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Herding in Financial Behaviour: A Behavioural and Neuroeconomic Analysis of Individual Differences

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HERDING IN FINANCIAL BEHAVIOR: A BEHAVIOURAL AND NEUROECONOMIC ANALYSIS OF INDIVIDUAL DIFFERENCES[1,2]

ABSTRACT

Experimental analyses have identified significant tendencies for individuals to follow herd decisions, a finding which has been explained using Bayesian principles. This paper outlines the results from a herding task designed to extend these analyses using evidence from a functional magnetic resonance imaging (fMRI) study. Empirically, we estimate logistic functions using panel estimation techniques to quantify the impact of herd decisions on individuals' financial decisions. We confirm that there are statistically significant propensities to herd and that social information about others' decisions has an impact on individuals' decisions. We extend these findings by identifying associations between herding propensities and individual characteristics including gender, age and various personality traits. In addition fMRI evidence shows that individual differences correlate strongly with activations in the amygdala – an area of the brain commonly associated with social decision-making. Individual differences also correlate strongly with amygdala activations during herding decisions. These findings are used to construct a two stage least squares model of financial herding which confirms that individual differences and neural responses play a role in modulating the propensity to herd.

Keywords: herding; social influence; individual differences; neuroeconomics; fMRI; amygdala
JEL codes: D03, D53, D70, D83, D87, G11

1. Introduction

Herding occurs when individuals' private information is overwhelmed by the influence of public information about the decisions of a herd or group. Evidence of group influence in many economic and financial decisions is consistent with bounded rationality: in an uncertain world, if we realise that our own judgement is fallible then it may be rational to assume that others are better informed and follow them (Keynes 1930,1936, 1937). Many microeconomic models of herding assume that social information about others' decisions is used in a process of statistical inference e.g. in a Bayesian reasoning process in which individuals adjust their *a posteriori* probabilities as new social information arrives. If decision-making is Bayesian and probabilistic judgements are being updated systematically and logically then rational updating of probabilities will propel information about others' choices through a group, generating herding and 'informational cascades' via social learning.

In a world of uncertainty, rationality may be bounded by cognitive and informational constraints and this may limit the use of Bayesian algorithms to guide decision-making. Nonetheless, an approximation of Bayesian social learning may still emerge as the outcome

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of procedurally rational decision-making devices such as heuristics and rules of thumb. Herding may be a quick decision-making tool via which people copy and imitate the actions of others because they make a qualitative judgement that others know more about the fundamental long-term values of goods and assets. Also, agreeing with a group may bestow a utility that is independent of the information implicit in others' decisions. Socio-psychological factors may also be important if normative influences such as social pressure encourage individuals to follow the decisions of others even in the face of contradictory objective information and individual differences in gender, age and personality may moderate this susceptibility to social influence. The importance of personality traits is consistent with other economic analyses focussing on the role of emotions and affect in economic and financial decision-making (e.g. Elster 1996, 1998; Kamstra *et al.* 2003; Cohen 2005; Lo *et al*. 2005; Shiv *et al.* 2005; DellaVigna 2009; Baddeley 2010).

In this paper, we present experimental evidence confirming that there are significant propensities to herd when people make financial choices. When deciding whether or not to buy a stock, this sample of experimental subjects were significantly more likely to agree with a herd than not. Panel fixed effects estimation shows that there is significant heterogeneity in individual propensities to herd within this sample. Further estimations establish that this heterogeneity can be captured by individual differences, including gender, age and a range of personality traits, in particular some of those usually associated with sociability. Then functional magnetic resonance (fMRI) evidence shows that herding decisions are strongly correlated with amygdala activations. These amygdala activations are in turn strongly correlated with almost all the individual differences that correlate with propensity to herd. Previous studies have shown that the amygdala is implicated in social decision-making and social learning. Overall our evidence confirms these previous studies and suggests that herding is a process of social learning and the extent of social learning varies across individuals according to their particular characteristics.

