple model for herding, in which people make decisions in sequence, and they get the information on the decisions of their predecessors. The author shows that people follow the decisions of the predecessors when they find it is optimal to do so. This theory is applicable in this context when participants find it is better to shift their risk preferences toward the direction of the peers' risk preferences.

Risk preferences can be measured by using survey, abstract experiment and contextual experiment. Every method has its advantages and limitations. For the survey approach, researchers can proceed towards a large number of participants (see, e.g. Silverman and Kumka, 1987; Flynn et al., 1994; Spigner et al., 1993). One could argue that the non-incentive feature of this method makes the answer less valid. Meanwhile, the experimental approach, which includes abstract experiment and contextual experiment, which makes the results more appropriate in the economics context since decision making is incentive-relevant (see e.g. Weber, Blais, and Betz, 2002; Holt and Laury, 2002, Moore and Eckel, 2003; Eckel and Grossman, 2002, 2008; Powell and Ansic, 1997; and Levy, Elron, and Cohen, 1999). The abstract experiment includes a simple task such as gambling decisions. This method is relatively easy to conduct; however, this sometimes makes the results less reliable. For instance, the fact that women are more risk-averse than men is one of the most common findings in the literature. In finance, women hold less risky wealth compared to men at a similar economic status (Jianakoplos and Bernasek, 1998; Sunden and Surette, 1998). Barsky et al. (1997) showed that women report lower risk propensity toward financial risks. However, Schubert et al., (1999) argued that the comparison between risk propensity of men and women is highly correlated with financial decision setting, which is limited to abstract gambling decisions. They prove that there is no gender difference in risk-taking when participants face contextual decisions. The contextual experiment includes different tasks embedded in different contexts, such as investment and insurance. This method is considered the most appropriate method to measure risk.

In this paper, we use Holt and Laury (2002) approach of ten choices between two gambles, to measure individual risk preferences. This experiment takes the switching point from a less risky asset to a highly risky asset as a measure of risk-taking. In specific, there are ten pairs of lottery choices that participants can choose from (Appendix 3.1). Participants can decide from which point they would like to switch from option A to option B, which means switching from a risk-free asset to a risky asset. Therefore, the lower switching point expresses a higher level of risk-taking. More particularly, the switching point from 1 to 3 indicates that participants are prone to risk-loving, the switching point of 4 indicates that participants are risk-neutral while any switching point higher than 4 means participants are risk-averse. In our design, we make the decision more contextual by changing from "Option A" and "Option B" to "Asset A" and "Asset B" with the same success probability.

The experiment introduced by Holt and Laury (2002) is widely used in the literature. The general conclusion is that participants are prone to risk-averse, although different switching points are captured. For example, Holt and Laury (2002) presented in their original paper that the average switching point is 5.17. Harrison et al. (2005) argued that the original design experienced order effect. After controlling for this issue, they found that the average switching point was 5.30. Holt and Laury (2005) conducted another experiment controlled for the order effect and showed that the average switching point was 6.10. Adding group effect in the design, Masclet et al. (2009) found that the individual choice was 6.6 while group choice was 6.9, indicating that participants are more risk-averse in a group. He, Martinsson and Sutter (2012) showed that the average switching point of male, female and couple is 4.48, 5.25 and 4.84, respectively, indicating that men are more risk-loving, which is considered as another widespread result in this context (see the survey paper of Eckel and Grossman, 2008). Other papers also show the average switching point is around 5, such as Goeree, Holt and Palfrey (2003) (5.3); Lusk and Coble (2005) (5.42); Baker, Laury and Williams (2008) (5.67); Anderson and Mellor (2008) (4.98); Anderson and Mellor (2009) (5.68); Bellemare and Shearer (2010) (4.62); and Dave et. al. (2010) (5.0).

3.3. Experimental Design

In our design, we measure whether participants shift their risk preferences when they know the risk preferences of others. This information is irrelevant for their own decisions. However, we expect that participants will take this information into account and change their risk preference.

We use the experiment of Holt and Laury (2002) in this context and make it as the *base* case. More specifically, participants are asked to choose the switching point from a safer Asset A to a riskier Asset B with the predetermined probability of success (Appendix 3.2). In other words, the switching point should be high for risk-averse participants. After making this decision, participants are automatically transferred to the second stage. At the beginning of this stage, participants are informed that the average switching point taken from a random session is 3.0 (H3), which means the peers are prone to risk-loving. After receiving this information, participants make the same decision as in the first stage. Similarly, at the beginning of stage 3, participants are informed that the average switching point taken from a random session is 7.0 (H7), which means the peers are prone to risk-averse. Then participants are asked to make the same decision from which point they would like to switch from Asset *A* to Asset *B*.

The historical switching points used in this research are obtained from the literature. Masclet et al. (2009) report the average switching point when participants make decisions in the group is 6.9 while He, Martinsson and Sutter (2012) report this threshold is 4.48 in the case of male students. We make the figures more extreme by turning it to 7.0 and 3.0. While 7.0 represents a relatively high level of risk-averse, 3.0 is the starting point of risk-loving. After making the three decisions, participants are asked to indicate which of the three stages they would prefer to be paid out. Although the payoff is randomly drawn and based on participants' decisions from the three stages, this reference is a benchmark for participants' beliefs on their decisions. The experiment ends with a questionnaire, which is used to measure the participant's personality and characteristics.

The design of this experiment allows the experimenter to measure risk preference shifting due to information on risk preferences of others. The reference-dependent utility suggests that participants obtain additional utility if they follow the decision of others.

> *Hypothesis 1: Participants shift their risk preferences after learning the risk preferences of their peers.*

Risk preference shifting may occur when participants mistakenly chose a different switching point compared to their original decisions or when they make a decision based on their short-run thought, but participants may change their evaluation right after. Therefore, at the end of the experiment, we ask participants from which stage they would prefer to get paid out. This question is directly relevant to the amount of money participants may receive from the experiment, participants should carefully think before they choose the stage. The stage from which participants would like to get their payoff is the stage they most prefer. For that reason, we could take the risk preference from that particular stage as the representative of the participant's risk preference. If this choice is stage 2 or stage 3, we could infer that risk preference shifting is a long-run phenomenon since participants believe more in the decisions after they know the preferences of others.

Hypothesis 2: Risk shifting is a long-run phenomenon.

For the experiment, we conducted two main sessions, one session with students from different disciplines studying at the University of Nottingham and the other session with finance students studying Master in Finance and Investment and PhD in Finance at the University. We separate the session for finance students since we are interested in whether finance students, who have a better knowledge of risk and financial decision-making, shift their risk preference or not. Participants were not aware of the session composition; finance students did not know that only finance students participate in their session, and the same holds true for the non-finance student sessions. Some articles indicate that professionals make better decisions in financial-market-related experiments. For example, Alevy, Haigh and List (2007) show that financial professionals engage in less following decisions since they can distinguish between good signals and bad signals compared to the students. In this research, finance students are considered as professionals; therefore, we would expect that they are more consistent with their risk preferences. To test the robustness of this result, we make the information on the switching point to be even more extreme, which is 9 (H9) in the case of finance students. Accordingly, the information finance participants get at the beginning of the third stage is that a number of participants chose "9" as their switching point. The extreme value encourages participants to follow since 7 indicates the relatively low level of risk-averse. With 53 finance participants, 26 participants play the third stage with the information on the average switching point of 7 while 27 participants play the third stage with information on the switching point of 9. We expect that finance students will not shift their risk preference even in the case they know that some participants chose 9 as the switching point.

Hypothesis 3: Finance students are more consistent with their risk preferences.

The experiment is conducted at The Centre for Research in the Behavioural Sciences (CRIBS), Nottingham University Business School. The experiment is designed by using z-tree (Fischbacher, 2007), and participants are recruited via ORSEE (Greiner, 2015).

3.4. Results and Discussions

3.4.1. Sample Descriptions

We recruit 186 participants from different disciplines across the University of Nottingham, in which 26 students are studying finance and 162 are mixed-discipline students, for the main session (H3 and H7). Four finance students did not finish the questionnaire; therefore, we end up with 22 finance participants and 162 non-finance participants. The characteristics of the dataset are shown in Table 3.1. We use miscalibration to measure overconfidence. More specifically, we include a questionnaire with ten questions related to general knowledge (Biais et al., 2005). The participants are asked to give the low and high values answering those questions which they are 90% sure that the correct value will fall inside the interval. If the participants are well-calibrated, only 10% of the right answers should fall outside their given range. From Table 3.1, participants express considerably high miscalibration level when they answer 1.88/ 10 questions correctly only. This result is relatively low compared to the other research. For example, Russo and Schoemaker (1992) show that business managers get 42% to 62% correct answer while 43% and 36% are the results found by Klayman et al. (1999) and Biais et al. (2005), respectively. For the risk preference, we can see that the average switching point is 6.59, which means that participants are prone to risk-averse. Maths and self-monitoring ability are measured using the questionnaires introduced by Eckel and Füllbrunn (2015) and Biais et al. (2005), respectively. Participants have 3.93 correct answers on average, over six maths questions and could entirely control themselves in 8.7 over eighteen given situations. Within the subject pool, 45.11% are male, 66.85% are studying social science, and 36.41% of participants come from Western countries. 59.24% of participants have lived in a foreign country for more than six months. Since the participants are students, we take living allowance as their income, which is £999.73 on average and the average age is 21.

The comparison between the characteristics and personalities of finance students and non-finance students is shown in Table 3.2. The results from Mann-Whiney U-test indicates that finance students are less miscalibrated, significantly more overconfident with the better-than-average measure and better in maths.

Table 3. 1 - Characteristics of the subject pool

This table reports the characteristics of the subject pool. The characteristics includes overconfidence (miscalibration), risk preference, maths skill, self-monitoring ability, gender, major, nationality, income and age. The fact that participants lived in a foreign country or not is also included.

Characterisations	Value
Overconfidence (Miscalibration)	1.88
Risk preference	6.59
Maths skill	3.93
Self-monitoring ability	8.65
Gender (Male over Female)	45.11 %
Major (Social over Natural Science)	66.85%
Nationality (Western over Asian)	36.41%
Living abroad	59.24%
Income	£ 999.73
Age	21
Observations	184

Table 3. 2 - Comparison between characteristics and personalities of finance and non-finance students

This table reposts the characteristics of two subject pools, including finance and non-finance students. The characteristics include overconfidence (miscalibration), risk preference, maths skill, self-monitoring ability, gender, major, nationality, income and age. The fact that participants lived in a foreign country or not is also included.

	Non-Finance	**Finance**	**p-value**
Overconfidence (Miscalibration)	1.82	2.31	0.545
Risk preference	6.59	5.69	0.498
Maths skill	3.86	4.45	**0.007*** **
Self-monitoring ability	8.75	7.82	0.304
Gender (Male over Female)	42.59%	63.64%	**0.063***
Nationality (Western over Asian)	38.27%	22.73%	0.156
Living abroad (Yes)	61.73%	59.09%	**0.062***
Income	1044	673.6	0.400
Age	20.58	24.6	**0.000*** **
Observations	162	22	

The p-values are taken from Mann-Whiney U-test
*** p<0.01, ** p<0.05, * p<0.1

3.4.2 Risk Preference Shifting

The average switching point from the three stages (H3 and H7) of non-finance students is shown in Table 3.3. In particular, the average switching point in the first stage is 6.57, indicating that participants are prone to risk-averse. In the second stage, when participants have the information of the average switching point from another experiment is 3.0, they shift their switching point to a lower average (6.21). Similarly, this number is shifted to 6.76 when participants know that the average switching point from another experiment is 7.0 in the third stage. The shifting decision in the second and third stage is entirely consistent with the informed information. In other words, participants take risk preferences of others into account before making their own decisions. More importantly, risk preference shifting in the second stage is found to be significant compared to the first stage. The shift in the third stage is not statically different compared to the first stage but significantly different compared to the second stage. A possible explanation is that the information, which is 7.0 on average is close to the average switching point in the first stage (6.57). Therefore, the information does not significantly affect the choice in the third stage.

When participants choose their preferred payout stage, 41% choose the second stage which is significantly higher than the number of participants who choose the first stage (significance of 1% level using the two-sample prtest, Table 3.4). The result indicates that participants are more confident in their decisions after learning the decisions of others. There is no time pressure when participants make decisions; therefore, we could consider risk-preference shifting as a long-run phenomenon. In addition to this, choosing a stage reveals and states their true preference.

We categorise the risk preference into risk-loving, risk-neutral and risk-averse (Table 3.5). In particular, the switching point of 0-3, 4 and 5-10 indicate risk-loving, risk-neutral and risk-averse, respectively. In the first stage, 4% of participants are found to be risk-loving, while 8% of participants are risk-neutral, and 88% of participants are risk-averse. The number of risk-loving participants significantly increases to 11%, and the number of risk-averse participants significantly decreases to 81% in the second stage when participants know that other participants are prone to risk-loving while the number of risk-neutral participants remains unchanged. Similarly, after being informed that most of the participants in a previous experiment are prone to risk-averse in the third stage, the number of risk-loving and risk-neutral participants significantly drops from 11% to 5% and from 8% to 3%, respectively while the number of risk-averse participants substantially rises to 92% compared to the second stage. Compared to the first stage, the number of risk-neutral participants in the third stage significantly decreases from 8% to 3% while the number of risk-averse participants increases from 88% to 92%, but this increase is not statistically significant. Consistently with the previous analysis, the shift in the second stage is significantly more substantial compared to the change in the third stage.

Table 3. 3 - Average switching points taken from the three stages

This table reports the average switching point of non-finance students in the three stages, which are the *base* stage, the stage in which participants are informed that the average switching point in a selected session is 3 (*H3*) and the stage in which the informed switching point is 7 (*H7*).

Stage	N	Average switching point
S1 (*Base*)	184	6.59
S2 (*H3*)	184	6.24
S3 (*H7*)	184	6.79
p-value (S12)		**0.002*** **
p-value (S13)		0.145
p-value (S23)		**0.000*** **

The p-values are taken from the Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

Table 3. 4 - The stage from which participants want to get payment

This table reports the percentage of participants chose stage 1 (b*ase*), stage 2 (*H3*) and stage 3 (*H7*) as their preferences for the payoff.

	Stage 1	Stage 2 (*H3*)	Stage 3 (*H7*)
Choose payment	26.63%	40.76%	32.61%
p-value S12	**0.002*** **		
p-value S13	0.104		
p-value S23	**0.052** **		

The p-values are taken from the two sample prtest
*** p<0.01, ** p<0.05, * p<0.1

Table 3. 5 - Risk preference classification in the three stages

The following tables report the percentage of participants who are prone to risk-loving, risk neutral and risk averse in stage 1 (*base*), stage 2 (*H3*) and stage 3 (*H7*).

(A) Stage 1 and Stage 2 (*H3*)

Switching point	**The range of relative risk averse** $\boldsymbol{U(x) = (\frac{x^{1-r}}{1-r})}$	**Risk preference classification**	**Proportion of choice**		**p-values**
			Stage 1	**Stage 2 (*H3*)**	
0-3	r < -0.15	Risk loving	0.04	0.11	**0.009*** **
4	-0.15 < r < 0.15	Risk neutral	0.08	0.07	0.684
5-10	r > 0.15	Risk averse	0.88	0.82	**0.070***

The p-values are taken from the two sample prtest
*** p<0.01, ** p<0.05, * p<0.1

(B) Stage 1 and Stage 3 (*H7*)

Switching point	**The range of relative risk averse** $\boldsymbol{U(x) = (\frac{x^{1-r}}{1-r})}$	**Risk preference classification**	**Proportion of choice**		**p-values**
			Stage 1	**Stage 3 (*H7*)**	
0-3	r < -0.15	Risk loving	0.04	0.05	0.402
4	-0.15 < r < 0.15	Risk neutral	0.08	0.03	**0.017****
5-10	r > 0.15	Risk averse	0.88	0.92	**0.080***

The p-values are taken from the two sample prtest
*** p<0.01, ** p<0.05, * p<0.1

(C) Stage 2 (H3) and Stage 3 (H7)

Switching point	**The range of relative risk averse** $U(x) = (\frac{x^{1-r}}{1-r})$	**Risk preference classification**	**Proportion of choice**		**p-values**
			Stage 2 (H3)	**Stage 3 (H7)**	
0-3	r < -0.15	Risk loving	0.11	0.05	**0.016****
4	-0.15 < r < 0.15	Risk neutral	0.07	0.03	**0.041****
5-10	r > 0.15	Risk averse	0.82	0.92	**0.002*****

The p-values are taken from the two sample prtest
*** p<0.01, ** p<0.05, * p<0.1

3.4.3. Herding (Contrarian) Behaviour and Reference-Dependent Utility

In the context of this research, herd behaviour indicates the tendency of following others, while contrarian behaviour indicates the opposite movement. For example, participants are informed about the average switching point from another experiment is 3.0 at the beginning of stage 2. Accordingly, a participant is regarded as herding when she increases her switching point in the case her first switching is lower than 3, while decreases her switching point in the case the first switching point is higher than 3. In other words, this participant takes 3 as the benchmark and adjusts her initial decision to be close to this reference point. In contrast, any participant who increases the switching point when her initial point is higher than 3 and decreases the switching point when her initial point is lower than 3 is considered as contrarian decision-maker. Similarly, according to the informed information that the average switching point taken from another experiment is 7.0, any decrease in case the previous switching point is higher than 7.0 and increase in the case the previous switching point is lower than 7.0 is considered as herding while the opposite decisions are considered as contrarian behaviour.

The number of participants makes herding, contrarian and the same decisions in the second and the third treatment is shown in Table 3.6. Specifically, the number of participants herd others in the second stage is significantly higher than the number of participants make contrarian decisions or stay unchanged (48.4% compared to 30.3% and 21.3%, respectively). This tendency applies to the third stage while the number of participants who decide to herd is significantly higher than the ones who express contrarian behaviour or stays unchanged (58% compared to 17.6% and 24.4%). Interestingly, while the number of participants who do not change their positions is nearly the same over the second and the third stage, the proportion of herding decisions significantly increase while the proportion of contrarian behaviour significantly decreases over the two stages (48.4% to 58% for herding and 30.3% to 17.6% for contrarian behaviour). In the second stage, participants may be sceptical about the rationality of the others (the average switching point is 3.0); therefore, they conduct more contrarian decisions. However, when convinced about the issue (the average switching point is 7.0), significantly more herding decisions take place. However, in either case, the proportion of herding is always higher than any other decisions, including contrarian and staying unchanged. This result confirms that participants tend to follow others in changing their personal preference. Similar results are found when we examine the magnitude of herding and contrarian decisions (Table 3.7). On average, participants significantly increase their switching point from 1.35 to 1.49 point in the herding direction while significantly decreases the switching-point shifting from 0.68 to 0.26 point in the contrarian direction. In both stages, the magnitude of herding is always significantly higher than the magnitude of the contrarian (significance at 1% level using the Wilcoxon signed-rank test). It is observed in Figure 1 that most participants herd in the interval of 1-4 points and this tendency maintains in both stages, whereas the magnitude of contrarian behaviour considerably drops from the interval of 1-4 points in the second stage to the interval of 1-2 points in the third stage. The frequency of herding is also higher than contrarian behaviour and increases over the stages, while the opposite tendency is found in the context of contrarian behaviour.

In the model independently introduced by Benerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992), herd behaviour forms when participants disregard their private information and follow the predecessors. However, Celen and Kariv (2004) argue that the previous decision can be inferred as information cascade while herding behaviour presences when participants make the same decisions. In other words, the concept of herd behaviour is more comprehensive. In this experiment, herd behaviour exists when individuals shift their initial risk preferences toward the direction of the risk preferences of their peers. Another theory which is developed by Scharfstein and Stein (1990) suggests that reputational externality could be one of the reasons for herding. Drehmann, Oechssler & Roider (2005) include this feature in their information cascade experiment to figure out whether the participants follow the one who gets the highest payoff (best reputation). This theory is also irrelevant in this context of our experiment since the participants are only informed the average switching points of the peers but not their payoffs. Therefore, the result becomes more relevant since only a small set of information about the decisions of others; approximately 80% of participants shift their initial decisions. As demonstrated in our model, participants update their belief after the information on their peers and choose to follow the given information. In other words, they find themselves as a part of the "crowd". In the experiment conducted by Chmura and Weiss (forthcoming), they show that consumers buy significantly more from seller 2 when they are informed that others also do so, even buying from seller 2 is not an optimal choice. It is demonstrated in their model that consumers gain reference-dependent utility besides reference-independent utility when they follow others.

However, it is also interesting to analyse the behaviour of the participants who adjust their choices against the given information. We call this decision contrarian behaviour. Drehmann, Oechssler & Roider (2005) suggest that people express contrarian behaviour when they are sceptical about the rationality of others. In this experiment, this is applicable since the number of contrarian decisions is significantly high in the second stage, where participants are informed that others are risk-loving in general (the average switching point is 3.0). This information seems unusual since people are risk-averse by nature. When the information on the decision of others is changed to 7.0, which is more reasonable, herding decision significantly increases while contrarian behaviour significantly decreases.