2. Theoretical Background: Theories of Herding and Group Influence

Herding occurs when individuals mimic others, ignoring their own substantive private information (Scharfstein and Stein 1990). There are many explanations for this impact of group influence on individuals' decisions including rational learning explanations based around Bayesian updating assumptions, and explanations based on individual differences, drawing particularly on insights from sociology and psychology. The approaches can be unified to an extent by assuming bounded rationality: in a world of uncertainty, cognitive and informational constraints mean that it is difficult quantitatively to identify a "correct" course of action and so, as Simon (1979) observes, people will be procedurally rational – decision-making will be based on "appropriate deliberation" and so, ultimately, will be the product of a subjective judgement. In this case, social learning still occurs as people adopt herding as a heuristic – a decision-making short-cut. If preferences are lexicographic rather than compensative then the decision to follow the group will not be the outcome of a compensative, updating process – as is seen in Bayesian models - but rather social information about what the group is doing will substitute completely for private information and private information will be ignored. Psychological factors will be important if an individual's propensity to use heuristics and rules of thumb is determined by their personal characteristics and personality traits.

2.1 Rational Learning and Informational Cascades

The most prominent microeconomic models of herding describe it as a rational learning process in which different people's decisions are interdependent and reinforcing. Individuals may rationally judge that others' actions contain useful information (Keynes 1930, 1936, 1937) and, in a world of uncertainty, rational inferences can be made using Bayes's rule (Salop 1987): Bayesian updating of *a priori* probabilities will draw upon an extensive set of information - including social information about the observed actions of others.

A key problem with Bayesian herding is that useful private information is discounted in favour of information about the actions of the herd (Scharfstein and Stein 1990). To illustrate the principles: Banerjee (1992) develops a herding model in which people look at what others are doing, e.g. when making fertility choices, in voting, and in financial decision-making. Herding will be the outcome of a rational but potentially misguided information gathering process. Banerjee gives the example of restaurant choice adapted here to the financial choices analysed in the empirical section. Let us assume that individuals have the option to buy a particular asset, e.g. a stock, and the "buy" versus "reject" decisions are favoured *a priori* 51% and 49% respectively. A group of 100 people are making sequential decisions about whether or not to buy the stock. If 99 out of 100 people have private signals (such as advice from an investment advisor) indicating that the stock price is likely to fall then, assuming complete access to all private signals, on the basis of the aggregate evidence it could be inferred that a given individual should reject the stock. Assume however that Person 1 is the 100^{th} person with a misleading private signal (favouring a "buy" decision) but is the first to decide. Then the group as a whole may buy the stock on the basis of the misleading financial advice upon which the first person based their decision. The sequence of events that generates this outcome is as follows. Person 1 buys the stock on the basis of their (misleading) private signal. Person 2 is the next to choose. She knows the *a priori* probability (favouring a buy decision), has a correct private signal favouring a reject decision and has public, social information about the prior actions of Person 1. Applying Bayes's rule and assuming that she weights these last two pieces of information equally, the information about Person 1's choice will cancel out Person 2's own private signal. So Person 2 will rationally choose to buy the stock on the basis of prior probabilities (marginally favouring a buy decision). Similarly Person 3 will decide to buy on the basis of Person 1 and 2's choices and so on – the impact of the incorrect signal will cascade through the herd and the herd will move towards a buy decision even though 99% of private signals favour a reject decision. Equally, the herd would have headed in the right direction if another person had been first to choose but nonetheless Banerjee emphasises that the herd may generate a negative 'herding externality' if important, relevant private information is ignored in the aggregate. The informational value of 99 pieces of correct private information recommending that the share should be rejected may be lost and, even though behaviour is Bayes rational, the impact of relevant private information will be limited.

Bikhanchandi, Hirshleifer and Welch (1992, 1998) develop a similar model of sequential decision-making in which informational cascades explain localised conformity which emerges when it is optimal for an individual to follow the actions of his/her predecessor and to disregard his private information. Just as is seen in Banerjee's model each sequential decision conveys no real new evidence to subsequent members of the herd. In both models, herding is described as a boundedly rational response to imperfect information and will generate convergence onto an outcome determined by social information about herd actions rather than private information. Private information becomes inefficiently uninformative, sometimes leading to convergence of behaviour onto stable outcomes but often leading to convergence onto idiosyncratic and fragile outcomes (Chamley 2003).[3]

A large number of economic experiments have been conducted to test Bayesian theories of rational herding, starting with Anderson and Holt (1996, 1997). Many of these experiments verify Bayesian hypotheses. Others have extended this experimental evidence to distinguish between herding as a broad descriptive category of copying behaviours and

[3] See also Kirman (1993) for a herding model based on different statistical assumptions.

informational cascades as a specific form of learning that arises in uncertain situations (e.g. see Sgroi 2003, Çelen and Kariv 2004, Alevy et al. 2007).