Table 3. 6 - Herd and Contrarian behaviour in the second and third stages

This table reports the percentage of participants who made herding, contrarian decisions and stayed unchanged with their risk preferences in stage 2 (H3) and stage 3 (H7)

Stage/ Behaviour	Stage 2 (H3)	Stage 3 (H7)	p-value (S23)
Herd	0.402	0.424	0.669
Contrarian	0.179	0.022	**0.000*****
Same	0.419	0.424	0.894
p-value (Herd vs. Contrarian)	**0.000*****	**0.000*****	
p-value (Herd vs. Same)	0.807	1.000	
p-value (Contrarian vs. Same)	**0.000*****	**0.000*****	

The p-values are taken from the Wilcoxon signed-rank test
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. 7 - Magnitude of herding and contrarian behaviour

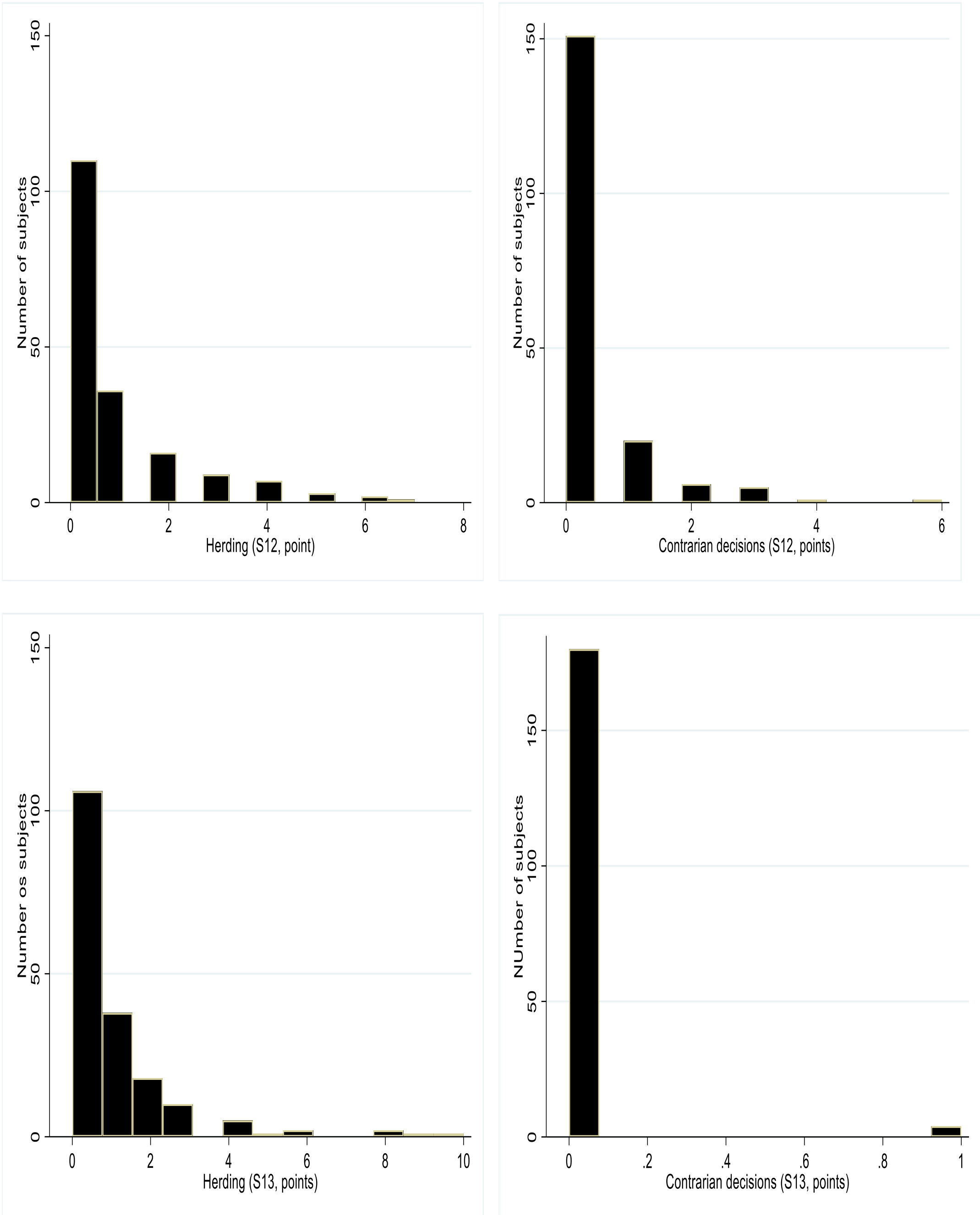
This table reports the magnitude of herd behaviour and contrarian behaviour in stage 2 (H3) and stage 3 (H7). The magnitude is measured by the number of switching points participants shift their risk preference compared to their original switching point in the *base* stage (stage 1).

Stage/ Behaviour	Stage 2 (*H3*)	Stage 3 (*H7*)	p-value (S23)
Herding magnitude	0.85	0.96	0.669
Contrarian magnitude	0.31	0.02	**0.000*****
p-value (Herd vs. Contrarian)	**0.000*****	**0.000*****	

The p-values are taken from the Wilcoxon signed-rank test
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 3. 1 - Frequency and magnitude of herd and contrarian behaviour

Frequency and magnitude of herd behaviour and contrarian behaviour in stage 2 (H3) and stage 3 (H7)



3.4.4. The comparison between finance students and non-finance students

To be able to compare non-finance and finance students, we first conduct the experiment with 162 students studying different disciplines at the University of Nottingham and 26 finance students who study Master in Finance and Investment and PhD in Finance at the University. We aim to shed light on financial literacy and the effect of financial knowledge on shifting risk preferences. Table 3.8 shows the decisions of the students in the three stages. While non-finance students significantly shift their risk preference in the second stage, finance students shift their risk preference in the direction of the risk preferences of their peers, but the change is not significant. Although the proportion of herding decisions is not different in the case of non-finance and finance students, the proportion of contrarian decisions is significantly less with finance students in the third stage, shown in Table 3.9 and 3.10.

The proportion of finance students who stay unchanged with their risk preferences is significantly higher compared to non-finance students. Similar results are found in terms of the magnitude of herding and contrarian decisions. To gain more insight into the difference in the decision-making of finance students, we recruited an additional 27 finance students who study Master in Finance and Investment, to take part in the experiment. In this session, we modify the design to test the robustness of the result in the case of finance students. Accordingly, instead of informing the participants that the average switching point taken from another experiment is 7.0, we make the information more extreme by telling them that a group of participants in a previous experiment chose 9.0 as their switching point. The switching point is significantly different from their initial choices; therefore, we expect that the shift in the third stage would become significant. Other features of the experiment remain unchanged.

Finance students do not significantly shift their risk preference even in the case they receive extreme information from their peers (Table 3.8). In contrast, the proportion of herding is significantly lower in the third stage with the history of 9 while the proportion of contrarian decision is significantly higher. Interestingly, more than 50% finance students, in this case, choose to stay unchanged with their initial switching point in both stage 2 and stage 3. The decisions of finance students in the case of the extreme signal are unexpected. They even do not follow the signal but choose to go against or stay unchanged. Being more overconfident and smarter, finance students can judge the quality of information and distinguish between good and bad signals, which is precisely the same with the findings of Alevy, Haigh and List (2007) in the case of comparing professionals and students. In this context, finance students have a better understanding of the concepts such as risk preference, financial decision-making; therefore, they make more rational decisions.

Table 3. 8 - Comparison between non-finance and finance students

The following tables report the switching point of finance and non-finance participants in the three stages, which are the *base* stage, the stage in which participants are informed that the average switching point in a selected session is 3 (H3) and the stage in which the informed switching point is 7 (H7). For finance participants, the switching points in the stage where participants are informed that some participants chose 9 as their switching point (H9) are also included.

(A) *H3* and *H7*

Stage	Non-Finance	Finance
S1 (*base*)	6.59	6.59
S2 (*H3*)	6.21	6.45
S3 (*H7*)	6.79	6.82
Observation	**162**	**22**
p-value (S12)	**0.000*** **	0.761
p-value (S13)	0.237	0.375
p-value (S23)	**0.000*** **	0.455

The p-values are taken from the Wilcoxon signed-rank test
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

(B) *H3* and *H9*

Stage	Non-Finance	Finance
S1 (*base*)	7.03	5.00
S2 (*H3*)	6.61	5.48
S3 (*H9*)	7.09	5.70
Observation	**33**	**27**
p-value (S12)	0.177	0.611
p-value (S13)	0.612	0.144
p-value (S23)	**0.046** **	0.543

The p-values are taken from the Wilcoxon signed-rank test
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. 9 - Herd and Contrarian behaviour in the second and third stages (non-finance vs. finance)

This table reports the percentage of herd behaviour, contrarian behaviour and staying unchanged with participants' switching point in stage 2 (*H3*) and stage 3 (*H7*/ *H9*) of finance and non-finance students. A comparison is also conducted to find the differences between the two subject pools.

(A) *H3* and *H7*

Stage 2 (*H3*)

Stage/ Behaviour	Non-Finance (%)	Finance (%)	p-value
Herd	40.74	36.36	0.695
Contrarian	16.67	27.27	0.225
Same	42.59	36.36	0.579

The p-values are taken from the Mann-Whiney U-test
*** p<0.01, ** p<0.05, * p<0.1

Stage 3 (*H7*)

Stage/ Behaviour	Non-Finance (%)	Finance (%)	p-value
Herd	40.12	59.09	**0.092***
Contrarian	1.85	4.55	0.417
Same	43.21	36.36	0.543

The p-values are taken from the Mann-Whiney U-test
*** p<0.01, ** p<0.05, * p<0.1

(B) H3 and H9

Stage/ Behaviour	Stage 2 (H3)		p-value
	Non-Finance (%)	Finance (%)	
Herd	36.36	37.04	0.503
Contrarian	21.21	11.11	0.388
Same	42.42	51.85	**0.074***

The p-values are taken from the Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

Stage/ Behaviour	Stage 3 (H9)		p-value
	Non-Finance (%)	Finance (%)	
Herd	58.02	57.69	0.957
Contrarian	19.75	3.85	0.300
Same	22.22	38.46	0.470

The p-values are taken from the Wilcoxon signed-rank test
*** p<0.01, ** p<0.05, * p<0.1

Table 3. 10 - Magnitude of herding and contrarian behaviour (Non-Finance vs. Finance)

This table reports the magnitude of herd behaviour and contrarian behaviour in stage 2 (H3) and stage 3 (H7) of finance and non-finance students. A comparison is also conducted to find the differences between the two subject pools in decision-making.

(A) Stage 2

Stage/ Behaviour	Stage 2 (H3)		p-value
	Non-Finance (%)	Finance (%)	
Herding magnitude	0.81	1.14	0.907
Contrarian magnitude	0.30	0.36	0.281

The p-values are taken from the Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

(B) Stage 3

Stage/ Behaviour	Stage 3 (H7)		p-value
	Non-Finance (%)	Finance (%)	
Herding magnitude	0.84	1.82	**0.045***
Contrarian magnitude	0.02	0.05	0.417

The p-values are taken from the Mann Whitney U-test
*** p<0.01, ** p<0.05, * p<0.1

3.4.5. The Determinants of Herd (Contrarian) Behaviour in Risk Shifting

This section examines the impact of participants' characteristics and personalities on herding, contrarian and staying-unchanged decisions. We explain the differences in decision making using the individual differences of our participants. We focus on the decision-making in the design with a history of the switching point at 3 and 7 (H3 and H7), which results in 188 observations in total. The additional treatment of finance students and third stage switching point (H9) is excluded from this analysis since the design difference may lead to a difference in decision-making. The examined characteristics and personalities include overconfidence, risk attitude, maths skill, self-monitoring ability, gender, major, nationality, age, the number of years living in a foreign country and income (Appendix 3.4).