The systematic patterns in herding identified in the experimental literature can be reconciled with a range of hypotheses about rationality. Following Avery and Zemsky (1998), Park and Sgroi (2009) allow rational herding and rational contrarianism (behaviour contrary to herd choices) in a herding experiment that allows multiple states and multiple signals. They observe both rational and irrational contrarianism but generally 70% of their experimental subjects' behaviour is consistent with their benchmark for rationality. When they correct for those who don't trade (i.e. the irrational non-traders) behaviour becomes predictable. They conclude that policy makers should be careful not to categorise all herding as irrational: with rational herding, improved information and clearer signals would lead to a decrease in herding. Cipriani and Guarino (2005) adapt Bayesian models to incorporate flexible prices in a model in which cascades cannot occur. They find that some subjects do not use their private information, choosing either not to trade or to ignore private information by engaging in contrarian trading. Ivanov *et al.* (2009) also assess Bayesian modes of thinking and find that experimental subjects are not necessarily using probabilistic thinking and may be using boundedly rational, insight-based rules of thumb, instead of belief-based reasoning.

2.2 The role of individual difference

Bayesian theories of rational updating of probabilistic judgements using social information describe individual decision-making emerging from the application of a mechanical algorithm in which information about group decisions is used to update individuals' probabilistic judgements, thus generating informational cascades. Çelen and Kariv (2004) distinguish between the precise phenomenon of informational cascades, which is sequential herding generated by Bayesian reasoning, and the more general phenomenon of herding just as following a group. There is general evidence that decision-making is not the outcome of statistical inference alone; furthermore, people are not necessarily competent in applying principles of statistical inference in practice (Salop 1987; Tversky and Kahneman 1974; Baddeley *et al.* 2005). For example, cognitive biases may limit rational behaviour in 'reverse cascades' –when incorrect decisions lead to information cascades down the wrong path (Sgroi 2003). Also, if herding is a time-saving decision-making heuristic, then certain personality types will be more likely to use a herding heuristic as a decision-making shortcut. This would be consistent with Herbert Simon's (1979) concept of procedural rationality, i.e.

behaviour is adapted to specific circumstances and will involve the application of common-sense rather than mathematical or statistical algorithms / rules (Baddeley 2006).

There is substantial evidence that economic and financial decisions are affected by individual differences and psychological factors; personality traits will affect decision-making if they generate particular emotional predispositions (Elster 1996, 1998; Baddeley 2010). Kamstra *et al*. (2003) and Hirshleifer and Shumway (2003) analyse the impact of weather-related mood changes on financial markets to show that fluctuations in emotions and mood affect financial and economic decisions. Lo, Repin and Steenbarger (2005) identified roles for personality traits and fear/greed in the behaviour of day traders. Shiv, Loewenstein, Bechara, Damasio and Damasio (2005), using lesion patient studies, identify a relationship between impaired emotional response and risk-taking behaviour. Kuhnen and Knutson (2005) identify deviations from rational behaviour in financial decision-making and use functional magnetic resonance imaging (fMRI) evidence to identify a role for emotion and affect. These analyses, and others, suggest that emotions and moods have significant impacts on economic / financial decisions and there may be similar interactions between tendencies to herd and specific psychological characteristics.

Evolutionary principles will also play a role. Herding instincts are widely observed throughout the animal kingdom, in species as diverse as honey bees, ants, antelope, sheep and cows and whilst such instincts may have impulsive aspects, evolutionary pressure may have led to the evolution of these instincts to enable social learning: animals better able to monitor the actions of others will acquire social information about resource availability and mating potential and these animals will be more likely to reproduce (Danchin *et al*. 2004). In a similar way, socially influenced herding instincts may have evolved as a learning heuristic enabling us easily to acquire important social information about the potential value of our acquisitions. Evolutionary forces may also encourage us to follow a group because there is safety in numbers.