The impacts of characteristics and personalities on herd and contrarian behaviour in the second and third stage are shown in Appendix 3.6. Overconfidence, risk preference, major and income significantly affect herding decisions. More specifically, overconfident participants follow significantly less in the second stage. This result is understandable since participants who think they are better than others are unlikely to follow others. Nöth and Weber (2002) show that overconfident people do not follow others since they are sceptical about their capabilities to solve a problem correctly. Differently, herding expresses a significant and positive correlation with risk preference in the second treatment. Accordingly, participants who are prone to risk-averse are more likely to follow the crowds. It can be argued that in this particular stage, the information that their peers are prone to risk-loving encourages risk-averse participants to follow more. To clarify this issue, we estimate the Spearman rank correlation between overconfidence and risk preference. The result indicates that overconfidence is positively correlated with risk-loving while negatively correlated with risk-averse (p= 0.004 and p=0.020, respectively). In other words, overconfident participants are prone to risk-loving. This correlation is in line with the findings in the literature. Menkhoff, Schmidt and Brozynski (2006) support the positive correlation between risk-taking and overconfidence and the negative impact of these two personalities on herding decisions. Barber and Odean (2001) state that overconfident investors tend to take risky investment while Moore and

Healy (2008); Törngren and Montgomery (2004) reveal that overconfidence is a common characteristic of market professionals such as fund managers, analysts and investment advisors. In the context of this paper, overconfidence and risk-loving participants are found to follow significantly less. Also, discipline is a significant factor. The results show that natural-science students follow more compared to social-science ones. The possible explanation is that a set of master and PhD students in Finance, who have better financial literacy, is included in the group of social-science students. Although the degree of herding between finance and non-finance students is not significantly different, the result shows that finance students do not follow as many as non-finance students. Interestingly, participants having a higher living allowance (income) express the higher tendency of following in the second stage. The similar results are found in the determinants of herd and contrarian magnitude; however, only risk preferences show a significant effect.

Regarding contrarian behaviour, risk-preference exhibits an adverse effect on the decisions and magnitude of shifting against the informed information. In particular, risk-averse participants make significantly fewer contrarian decisions in the second stage. The results relating to risk preference imply that herding or contrarian decisions mostly depends on the current position of participants' risk preference. The students who are studying natural science also make more contrarian decisions compared to the ones who study social science. In contrast, Western and older participants make significantly fewer contrarian decisions. Literature suggests that the motivation behind contrarian behaviour is the scepticism about the rationality of the others (Drehmann, Oechssler & Roider, 2005). We include a short questionnaire to measure trust and correlate this with contrarian behaviour in this context. Interestingly, participants who exhibit a higher degree of trust in people (strangers, foreigners) or different authorities (Parliament, European Union, Press, Labour Unions) engage in significant more contrarian decisions. Whereas, participants who trust their family members shift against the crowds significantly less (Appendix 3.5). In other words, participants may not be sceptical about the rationality of the others, but they still make contrarian decisions. This point needs further research to clarify.

The determinants of staying unchanged regarding risk preference (Appendix 3.6) reveal the fact that finance participants and the older participants tend to stay stable with their decisions. Notably, participants, with better self-monitoring ability, express significantly less motivation to stay unchanged with their decisions.

3.5. Conclusion

In this paper, we found that participants update their beliefs after knowing the risk preferences of others and shift apart from their initial risk preferences. This finding is interesting since the additional information is irrelevant to the participants' decision-making in this context. Herd behaviour is found to be the dominant tendency in the experiment. Some participants make contrarian decisions by going against the decisions of their peers; however, this tendency significantly decreases in the last stage. Finance students, who are considered as professionals and financial literate since they have better knowledge about risk preferences and financial decision-making, stay unchanged with their initial risk preferences significantly more.

The proportion of participants not changing their initial preference significantly increases after the received information in the third stage is more extreme (the switching point is 9). Finance participants tend to sceptical about the rationality of others and choose to stay the same with their decisions. This point may be useful for market's implication in the sense that investors should be trained to get the essential background about the markets before making any investment to protect themselves from abnormal losses and to maintain the stability of the markets. Overconfident participants are less likely to make herding decisions. Current risk position of participants is important and significant in herding decisions and the magnitude of herding. More importantly, herd behaviour is found to be a long-run phenomenon since participants choose the stage in which they significantly shift their risk preferences for the payoff. This result demonstrates that participants make herding decisions with appropriate judgement and participants do believe in the decisions after they update their beliefs based on the signal from their peers.

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APPENDIX 3.1 - THE TEN-PAIRED LOTTERY-CHOICE DECISIONS

Choice	Option A	Option B	Expected Difference
1	1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.1	$1.17
2	2/10 of $2.00, 8/10 of $1.60	2/10 of $3.85, 8/10 of $0.1	$0.83
3	3/10 of $2.00, 7/10 of $1.60	3/10 of $3.85, 7/10 of $0.1	$0.50
4	4/10 of $2.00, 6/10 of $1.60	4/10 of $3.85, 6/10 of $0.1	$0.16
5	5/10 of $2.00, 5/10 of $1.60	5/10 of $3.85, 5/10 of $0.1	-$0.18
6	6/10 of $2.00, 4/10 of $1.60	6/10 of $3.85, 4/10 of $0.1	-$0.51
7	7/10 of $2.00, 3/10 of $1.60	7/10 of $3.85, 3/10 of $0.1	-$0.85
8	8/10 of $2.00, 2/10 of $1.60	8/10 of $3.85, 2/10 of $0.1	-$1.18
9	9/10 of $2.00, 1/10 of $1.60	9/10 of $3.85, 1/10 of $0.1	-$1.52
10	10/10 of $2.00, 0/10 of $1.60	10/10 of $3.85, 0/10 of $0.1	-$1.85

Source: Holt and Laury (2002)

APPENDIX 3.2 - SCREENSHOT OF HOLT AND LAURY (2002)

	Asset A	Asset B
	Option 1: Choose Asset B for ALL Scenarios	
1	10% chance of 20.00 ECU & 90% chance of 16.00 ECU	10% chance of 38.50 ECU & 90% chance of 1.00 ECU
	Option 2: Choose Asset A for Scenario 1, and Asset B for Scenario 2 to 10	
2	20% chance of 20.00 ECU & 80% chance of 16.00 ECU	20% chance of 38.50 ECU & 80% chance of 1.00 ECU
	Option 3: Choose Asset A for Scenario 1 to 2, and Asset B for Scenario 3 to 10	
3	30% chance of 20.00 ECU & 70% chance of 16.00 ECU	30% chance of 38.50 ECU & 70% chance of 1.00 ECU
	Option 4: Choose Asset A for Scenario 1 to 3, and Asset B for Scenario 4 to 10	
4	40% chance of 20.00 ECU & 60% chance of 16.00 ECU	40% chance of 38.50 ECU & 60% chance of 1.00 ECU
	Option 5: Choose Asset A for Scenario 1 to 4, and Asset B for Scenario 5 to 10	
5	50% chance of 20.00 ECU & 50% chance of 16.00 ECU	50% chance of 38.50 ECU & 50% chance of 1.00 ECU
	Option 6: Choose Asset A for Scenario 1 to 5, and Asset B for Scenario 6 to 10	
6	60% chance of 20.00 ECU & 40% chance of 16.00 ECU	60% chance of 38.50 ECU & 40% chance of 1.00 ECU
	Option 7: Choose Asset A for Scenario 1 to 6, and Asset B for Scenario 7 to 10	
7	70% chance of 20.00 ECU & 30% chance of 16.00 ECU	70% chance of 38.50 ECU & 30% chance of 1.00 ECU
	Option 8: Choose Asset A for Scenario 1 to 7, and Asset B for Scenario 8 to 10	
8	80% chance of 20.00 ECU & 20% chance of 16.00 ECU	80% chance of 38.50 ECU & 20% chance of 1.00 ECU
	Option 9: Choose Asset A for Scenario 1 to 8, and Asset B for Scenario 9 to 10	
9	90% chance of 20.00 ECU & 10% chance of 16.00 ECU	90% chance of 38.50 ECU & 10% chance of 1.00 ECU
	Option 10: Choose Asset A for Scenario 1 to 9, and Asset B for Scenario 10	
10	100% chance of 20.00 ECU	100% chance of 38.50 ECU
	Option 11: Choose Asset A for ALL Scenarios	
		Confirm

APPENDIX 3.3 - EXPERIMENTAL INSTRUCTION

This is a lottery choice. There will be three stages in this experiment, therefore, every participant will make three decisions.

In the first stage, you have to choose one from eleven options expressing at which point you want to switch from Asset A to Asset B.

The applied scenario and "Win"/ "Loss" mechanism will be chosen by rolling a dice. This dice has 10 faces which are appropriate for the number of scenarios and the percentage of "Win" and "Loss". The dice will be rolled after you make your decision.

For example, if you choose Option 7, which means you will "Choose Asset A for Scenario 1 to 6 and Asset B for Scenario 7 to 10**". The first rolling number is 5** which means Scenario 6 will be applied. In Scenario 6, the payoff of Asset A could be 20 ECU (60% chance) or 16 ECU (40% chance) and the payoff of Asset B could be 38.5 ECU (60% chance) or 1 ECU (40% chance). Because you chose Asset A in Scenario 6, there will be 60% the payoff will be 20 ECU and 40% the payoff will be 16 ECU. In this case, if **the second rolling number is from 1 to 6**, your payoff will be 20 ECU. If **the second rolling number is from 7 to 10**, your payoff will be 16 ECU.

In the second and third stages, you have to make the similar decision. However, you will receive the average switching points from the previous experiments as additional information.

After three stages, you will have the right to choose from which stage you want to get the payoff. However, the real payoff will be randomly decided.

The exchange rate for this experiment is **10 ECU = 1 GBP.**

APPENDIX 3.4 - PERSONALITIES AND CHARACTERISTICS

Variables	Measures	Expectation	References
Overconfidence (Miscalibration)	Questionnaire (10 questions) Participants are asked to give the low and high values which they are 90% sure that the true value will fall inside the interval. Overconfident participants will get a less correct answer.	Overconfidence participants do not herd/ make more contrarian decisions.	Biais et al., (2005)
Overconfidence (Better than average)	Asset market experiment After participants play asset market experiment, we ask participants to rank their performance with the other participants in the groups. Overconfident participants are the ones who overestimate their performance.	Overconfidence participants do not herd/ make more contrarian decisions.	Glaser and Weber (2007); Deaves, Luders and Luo (2008)
Maths skill	Questionnaire (6 questions)	Participants who get better maths skill do not herd.	Eckel and Füllbrunn (2015)
Self-monitor ability	Questionnaire (18 questions)		Biais et al., (2005)
Risk preference (Holt and Laury, 2002)	Experiment	Risk-averse participants herd more.	Holt and Laury (2002)
Risk preference (questionnaire)	Risk attitude in different issues		
Gender	Male/ Female		
Major	Natural science/ Social science		
Nationality	Western/ Asian		
Living abroad	Number of years living abroad		
Income	Living Allowance		
Trust	Trust in different contexts		

APPENDIX 3.5 - CORRELATIONS BETWEEN TRUST AND HERDING AND CONTRARIAN BEHAVIOUR

	T12	***Herd12***	***Contra12***	***Same12***	***T13***	***Herd13***	***Contra13***	***Same13***
Trust Foreigners within country	**-0.132***	-0.058	-0.096	**0.132***	-0.109	-0.105	-0.066	0.109
Trust Pilots	**-0.173****	-0.074	**-0.128***	**0.173****	-0.019	-0.074	-0.025	0.019
Trust Banks	-0.122*	-0.069	-0.068	**0.122***	-0.054	-0.095	0.014	0.054
Trust Public Authorities	-0.110	**-0.164****	0.067	0.110	-0.003	-0.006	0.019	0.003
Trust European Union	-0.113	-0.048	-0.084	0.113	-0.079	**-0.149****	0.053	0.079
Trust Press	-0.054	-0.024	-0.038	0.054	-0.101	**-0.130***	-0.017	0.101
Trust Foreigners outside country	-0.091	0.027	**-0.152****	0.091	-0.114	-0.103	**-0.151****	0.114
Trust Public Health Service	-0.076	-0.024	-0.066	0.076	0.089	-0.062	**0.179****	-0.089

The p-values are taken from the Spearman's Rank Correlation

*** p<0.01, ** p<0.05, * p<0.1

APPENDIX 3.6 - THE IMPACT OF CHARACTERISTICS AND PERSONALITIES ON RISK-SHIFTING BEHAVIOUR

Table A3.1 - The impact of participants' characterisations on risk-shifting behaviour in the second stage

VARIABLES	(1) t12	(2) herd12	(3) contra12	(4) same12	(5) herd12p	(6) contra12p
Miscalibration	0.010	0.025	-0.015	-0.010	**0.144****	-0.024
	(0.023)	(0.024)	(0.019)	(0.023)	(0.070)	(0.041)
Math skills	-0.003	0.012	-0.015	0.003	-0.080	**-0.103***
	(0.035)	(0.036)	(0.028)	(0.035)	(0.104)	(0.060)
Self-Monitor	-0.003	0.007	-0.009	0.003	0.022	-0.026
	(0.011)	(0.011)	(0.009)	(0.011)	(0.032)	(0.018)
Risk preference	-0.020	-0.001	-0.019	0.020	-0.032	-0.053
	(0.019)	(0.020)	(0.015)	(0.019)	(0.057)	(0.033)
Gender	0.003	-0.073	0.076	-0.003	-0.144	**0.264****
	(0.076)	(0.080)	(0.062)	(0.076)	(0.230)	(0.132)
Major	**-0.144***	-0.051	-0.093	**0.144***	-0.124	-0.101
	(0.080)	(0.083)	(0.065)	(0.080)	(0.241)	(0.139)
Nationality	**-0.155***	-0.104	-0.051	**0.155***	-0.382	-0.127
	(0.087)	(0.091)	(0.070)	(0.087)	(0.262)	(0.151)
Age	-0.090	-0.291	0.201	0.090	-0.435	0.206
	(0.324)	(0.337)	(0.261)	(0.324)	(0.974)	(0.562)
Income	**-0.132***	-0.045	-0.088	**0.132***	0.162	-0.124
	(0.070)	(0.073)	(0.056)	(0.070)	(0.210)	(0.121)
Constant	1.313	1.309	0.004	-0.313	2.231	0.840
	(1.050)	(1.092)	(0.846)	(1.050)	(3.153)	(1.818)
Observations	184	184	184	184	184	184
Pseudo R – squared	0.0568	0.0238	0.0811	0.0568		
R – squared					0.0582	0.0968

The results are taken from logistic regression and OLS regression
*** p<0.01, ** p<0.05, * p<0.1

Table A3.2 - The impact of participants' characterisations on risk-shifting behaviour in the third stage

VARIABLES	(1) t13	(2) herd13	(3) contra13	(4) same13	(5) herd13p	(6) contra13p
Miscalibration	-0.003	-0.010	-0.007	0.003	0.037	-0.007
	(0.024)	(0.024)	(0.007)	(0.024)	(0.077)	(0.007)
Math skills	-0.001	-0.011	-0.014	0.001	-0.113	-0.014
	(0.035)	(0.035)	(0.011)	(0.035)	(0.114)	(0.011)
Self-Monitor	-0.012	-0.007	-0.000	0.012	-0.016	-0.000
	(0.011)	(0.011)	(0.003)	(0.011)	(0.035)	(0.003)
Risk preference	-0.025	**-0.038***	**0.013****	0.025	**-0.161****	**0.013****
	(0.019)	(0.019)	(0.006)	(0.019)	(0.063)	(0.006)
Gender	0.007	0.008	0.021	-0.007	0.154	0.021
	(0.078)	(0.078)	(0.023)	(0.078)	(0.253)	(0.024)
Major	-0.105	**-0.183****	0.039	0.105	-0.315	0.039
	(0.082)	(0.081)	(0.024)	(0.082)	(0.265)	(0.025)
Nationality	-0.110	**-0.168***	0.012	0.110	-0.106	0.012
	(0.089)	(0.089)	(0.027)	(0.089)	(0.288)	(0.028)
Age	0.173	0.129	**0.281*****	-0.173	0.761	**0.281*****
	(0.332)	(0.329)	(0.099)	(0.332)	(1.072)	(0.102)
Income	-0.030	-0.035	0.017	0.030	0.084	0.017
	(0.072)	(0.071)	(0.021)	(0.072)	(0.231)	(0.022)
Constant	0.459	0.609	-0.894***	0.541	0.073	-0.894***
	(1.076)	(1.065)	(0.321)	(1.076)	(3.468)	(0.332)
Observations	184	184	184	0.003	184	184
Pseudo R – squared	0.0363	0.0619	0.1341	0.0363		
R – squared					0.0927	0.1172

The results are taken from logistic regression and OLS regression
*** p<0.01, ** p<0.05, * p<0.1

ESSAY 4:

BIG FIVE PERSONALITY TRAITS AND FINANCIAL DECISION MAKING

Abstract.

This paper examines the impacts of Big Five Personality Traits on financial herding decisions. By using three separate experiments: asset market, information cascade and Holt and Laury (2002), we find that the traits significantly correlate and impact financial decisions. Participants with high levels for extravert and open-to-experience are less likely to follow others in financial decisions; however, participants, open-to-experience, are willing to make irrational decisions to enjoy the higher payoff. Participants, high on the neurotic scale, pay a relatively high amount of money to receive additional information, despite not using the data later. Participants, that score high on agreeableness are less likely to purchase an asset against their beliefs while the extravert ones do. The Big Five Personality Traits are found to have significant correlations with the self-monitoring ability, risk preferences, trust and life satisfaction.

JEL Classification:

Keywords: Big Five Personality Traits, Herd behaviour, Asset Market, Information Cascade, Holt and Laury (2002)

4.1. Introduction

The volatility in the bitcoin market makes it attractive and vulnerable to investors at the same time. Just in the last week of June (June 26) and the beginning of July (July 2), bitcoin prices significantly decrease from $14,000 to $9,600 (Monica, 2019), which is normal with this market. According to Williams (2014), bitcoin has volatility seven times higher than gold, eight times higher than the S&P 500, and eighteen times higher than the U.S. dollar. Grinberg (2011), Cheah and Fry (2015) and Katsiampa (2017) indicate that the market is significantly speculative, more volatile and vulnerable to speculative bubbles. In fact, the bitcoin market is found to be weakly efficient (Nadarajah and Chu, 2017) or even not efficient (Urquhart, 2016). The trading volume in the market increases significantly on the days with suspicious activities, indicating that the market is susceptible to manipulation (Gandal et al., 2018).

Interestingly, many studies confirm the presence of herd behaviour in the bitcoin market. Bouri, Gupta and Roubaud (2019) show that herd behaviour exists in the bitcoin market when uncertainty increases. Vidal-Tomás, Ibáñez and Farinós (2018) show that traders are not solely basing their investment decisions on the behaviour of Bitcoin. Nevertheless, they herd other traders, especially in the down markets. The smallest bitcoin markets are also herding with the largest ones. Ajaz and Kumar (2018) suggest that the presence of herd behaviour in down markets is due to overenthusiasm and overreaction of investors. Market volatility does not have a significant impact on herd behaviour. This finding is the motivation for this paper, in which we examine the impacts of individual differences on herding behaviour and other financial decisions.

Behavioural finance unfolds the impact of personality on investment decision making. The literature has shown the impacts of different personalities such as overconfidence, narcissism and self-monitoring ability on investment decisions. Daniel, Hirshleifer and Subrahmanyam (1997) show that the existence of overconfidence can explain many anomalies of the efficient market hypothesis (EMH) such as post-corporate event and post-earnings announcement stock price "drift", negative long-lag autocorrelations (long-run "overreaction"), and excess volatility of asset prices. Statman, Thorley and Vorkink (2006) and Grinblatt and

Keloharju (2009) conclude that overconfidence could lead to an increase in trading volume in financial markets. In the same line, Chuang and Lee (2006) indicate that overconfident investors underreact to public information and overreact to private information. They trade aggressively in subsequent periods, contribute to the observed excessive volatility and underestimate risk. Biais et al. (2005) show that a high level of self-monitoring helps to enhance trading performance. Foster et al. (2011) conclude that the level of narcissism is correlated with risky stock market investing.

However, the impact of big five personality traits, which is one of the most popular measures for personality in psychology, on investment decision-making has not been widely examined. "Personality traits are the relatively enduring patterns of thoughts, feelings, and behaviours that reflect the tendency to respond in certain ways under certain circumstances."(Roberts, 2009, p.140). The Big Five factors, which include extraversion, agreeableness, conscientiousness, neuroticism and openness to experience, represent personality at the broadest level of abstraction. Many studies apply the concept of big five personality traits in the context of risk preferences and finance. Lauriola and Levin (2001) state that openness to experience leads to higher risk-taking, while neuroticism is negatively associated with risk-taking. Brown and Taylor (2014) show that extraversion is significantly correlated with household financial decisions in terms of debt and asset held.

In this paper, we employ an experimental approach to examine the impact of big five personality traits on financial decision-making, especially in the context of herd behaviour. We use three different experiments, which are asset market experiment (Smith, Suchanek and Williams, 1988; hereafter SSW, 1998); information cascade experiment (Anderson and Holt, 1997; hereafter AH, 1997); and risk preference measure (Holt and Laury, 2002; hereafter HL, 2002). These experiments not only replicate the financial markets but also allow the experimenters to examine the presence of herd behaviour and other financial decisions. The three experiments differ in tasks, group size, interaction schemes and represent different classes of games. We use three separate experiments to make sure the presence of herd behaviour is measure appropriately. Also, the three experiments allow us to capture other financial decisions such as fundamental belief and investment, buying information and irrational decisions. Big Five Inventory (BFI) (Benet-Martínez and John, 1998) will be used to examine extraversion, conscientiousness, agreeableness, neuroticism and openness to experience in this context. In addition, the correlations between big five personality and other individual characteristics and personalities, including demographic characteristics, risk preferences, self-monitoring, trust and satisfaction, are also examined.

The results show the significant impacts of big five personality traits on herding and other financial decisions. Specifically, extraversion, conscientiousness and openness to experience express negative effect on herding decisions but positive effect on irrational decisions. The irrational decisions described as the situation a participant makes a decision which is against the public information and private signal. Extravert and agreeable participants tend to buy an asset against their beliefs. Neurotic participants do not pay a relatively high price to get the trading decisions of the leaders.