Social forces will also play a role and herding may be partly explained via principles of social psychology, particularly sociological analyses of crowd influence and group pressure e.g. as developed from le Bon’s (1896) analysis of mob psychology. Sociological studies emphasise the importance of situational factors including normative influences from wanting to conform versus informational influences emerging with learning from others’ actions. This distinction between normative and informational influences is a distinction that also surfaces in the economic literature on conformity (e.g. see Bernheim 1994; Becker and Murphy 2000). Bayesian learning theories cannot account fully for the impact of normative influence, in part reflecting difficulties of effectively modelling and quantifying social factors (though these difficulties can be partly overcome by embedding social factors such as status and reputation into individuals' preferences, see Bernheim 1994; Scharfstein and Stein 1990). However, the emphasis in sociology on informational influence parallels more closely social learning models in economics. For example, Asch (1951, 1955) presented evidence from controlled experiments which showed that, when asked to make simple judgements about the lengths of lines, a substantial minority of experimental subjects were susceptible to intra-group pressure and were persuaded to change their minds in the face of deliberately misleading decisions from experimental confederates, with effects increasing as group size and consensus increased.[4] Wrong choices in Asch-style tasks may reflect social learning if they are the result of the subjects' perceptions of their own visual limitations rather than an attempt to avoid conflict: for example, Shiller (1995) argues that Asch's findings are not inconsistent with a rational learning process because experimental subjects tend to attribute their mistakes to their own physical limitations, such as poor eyesight. There is also evidence that people will follow decisions of a group of computers in much the same way that they will follow a human herd's decision suggesting that following the crowd is not just about peer pressure; social influence even without human face-to-face interactions is consistent with social learning from a group's decisions (Deutsch and Gerard 1955; Bikhchandani *et al.* 1992).

In a world of bounded rationality, these different approaches from economics, psychology, sociology and evolutionary biology can be reconciled as different ways of explaining social learning. Herding behaviour may be the outcome of interplays between rational/cognitive and instinctive/emotional processes as well as a reflection of economic, sociological and psychological impacts emerging in different situations and individual predispositions (Baddeley 2010). Neuroeconomics can also offer useful lessons because when people are influenced by social information then this may reflect an interaction between a deliberative learning process and a more instinctive, affective, emotional responses – and these interactions can be quantified using neuroimaging techniques.

3. Experimental Hypotheses

In testing the range of issues explored above, we develop the following hypotheses:

3.1 In uncertain situations, people tend to follow others.

In the empirical analysis, following Çelen and Kariv's (2004) distinction between sequential

[4] See Bond and Smith (1996) for a survey of evidence on Asch-style tasks.

decision-making generating informational cascades and the broader phenomenon of herding as the tendency to agree with group decisions, we adopt the latter more general definition. As explored above, the tendency to follow others may reflect a range of factors. Primarily it may be the outcome of social learning. In some situations, this may reflect Bayesian updating but in a world of bounded rationality when informational and cognitive constraints limit Bayesian reasoning, herding may be the outcome of a quick and simple rule of thumb i.e. the heuristic of following others reflects a judgement that others may know more and so their actions signal the best strategy. This latter explanation is also consistent with herding hypotheses seen in sociology and evolutionary biology. A further reason for people to herd comes from economics and/or sociology: doing what others do may increase an individual's utility; peer pressure may encourage people to do what others are doing.

3.2 Propensities to herd will vary across people and will be affected by individual differences in gender, age and personality.

If herding reflects individual differences then individual characteristics and heterogeneity amongst people will have a significant and systematic impact. More sociable individuals will be more responsive to social influence, they will be more likely to herd and so personality traits including empathy, socialisation and extraversion will correlate positively with the propensity to herd. In a world of bounded rationality, herding may be a quick decision-making heuristic in which case herding is more likely to be seen in impulsive and venturesome individuals. In addition, gender and age are included in the econometric analysis on the basis of evidence that conformity is an (inverse) function of age (Walker and Andrade 1996) and is more prevalent amongst women (Milgram 1963).

3.3 Decisions to herd will correlate with amygdala activation

Neuroeconomic studies show that decision-making may reflect an interaction of deliberative and affective factors. The amygdala is implicated in processing social and emotional salience (Todd and Anderson 2009). In the context of social situations, the amygdala plays a role in social decision-making, e.g. in social judgements (Adolphs *et al.* 1998) and in observational / social learning and memory conformity (Burke *et al.* 2010*b*, Davis *et al.* 2009, Edelson *et al.* 2011). Also, amygdala volume correlates with social network size (Bickart et al. 2011), it is implicated in social learning specifically when processing fearful faces in dangerous situations (Whalen *et al.* 1998) and it is differentially activated in regulating social distance (Kennedy *et al.* 2009). On the basis of these studies, we hypothesis that the amygdala is also activated when doing what others do, perhaps reflecting the influence of social learning.

4. Experimental Design

4.1 Experimental Context

Following Pillas (2006) and Baddeley *et al.* (2007) the stock-picking task used here was designed (using COGENT graphics and MATLAB7) as a computer simulated task for fMRI analysis (see also Burke *et al.* 2010a). Whilst the context of the experiment is therefore relatively artificial the use of a computer-based design was justified on the basis of evidence that experimental subjects are affected in similar ways by the actions of virtual and real experimental confederates (Reysen 2005). The presentation of the information adopts a similar task design to that used by Berns, Chappelow, Zink, Pagnoni, Martin-Skurski and Richards (2005) in their exploration of the impact of social conformity in mental rotation tasks; in particular our design adopts their approach to task sequencing and the presentation of social information.

4.2 Task Structure

The experiments analysed here capture the propensity to herd in a stock-picking task for which each experimental subject has to decide whether or not to buy a particular stock. In making their decisions, experimental subjects were given two sources of information sequentially. First they were given private information in the form of a chart of past stock prices. Then they were given social information about the decisions of a group of four (the “herd”).

Each trial of the task consisted of the following stages:

Stage 1: Subjects were given their own "private" information about the past performance of the stock in the form of an artificially generated time series of daily stock returns over a year. These charts were presented to all subjects in four combinations of high /low mean and high/low variance stocks. In addition, charts of scrambled stock images were used as controls. See Fig *1a*.

Fig. 1a: Stage 1 Private Information: Stock chart presented

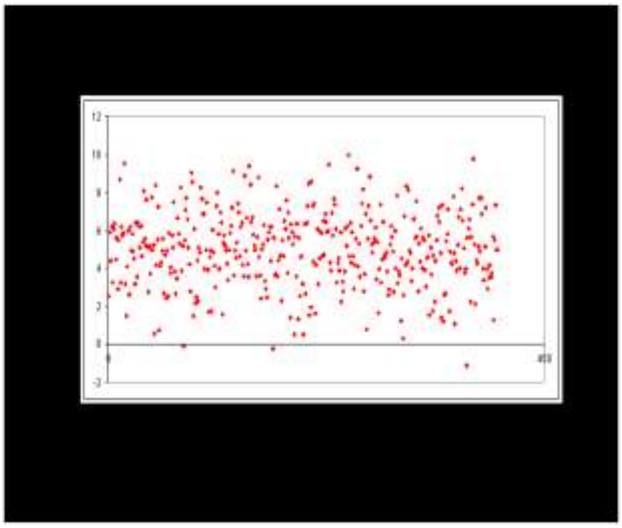
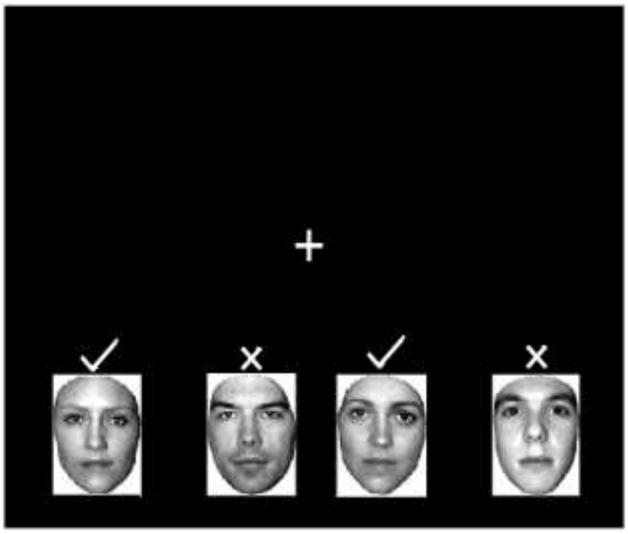