We contribute to the existing literature in several strands. First, this is the first paper examining the impacts of big five personality traits on herd behaviour and other financial decisions. Second, the correlations between big five personality and other characteristics such as self-monitoring ability, risk preferences and trust are estimated. The findings help to analyse investing behaviour in the markets. Finally, the implementation of the three experiments reduces the noise of the data and makes the results more robust.

The paper continues with the experimental design (section 2), results and discussions (section 3) and a conclusion (section 4).

4.2. Experimental design

In this paper, we measure herding decisions using three experiments. The big five personality traits and other personalities are measured using a questionnaire. The experiments are conducted at The Centre for Research in the Behavioural Sciences (CRIBS), Nottingham University Business School using z-tree (Fischbacher, 2007). Students are recruited using ORSEE (Greiner, 2015).

We use three separate experiments to measure herding decisions, which are asset market (SSW, 1988), information cascade (AH, 1997) and Holt and Laury (2002). The nature of herding is relatively different in the three experiments; however, they follow a similar concept which indicating the situation people make identical decisions (Çelen and Kariv, 2004). We describe the game briefly and then move on to the analysis.

Experiment 1: Asset market

We have nine participants playing the trading game in the asset market experiment, which follows the structure of a double auction. The experiment includes 15 periods. At the beginning of period 1, every participant is endowed with a certain amount of cash and assets (280 ECU - Experimental Currency Unit, which would be converted to GBP at the end of the experiment, and 4 assets). Participants make decisions to keep the assets to earn dividends at the end of each period or trade the assets to earn price differences. The structure of the dividend is as follows: P(div)=1/4{0, 8, 16, 40), indicating that the expected value of the dividend is 16. The fundamental value of each asset at the beginning of the experiment is 240 (16*15). This value is decreasing each period and turn to 0 at the end of period 15. This information is quite important to the participants since they should offer the trading price based on the fundamental value. Any trading price above or below the fundamental value is regarded as mispricing (overvalued or undervalued). We conduct three treatments based on this design, which are the *base*, the *leaderboard* and the *costly-information*. The previous setting describes the features of the *base* case. The other two treatments share the same characteristics. However, in the *leaderboard*, the participants receive a leaderboard at the beginning of each period starting from period 2. This leaderboard includes the ranking of all participants in a period and the trading decisions of these participants. We expect that the market takes decisions made by the top-ranked leaders into account and follow these decisions in the next period by copying the same prices. These following decisions are considered as herding behaviour due to reputational effect. In the *costly-information* treatment, participants could not receive the leaderboard for free. If they think the information in the leaderboard is useful, they could choose to pay a relatively high price (7% of their cash) to get the information. We expect that participants would pay to get the leaderboard and follow the trading prices offered by the top leaders. For this experiment, we have 54 participants (6 groups) play the *base* treatment, 105 participants (12 groups) play the *leaderboard* treatment, and 54 participants (6 groups) play the *costly-information* treatment.

Experiment 2: Information Cascade

This experiment is introduced by AH (1997) based on the model of Banerjee (1992). There are six participants in each group. The task is choosing which asset participants think would be successful, Asset A or Asset B. Participants make decisions in sequence. Before choosing the asset, each participant receives a private signal, which is "a" or "b". The "a" signal indicating that 67% Asset A would be successful, and 33% Asset B is successful. Similarly, the "b" signal indicating that 67% Asset B would be successful, while 33% Asset A would be successful. The structure of the probability could be explained as follows:

$$P(A) = P(B) = 50\%$$
$$\mathrm{P}(A|a) = \mathrm{P}(B|b) = 67\%$$
$$\mathrm{P}(B|a) = \mathrm{P}(A|b) = 33\%$$

Besides the private information, participants also receive information about the decisions of the previous participants starting from the second decision-makers. In this experiment, herding decisions expressed in the situations where participants disregard their private information and follow others. Participants receive 10 ECU if they choose the right asset and 0 ECU if they choose the wrong asset. There are ten periods in this experiment, which means participants make similar decisions for ten times. However, the order is different in each period. For example, if participant 1 is the first decision-maker in period 1, she would be in the second position in period 2 and third position in period 3 and so on. The highest payoff each participant could achieve is 100 ECU.

The previous description indicates the *base* treatment. Besides, we have three additional treatments, which are the *info*, the *price* and the *info&price*. In the *info* treatment, participants receive additional information about the decisions of the participant who earns the highest payoff in the previous session. This information is irrelevant; however, we expect participants take into account before making decisions. Herding decisions, in this case, are expected to occur due to reputational effects. The *price* treatment is unique when we introduce a price mechanism into the information cascade model. The price mechanism expresses the available information supporting the success of a particular asset, based on Bayesian updating. For example, if more signals are supporting the success of Asset A, the price of Asset A would be higher, and the price of Asset B would be lower. In this particular treatment, participants make two decisions: the first decision is about the belief of the successful asset and the second is which asset they would like to purchase based on the provided price. By introducing this setup, we can distinguish between participants' beliefs and purchasing decisions. The final treatment is the combination between the Info and the *price* treatment (*info&price*). In experiment 2, 36 participants (6 groups) participated in the *base*, 48 participants (9 groups) in the *info*, 48 participants.

Experiment 3: Individual Risk Preferences

The last experiment is the Holt and Laury (2002), which is used to measure individual risk preferences. In this experiment, participants choose to switch from a risky asset to as a risk-free asset. There are ten options, in which the switching point 0-3 represents risk-loving, 4 is risk-neutral, and 5-10 indicates risk-averse. Every participant makes three decisions. The first is to choose the switching point, the second one is to choose the switching point again after knowing the average switching from a previous treatment is 3, and the last decision is choosing the switching point after knowing that the average switching point from a previous treatment is 7 (or 9). Herding decision is captured when participants change their risk preferences toward the informed information after knowing the risk preferences of others. We have 243 participants in this experiment.

After the experiments, participants fill a questionnaire, including questions used to measure big five personality traits (Benet-Martínez and John, 1998), overconfidence and self-monitoring (Biais et al., 2005), satisfaction, trust and other individual characteristics.

There are two main hypotheses are examined in this paper:

> *Hypothesis 1: Big five personality traits express a significant impact on herding decisions.*
>
> *Hypothesis 2: Big five personality traits are significantly correlated with other individual characteristics, including overconfidence, self-monitoring, trust and life satisfaction.*

4.3. Results and Discussion

4.3.1. Big five personality traits, **participant*s' characteristics and personalities***

4.3.1.1. The correlations between Big five personality measures

The internal consistency (Cronbach's alpha) and the correlation between the big five personality traits are shown in Table 4.1. In general, the internal consistency of the data set is acceptable. The Spearman rank correlation coefficient indicates that extraversion and agreeableness are positively and significantly correlated with openness. The same result is found with agreeableness and conscientiousness. In contrast, neuroticism is negatively and significantly associated with other four traits, including extraversion, agreeableness, conscientiousness and openness. Interestingly, it is found that women are more extravert than men. This result is consistent with Schmitt et al. (2008), who find that women express a high level of neuroticism, extraversion, agreeableness and conscientiousness in most countries across 55 countries they examined big five personality traits. The results also show that finance students are more conscientious compared to students from other disciplines.

Table 4. 1 - Correlations between Big five personality measures (n=243)

This table reports the description of big five personality traits and the Cronbach's alpha. In addition, the correlations between the traits and the correlations between big five personality traits and other characteristics are also presented.

(A) Mean, standard deviation and Cronbach's alpha value

	Mean	SD	Cronbach's alpha
Extraversion	3.18	0.69	0.838
Agreeableness	3.64	0.55	0.716
Conscientiousness	3.42	0.54	0.732
Neuroticism	3.09	0.70	0.809
Openness	3.44	0.51	0.684

(B) Correlation between Big Five Personal Traits and other characteristics

	Extraversion	Agreeable-ness	Conscientious-ness	Neuroticism	Openness
Extraversion	1.000				
Agreeableness	0.077	1.000			
Conscientiousness	0.081	**0.290*** **	1.000		
Neuroticism	**-0.367*** **	**-0.234*** **	**-0.224*** **	1.000	
Openness	**0.171*** **	**0.184*** **	0.090	**-0.123* **	1.000
Gender	**2.174** **	1.279	-0.207	0.482	-0.117
Finance	-0.551	-0.315	**-2.736*** **	1.281	-0.190

z values are taken from Mann Whitney U test (for Gender and Finance. Gender includes 0: Female; 1: Male and Finance includes 0: Non-finance students and 1: Finance students); The correlations taken from the Spearman rank correlation

*** p<0.01, ** p<0.05, * p<0.1

4.3.1.2. Big Five and herd behaviour

Chitra and Sreedevi (2011) show that personality traits express considerably more influence on investment decisions compared to demographic variables. In this context, we examine the impacts of big five personality traits on herding decisions and participants' performance. The results of the asset market experiment, information cascade and Holt and Laury (2002) are shown in Table 4.2, 4.3 and 4.4, respectively.

In the asset market experiment, we measure herding by estimating the number of times participants copy the offered prices of the first-ranked, second-ranked and third-ranked leader in the market. We examine the case of copying the exact prices and the prices with 5% interval. The interval is small enough to keep the prices in line with the prices offered by the leaders but large enough to make the offered prices more competitive. We also examine the case copying prices are executed and not executed in the next period. Participants' performance is measured by considering the total wealth, including the amount of cash and the value of holding assets. In the *costly-information* treatment, we examine the number of time participants pay to get the information of the leaderboard and whether they follow this additional information or not.

The results from table 4.2 show that introvert participants and participants who are not open to new experiences follow the leaders to a significantly greater extent. The result is robust in the case of openness when most correlations between this trait and herding measures are significant. The open to experience trait refers to people who are original, always come up with new ideas, curious about many different things, are a deep thinker and active imagination. These characteristics explain why the open to experience participants do not have a herding tendency. They choose to offer new prices, rather than following the prices placed by their peers. The extravert participants share some similar characteristics with the open to experience ones, which prevent them from herding decisions. For example, they are assertive, confident, outgoing and sociable. Herd behaviour in this context does not lead to a significantly higher payoff, indicating that it is not rational to make such decisions. Interestingly, neurotic participants are more willing to pay a relatively high price for the leaderboard. However, they do not follow the others after they get the information. The neurotic participants are willing to pay a relatively high cost to get the additional information but do not use it later. Even in the case the leaderboard is free, the neurotic participants do not follow the leaders significantly.

In the information cascade experiment, we indicate the number of time participants follows their peers in the imbalanced events as herding decisions. An imbalanced event is a situation the available information suggests participants disregard their private information and follow the market. We also identify the irrational decisions where participants follow their peers in balanced events, which is the indifferent situations to follow the crowds or private information. In such situations, participants should follow their private signals. Also, the irrational decisions include the number of times participants do not follow the crowds as well as their private signals. They make decisions against all available information. We measure herd behaviour and irrational decisions (against-signal decisions in general) in all four treatments. As discussed earlier, in the Price treatment, we could separate participants' beliefs and purchasing decisions. Therefore, we could identify the situations participants make decisions against their beliefs. In other words, they may think one asset would be successful, but they purchase another asset to get the lower price. We consider this as against-belief decisions. Interestingly, some participants make against-belief decisions to get the same price or even a higher price, which is irrational decisions.