Fig. 1b: Stage 2 Social Information: Herd decisions revealed



Stage 2: Subjects were then presented with social information about the herd choices – with the "herd" represented as 4 faces.[5] The choices of the group/herd were represented on the computer screen with a tick mark ('buy') or a cross ('reject') above each face photo. There

[5] The face stimuli were kindly provided by Bruno Rossion of the Cognition & Development Research Unit, Université Catholique de Louvain, Belgium.

were four types of herd decision: +4 (all decided to buy), 2-2 (half of the herd buys, the other half rejects), -4 (all reject), and a control scenario in which no group decision was conveyed. See Fig *1b*. The experimental subjects were told that the people represented by these faces had been involved in a pilot experiment and that their choices were real, informed choices based on the same information shown to the experimental subjects.[6]
For Stages 1 and 2, the images of private and social information were shown for 1.5 seconds for each image, considerably longer than the average reaction time (0.4s) of human traders (Broyon and Duka, 2006).

Stage 3: After seeing the social information about the herd's choice, subjects were then asked to decide whether or not to buy the stock by pressing one of two buttons on a button-box.

To summarise, in total there were 20 task scenarios (5 private information scenarios x 4 social information scenarios) as shown in the following matrix:

SCENARIO MATRIX

Private information*: Stock Image*

i. High mean, high variance (HMHV)

ii. High mean, low variance (HMLV)

iii. Low mean, high variance (LMHV)

iv. Low mean, low variance (LMLV)

v. Scrambled image (SCRAMBLE)

Social information: *Herd choices*

i. Herd buys (+4)

ii. Herd split (2-2)

iii. Herd rejects (-4)

iv. No herd signal (NS)

	+4	*2-2*	*-4*	*NS*
HMHV	1	2	3	4
HMLV	5	6	7	8
LMHV	9	10	11	12
LMLV	13	14	15	16
SCRAMBLE	17	18	19	20

There were 12 repetitions for each of the 20 task scenarios. This analysis focuses specifically on the social information scenarios in which the herd decision was unambiguous i.e. Herd buys (+4) and Herd rejects (-4) over all the private information scenarios. So overall 12 repetitions of 10 of the above scenarios were used for each subject in this analysis. To

[6] A separate herding control condition was used in which the task was run with a herd represented by 4 chimpanzee faces. The responses to chimp choices are not used in this paper because they are not relevant to the issues explored here but an analysis of the chimp scenarios can be found in Burke *et al.* (2010*a*).

prevent learning and superstitious effects, no feedback was given whilst the subjects were performing the task.

4.3 Experimental subjects and participant incentives

The 17 right-handed healthy subjects (11 females and 6 males) were recruited via advertisements on the University of Cambridge campus and on a local community website. The mean age of participants was 24.3 years and all were native English speakers. All participants gave informed consent, and the Local Research Ethics Committee of the Cambridgeshire Health Authority approved the study.

The experimental incentives were designed following behavioural piloting to ensure that the participants did not mindlessly buy every stock offered to them. To avoid the interpretative complications of non-linearity in value functions, as highlighted both in critiques of subjective utility theory and in developments of cumulative prospect theory, the task and its context was simplified in a number of ways. Participants were paid a “show-up” fee of £20 and instructed that they could buy each stock at the mean price of its particular distribution and would be rewarded if they bought high performing stocks. To prevent loss aversion biases, the participants were told that they could not lose more than their initial show-up fee. Participants earned £32.50 on average (including the initial £20).

Before the official experimental trials, the design and purpose of the experiment was made clear by issuing the experimental subjects with detailed instructions in the form of a powerpoint slide presentation (see Appendix 1) as well as giving them prior training in the execution of the task. To minimise error trials during scanning, participants learned the timings and sequencing of task events for 20 training trials no more than 7 days prior to scanning.

4.4 Measuring individual differences

After the task had been completed, the experimental subjects completed a range of personality and other questionnaires as well as post-scanning interviews to test the hypothesis that individual characteristics, including psychological traits, will predispose individuals to a herding response. A range of psychological traits were measured using published psychometric tests. Impulsivity, venturesomeness and empathy were measured using Eysenck’s Impulsivity, Venturesomeness and Empathy (IVE) questionnaire (Eysenck and Eysenck 1978). Extraversion and Psychoticism were measured using Eysenck’s Personality Revised Questionnaire – EPQR (Eysenck and Eysenck 1975, 1976; Eysenck, Eysenck and Barrett 1985).