Participants who are open to experience make significantly more against-signal decisions, in which the irrational decisions are dominant, shown in Table 4.3. The number of irrational decisions is also significantly correlated with extraversion and conscientiousness. As previously explained, the irrational decisions are the ones which are inconsistent with the private signals and the choices in the market. In the higher-order factors of the Big Five introduced by DeYoung, Peterson and Higgins (2002), the authors indicate that emotional stability, agreeableness, and conscientiousness positively predict conformity while extraversion and openness negatively predict conformity. In this case, extravert, conscientious and open to experience participants do not choose to follow the market but make irrational decisions. These participants look for better outcomes by going against the market. Interestingly, irrational decisions significantly lead to higher payoffs (Spearman's rho = 0.1306 and p = 0.078). In the Price treatment, we find that the agreeable participants do not purchase an asset against their prior belief to get a lower price. Differently, the extravert participants are willing to make against-belief decisions to get a higher price. Unfortunately, these decisions do not result in significantly higher income.

In the last experiment, we measure the herding decisions by recording the situations participants shift their risk preferences (switching points) toward the risk preferences of their peers (the benchmark). We also include the states in which participants shift their risk preferences against the informed information and the cases they stay unchanged. The results in Table 4.4 show that the conscientious and open to experience participants shift their risk preferences to a significantly higher extent. Again, these participants are willing to change to look for better outcomes, even by changing their initial risk preferences. The risk preferences of their peers are irrelevant; therefore, they should not imitate. When we look at the payoff of participants who shift their risk preferences toward the benchmark in the second stage, it is almost significantly and positively correlated with the open to experience trait (Spearman's rho = 0.1143, p = 0.1233).

Table 4. 2 - Big Five Personality Traits and SSW

This table reports the correlations between big five personality traits and participants' wealth, herding decisions and buying-historical-information decisions.

	Extraversion	**Agreeable -ness**	**Conscientious -ness**	**Neuroticism**	**Openness**
Wealth	0.012	-0.055	-0.007	0.064	0.039
F1	-0.017	-0.016	0.018	-0.087	**-0.173***
F2	0.009	-0.016	-0.145	0.075	-0.041
F3	**-0.176***	0.095	0.107	-0.029	-0.116
F	-0.052	-0.037	-0.025	-0.058	**-0.183***
F1-In	-0.041	-0.009	0.005	-0.100	-0.139
F2 - In	-0.052	-0.069	-0.153	0.151	-0.095
F3 - In	-0.051	-0.021	0.074	-0.003	-0.086
F- In	-0.045	-0.037	-0.040	-0.062	-0.152
F1 (Ex)	-0.046	-0.050	0.006	-0.026	**-0.236****
F2 (Ex)	0.088	0.001	-0.152	0.037	-0.119
F3 (Ex)	**-0.167***	0.134	0.010	0.089	-0.127
F (Ex)	-0.067	-0.049	-0.096	0.039	**-0.256*****
F1 - In (Ex)	-0.013	-0.015	0.004	-0.011	**-0.207****
F2 – In (Ex)	0.034	0.039	-0.050	-0.019	**-0.212****
F3 - In (Ex)	-0.063	-0.063	-0.031	0.059	0.011
F - In (Ex)	-0.016	-0.038	-0.031	0.014	**-0.239****
Buy Info	1.295	-0.731	1.097	**-1.731***	-0.287

F1, F2 and F3 is following the first, second and third-ranked leaders. F stands for following the first three leaders. Similarly, F1 – In, F2 – In and F3 – In denote following the first, second and third-ranked leaders with 5% interval. F – In is following the first three leaders with 5% interval. Ex stands for executed transactions. Buy Info indicates whether participants pay to buy the information. The correlations are taken from the Spearman rank correlation; z values are taken from Mann Whitney U test (Buy Info, 1: Yes; 0: No); There are 54 participants (6 groups) play the *base* treatment, 108 participants (12 groups) play the *leaderboard* treatment and 54 participants (6 groups) pay the *costly-information* treatment. Six participants in the *leaderboard* treatment did not finish the questionnaire; therefore, we have 102 observation for the *leaderboard* treatment only and 210 observations for this experiment.
*** p<0.01, ** p<0.05, * p<0.1

Table 4. 3 - Big Five Personality Traits and Information cascade

This table reports the correlation between big five personality traits and participants' decision-making in the information cascade experiment. Participants' payoff is also correlated with the traits.

	Extraversion	**Agreeable-ness**	**Conscientious-ness**	**Neuroticism**	**Openness**
Payoff	-0.021	-0.008	0.098	-0.035	0.056
AS	0.059	-0.040	0.094	-0.079	**0.124***
Herd (Imb)	-0.000	-0.099	-0.038	-0.010	-0.046
Own (Imb)	0.027	-0.012	-0.024	-0.029	-0.058
Irrational	**0.164****	0.054	**0.242*****	-0.071	**0.181****
Herd (Ba)	-0.015	-0.040	0.025	-0.032	0.062
Own (Ba)	-0.031	0.020	-0.011	0.001	0.027
AB	0.148	**-0.260****	-0.054	0.011	-0.046
AB (Cheaper)	0.049	**-0.304*****	0.001	0.067	-0.097
AB (Higher)	**0.242****	0.016	-0.030	0.026	0.024
AB (Same)	0.094	0.048	-0.082	-0.126	0.110

The correlations are taken from the Spearman rank correlation. Herd (Imb) indicates herd behaviour in the imbalanced events; Own (Imb) indicates following the private signal in imbalanced events; Irrational indicate decisions that are not consistent with the market or the private signals , Herd (Ba) indicates herd behaviour in balanced events, Own (Ba) indicates following the private signal in balanced events; Against-belief decisions are making decisions to purchase an asset against participants' beliefs on the success of the asset, the cheaper, higher and same is making purchasing decisions against beliefs to get cheaper, higher or same prices. There are 186 participants (31 groups) play this experiment. However, there are three participants did not finish the questionnaire; therefore, we have 183 observations in total.

*** p<0.01, ** p<0.05, * p<0.1

Table 4. 4 - Big five personality traits and Risk preference shifting

This table reports the correlations between big five personality traits and participants' decision-making in the Holt and Laury (2002) experiment.

	Extraversion	Agreeable -ness	Conscientious -ness	Neuroticism	Openness
Herd (S12)	-0.490	0.300	**-1.940***	-0.446	0.623
Contrarian (S12)	-0.814	-0.470	1.130	0.497	-0.340
Same (S12)	1.120	0.068	1.044	0.055	-0.353
Herd (S13)	-1.096	-0.974	-0.674	1.397	**-1.993****
Contrarian (S13)	-1.228	-0.622	0.875	-0.923	-0.053
Same (S13)	1.409	-0.263	0.137	-0.809	0.953

z values are taken from Mann Whitney U test (Herd S12 indicates herding in the second stage, contrarian S12 indicates contrarian behaviour in the second stage, same S12 is keeping the decision unchanged in the second stage while Herd S13 indicates herd behaviour in the third stage, contrarian S13 indicates contrarian behaviour in the third stage and same S13 is keeping the choice unchanged in the third stage. All are dummy variables, in which 1 means Yes and 0 means No). We have 183 participants in total.
*** p<0.01, ** p<0.05, * p<0.1

4.3.1.3. Big five personality traits and participants' characteristics and personality

Besides big five personality traits, we examine other characteristics in the questionnaire and correlate with the traits. Some of the main characteristics included are self-monitoring ability, risk preference and trust.

The first character is self-monitoring ability, indicating the extent to which individuals could monitor, adjust and control their behaviour depending on how others perceive it (Snyder, 1974). People with high self-monitoring ability are more likely to take leadership positions (see, e.g. Day et al., 2002; Zaccaro, Foti and Kenny, 1991) or central positions within organisations (Mehra, Kilduff, & Brass, 2001). In this context, self-monitoring ability is measured using the 18-item scale introduced by Snyder and Gangestad (1986). This questionnaire includes 18 situations that participants could change their behaviour to please or to impress others. The results from Table 4.5 show that extravert and open-to-experience participants have better self-monitoring ability. This finding is consistent with Barrick, Parks and Mount (2005), who examined 102 employed Executive MBA and found that self-monitoring positively and profoundly correlated with extraversion, emotional stability (against with neuroticism) and openness to experience.

The second personality trait is risk preferences, which is measured by an incentivised experiment (HL, 2002) and a self-reporting measure ten-point scale (Dohmen et al., 2011). The former measure is taken from the first stage of the HL experiment discussed earlier while the latter is recorded using the questionnaire. More specifically, we ask participants for their willingness to take a risk in different issues such as general issues, finance, driving, faith and health issues. Nicholson et al. (2005) show that risk propensity is high with extraversion and openness while low with neuroticism, agreeableness and conscientiousness. According to Eysenck theory, extravert people are expected to follow the pattern for sensation-seeking (Eysenck, 1973; Segal, 1973) while openness to experience could be willing for risk-seeking, tolerance of uncertainty, change and innovation (McCrae and Costa, 1997b).

In contrast, conscientious people desire to seek for achievement under conditions of conformity and control, which is inversely correlated with risk propensity (Hogan and Ones, 1997). Klein and Kunda (1994) suggest that risk-seeking requires resilience, implying a low score in emotional sensitivity, neuroticism and agreeableness. The results taken from the HL (2002) measure show a similar tendency. Accordingly, extravert participants are prone to risk-loving, while neurotic participants are risk-averse. Regarding the measure of Dohmen (et al., 2011), the conscientious participants are willing to take a risk in general, especially in financial issues. However, the neurotic participants do not take a risk in general issues while the agreeable participants do not want to take a risk in driving.

For other characteristics, extravert, agreeable and conscientious participants are happier while neurotic participants are not. Extravert people are likely to return kindness to others and have a good intuition. They are not patient and think they are in a high position of the ladder steps. The agreeable people are less likely to return difficulties, offends and take advantage of others. They also have good intuition and know exactly why they develop a hobby. They are confident about their judgement and are not nervous. Similarly, the conscientious people are optimistic about their judgement, are more likely to return favours and revenge and are good at financial management. The case of neurotic people is quite different. They are nervous; they do not understand their hobbies; they do not have a good intuition and are not confident with their judgement. Not many people think the neurotic people are exceptional, and they are more likely to lose things since they cannot make up their mind soon enough. Interestingly, neurotic people are more likely to take advantage of others.

Another behaviour we are interested in this study is the correlation between the big five personality traits and trust behaviour. We introduce several questions in the survey to ask participants how they trust their friends, neighbours, private and public institutions. The results in table 4.6 show that extravert participants express a high level of trust in neighbours and friends. Agreeable participants trust the education system, their neighbours and friends and the public health services. Differently, the conscientious participants express a low level of trust in the labour union, while the open-to-experience participants do not trust insurance companies and police.

Finally, we want to know how personalities correlate with satisfaction. We ask the participants whether they satisfy with their health, sleep, study, income, dwelling, free time and life. The literature indicates that the predictive power of neuroticism and extraversion is strongest among the big five personality traits (see, e.g. Schimmack, Diener, & Oishi, 2002; Schimmack et al., 2002). According to Schimmack et al. (2004), the depression facet of neuroticism and positive cheerfulness of extraversion are the most consistent predictor of life satisfaction. This finding is confirmed by Joshanloo and Afshari (2011) with students from Iran. For job satisfaction, Spector (1997) show that there is a strong connection between job satisfaction and life satisfaction. Judge, Heller and Mount (2002) conclude that neuroticism, extraversion and conscientiousness express moderate correlation with job satisfaction while agreeableness and openness to experience express weak correlation. Tokar, Fischer, and Subich (1998) indicate that job satisfaction is negatively correlated with neuroticism and positively correlated with extraversion. Randler (2008) shows that neuroticism is associated with eveningness, meaning people who are most productive in the evening. Neurotic participants also extend their sleep length over the weekend. According to Jerram and Coleman (1999), the neurotic participants experience more medical problems and visit GP (medical Doctor) more frequently. In this study, we find that agreeable participants satisfy with their health, study, free time and life while conscientious participants satisfy with their study and life only. Consistently with the literature, the neurotic participants do not satisfy with their health, sleep, study, dwelling and life. Interestingly, open-to-experience participants are not happy with their income. However, the income is the amount of money the students get from their parents as the allowance. Therefore, the open-to-experience may think it is not enough for them to explore what they would like as students.

Table 4. 5 - Relationship between big five personality traits and participants' personalities

This table reports the correlations between Big five personality traits and other personalities including self-monitoring ability, risk preferences, nervousness, patience, return favours, difficulties and offends, Intuition, Hobbies understanding, Exception, Mind understanding, Judgemental confidence, Lie telling, Taking advantages and Ladder steps.

	Extraversion	Agreeable-ness	Conscientious-ness	Neuroticism	Openness
Self-monitor	**0.197*** **	-0.089	-0.057	0.024	**0.148** **
Risk (HL)	**-0.110***	0.072	-0.032	**0.130** **	0.104
Risk (Q-general)	0.092	0.002	**0.114***	**-0.148** **	0.012
Risk (Q-finance)	0.088	-0.028	**0.108***	-0.095	-0.014
Risk (Q-driving)	-0.024	**-0.108***	-0.022	0.012	0.030
Risk (Q-faith)	0.042	-0.099	-0.025	-0.053	0.067
Risk (Q-health)	-0.031	**-0.181*** **	-0.031	-0.058	-0.006
Happiness	**0.219*** **	**0.203** **	**0.154** **	**-0.310*** **	0.030
Nervous	0.075	**-0.124***	-0.006	**0.154** **	-0.100
Patient	**-0.208*** **	0.059	0.046	-0.056	-0.010
Return Favours	0.040	0.020	**0.123***	-0.058	-0.063
Revenge	0.026	-0.057	**0.114***	0.007	0.007
Return difficulties	-0.004	**-0.128** **	0.035	0.060	0.036
Return kindness	**0.118***	0.063	0.035	-0.062	0.006
Return Offends	0.076	**-0.110***	-0.008	0.063	-0.000
Intuition (First Impression)	**0.147** **	**0.189*** **	0.091	**-0.119***	-0.033
Hobbies understanding	0.050	**0.119***	0.094	**-0.156** **	-0.013
Exception	0.038	0.070	0.078	**-0.134** **	0.085
Mind understanding	-0.063	-0.002	-0.072	**0.121***	-0.021
Judgemental confidence	-0.009	**0.124***	**0.111***	**-0.200*** **	0.035
Lie telling	0.031	**-0.149** **	-0.063	0.086	-0.020
Take advantage of others	0.020	**-0.219*** **	-0.056	**0.136** **	-0.018
Ladder steps	**0.106***	-0.000	0.095	-0.102	0.045
Financial Management	-0.057	-0.023	**0.135** **	-0.043	0.003

The correlations are taken from the Spearman rank correlation
*** p<0.01, ** p<0.05, * p<0.1

Table 4. 6 - Relationship between big five personality traits and trust

This table reports the correlations between Big five personality traits and Trust

	Extraversion	**Agreeable-ness**	**Conscientious-ness**	**Neuroticism**	**Openness**
Education	-0.034	**0.159****	0.074	-0.025	0.019
Labour Union	0.011	-0.012	**-0.121***	0.105	-0.061
Insurance Company	-0.049	-0.004	-0.036	0.038	**-0.114***
Police	-0.023	0.052	-0.037	0.002	**-0.143****
Neighbours	**0.158****	**0.175*****	0.001	-0.017	-0.018
Friends	**0.192*****	**0.110***	0.005	-0.055	-0.019
Public health services	0.036	**0.133****	-0.046	-0.016	0.040

The correlations are taken from the Spearman rank correlation
*** p<0.01, ** p<0.05, * p<0.1

Table 4. 7 - Relationship between big five personality traits and satisfaction

This table reports the correlations between Big five personality traits and satisfaction

	Extraversion	**Agreeableness**	**Conscientious-ness**	**Neuroticism**	**Openness**
Health	-0.008	**0.171*****	0.024	**-0.189*****	-0.036
Sleep	-0.016	0.054	0.085	**-0.218*****	-0.002
Study	0.014	**0.133****	**0.179*****	**-0.125***	-0.015
Income	-0.043	-0.003	0.050	-0.025	**-0.156****
Dwelling	0.055	0.039	0.067	**-0.112***	0.017
Free time	0.093	**0.127****	0.031	-0.053	-0.082
Life	0.066	**0.153****	**0.150****	**-0.132****	-0.016

r values are taken from Pearson's Correlation
*** p<0.01, ** p<0.05, * p<0.1

4.4. Conclusion

We make the first attempt to investigate the impacts of personality traits on herding decisions. We use three experiments to examine herd behaviour, which are the asset market, the information cascade and the HL (2002) experiment.

The asset market experiment helps us to identify herd behaviour due to reputational effect. More specifically, participants have the opportunity to imitate the trading price offered by the leaders. In the information cascade, we could measure herd behaviour due to informational and reputational externalities. Accordingly, participants choose to follow their private information or public information. In some treatments, they also know the decisions of the participant who earns the highest payoff. Using this design, we could measure the impacts of information and reputation on herding decisions. Also, the separation of participants' beliefs and purchasing decisions in the price treatment allow us to measure the rationality of the participants. The last experiment, which is the HL (2002), is used to measure the risk preferences of the participants. Herd behaviour, in this case, is the situation participants shift their risk preferences toward the risk preferences of their peers. The application of three separate experiments helps us to examine heard behaviour from different angles. This design also supports the robustness of the results.

In general, the findings are similar within the three experiments. More specifically, openness to experience show the negative impacts on herding decisions in the asset market experiment and the HL (2002). Extraversion and conscientiousness express the similar impacts in the asset market experiment and HL (2002), respectively. These three traits also positively correlate with irrational decisions in the information cascade experiment. In contrast, agreeableness shows the negative impact on irrational decisions in this experiment. Interestingly, participants with a high level of neuroticism refuse to pay a relatively high price to get the extra information on the leaderboard. Finally, other characteristics, such as risk preferences, self-monitoring ability, trust and satisfaction, significantly correlate with the big five personality traits.

The results of this paper are important to the stakeholders in financial markets. For example, the presence of herd behaviour in the bitcoin market introduced earlier could be explained by analysing the characteristics of the participants in the market, which helps to increase the efficiency and stability of the market. The understanding of the correlation between big five personality traits and herding decisions as well as other financial decisions helps the policymakers to regulate the markets more appropriately. The investors could also understand the behaviour in the markets and protect themselves with suitable hedging strategies. From the perspective of the researcher, this correlation could be extended to other financial decisions besides herd behaviour.

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Concluding remarks

The performance of financial markets is partly determined by the participants of the markets. Also, the policymakers would like to understand the markets to conduct appropriate policies, which promote market development and efficiency. The main contribution of this thesis is helping the stakeholders understand the correlation between individual differences and financial decisions. The three separate experiments lead to an identical conclusion; herding is one of the features of the financial markets, which is hard to remove. People feel safer when they stay together, especially in case they do not have enough information, or they are sceptical about their ability. However, the participants' characteristics and personalities significantly affect herding decisions.

The main contribution of the first paper is that this is the first time the asset market experiment is used to examine herding. Given the controversial findings in the literature on the presence of herd behaviour in financial markets using other experiments, this design is a novel approach, which makes the results to be directly applicable in financial markets. Also, the distinguish between free information and costly information helps us to understand the investors' behaviour toward information. Most participants appreciate the additional information in the markets. The evidence for this fact is that whenever they have information, they make decisions to follow. However, they become reluctant when they are asked to pay for the information. This tendency is another evidence for the free-rider behaviour in financial markets. Due to a lack of information, which leads to the belief of the information asymmetry in the market, participants miss out the opportunity to earn an abnormal return. In this particular situation, this tendency is better for the markets since it reduces the magnitude of price bubbles. Another contribution of this paper is the investigation of the correlation between individual differences and herding decisions. One of the most noticeable results is that the level of financial literacy significantly reduces herding decisions. This result is important from the perspective of policymakers. Accordingly, to improve the efficiency of the financial markets, people should have received appropriate training before participating in the markets and understanding the characteristics of a financial market before investing is also crucial to investors. For example, if we know that a market is relatively aggressive with more overconfident participants, we should have been more cautious before investing in any asset. The correlations between characteristics and investing decisions are essential not just for practitioners but also for policymakers.

For the second paper, we prove that the presence of herd behaviour in financial markets is substantial, irrespective to the applied experiments. Given the results taken from the standard experiments, which is information cascade, with a price mechanism, we find that people have the mimic mindset. However, they are willing to pay for an asset which they are not confident with, to get a lower price. The seeking of abnormal returns leads participants to irrational decisions, which could be easily observed from the markets, especially before and during crisis periods. The main contribution of this paper is the modification of the standard design by adding a price mechanism. The fact that participants pay for the asset they want to purchase makes the design more comparable with what is happening in financial markets. With this design, it is also possible to test for the validation of the efficient market hypothesis, which is another contribution of this paper. Again, the correlation between individual differences and financial decisions is beneficial for practitioners and academics.

The third paper helps us to understand herd behaviour does not only exist with decision-making in groups and decision making in general; participants follow others even with their risk preferences. The idea of risk-preference shifting demonstrates the validity of herd behaviour, which is believed to be the origin of many problems in financial markets. Finally, the last paper illustrates individual personalities; in this case, the big five personalities has significant impacts on herding decisions. More specifically, the level of extraversion, openness to experience and conscientiousness negatively correlate with herd behaviour. This result is one of the milestones to understand the rationale of herd behaviour and the differences in various financial markets.

The results of this thesis contribute to the literature on behavioural finance and shed light on reasons for heard behaviour, advantages and disadvantages of this phenomenon. Individual differences help us to understand the underlying reasons behind every financial decision. This thesis supports for the presence of herd behaviour in financial markets; however, it should not be limited to herd behaviour, the research could be continued to other anomalies in the market using the behavioural and experimental approach. Also, more treatments could be added to the current experiments to study different aspects of herding decisions.