4.5 Econometric analysis

Below we assess the impact of the economic, sociological and psychological factors outlined above using econometric techniques to test the experimental hypotheses introduced in section 3. As explained above, the experimental subjects were making binary choices about: firstly – whether or not to buy a particular stock; and secondly –whether or not to buy a stock conditioned upon the social information provided about a herd's decision. Denoting H=1 as a decision that coincides with the herd's decision and *Ω* as the information set, including both private and social information, the probability of herding is given by:

$$E(H \mid \Omega) = \Pr(H = 1 \mid \Omega) = p_{herd} .$$

Following Brock and Durlauf (2000), behaviour is modelled as a discrete choice and estimated using binary dependent variable estimation techniques *viz.* logit using the logistic function[7]:

$$p_{herd} = G(x\beta) = \frac{\exp(x\beta)}{1 + \exp(x\beta)} \qquad (1)$$

where $x\beta$ is a matrix of explanatory variables and accompanying parameters.

Panel fixed effect (FE) estimation was used to capture the fact that the preferences of individual experimental subjects may vary and to overcome problems of endogeneity created by heterogeneity bias in a panel estimation context. FE estimation was used in preference to random effects because FE generates concrete parameter estimates for subject-specific differences and the heterogeneity in the econometric models is not purely the outcome of randomness; also, FE is informative when panel estimation is applied to data that do not involve time (Wooldridge 2003, p. 473-4).

We use z tests to test the individual significance of each explanatory variable ($H_0 : \beta_k = 0$) and we use a likelihood ratio test to test the overall explanatory power ($H_0 : \sum |\beta_k| = 0$). Estimations were conducted using the statistical package STATA 11 MP.

4.6 fMRI methods

Standard rapid event-related fMRI methods were used to capture neural activity. These methods are based upon the fact that, as activity increases in a specific neural area, more oxygen is needed and so the ratio of oxyhemoglobin to deoxyhemoglobin increases. These hemodynamic responses were measured using blood oxygen level dependent (BOLD)

[7] In capturing preferences to buy and/or to herd, logit was selected over probit because we could not assume that the distribution of choices would follow a standard normal distribution.

signals. Specifically, the BOLD signal contrast was captured for decisions to agree versus disagree with the herd. These data were analysed using Statistical Parametric Mapping (SPM5; Functional Imaging Lab, UCL).

5. Results and Interpretation

Our statistical / econometric analysis is designed to discover first –whether social information about the choices of a herd or group of people changes the probability that our experimental subjects will buy a particular stock, and second– in decisions to go with the herd, which individual differences increase the probability that a person will follow the herd, and thirdly – whether differential amygdala activations correlate with decisions to follow a group. The econometric analysis assesses these questions in turn. The first set of estimations corroborates existing economic experimental evidence (cited earlier) about tendencies to herd. The probabilities of buying a stock are significantly higher when the subjects are told that the herd has bought the stock. The second set of estimations focuses on capturing the decision to follow the herd in terms of individual differences.

Table 1 shows the conditional probabilities of buying and herding in the various experimental scenarios.

TABLE 1 - CONDITIONAL PROBABILITIES OF BUY AND HERD DECISIONS

		Pr(Buy)	*Pr(Agree with herd)*
n=2040			
All scenarios		52.0%	77.4%
Private information scenarios for share price changes:			
	High mean	56.3%	76.1%
	Low variance	58.1%	77.2%
	Scrambled	37.5%	80.1%
Social information scenarios:			
	Herd buys (+4)	79.4%	79.4%
	Herd rejects (-4)	24.5%	75.4%

Assuming no social or private information is available, the baseline probability that a person will buy a stock is $\Pr(Buy = 1) = p_{buy} = 0.50$. There is no *a priori* reason to expect the person to favour a buy versus reject decision because there were equal numbers of low/high mean and high / low variance stocks. The results in Table 1 confirm that the unconditional p_{buy} for subjects in our sample is 0.52. Experimental subjects were more likely to buy stocks with a high mean and/or a low variance and this is consistent with the behaviour predicted by mean-variance analysis.

As explained in section 2, the concept of herding implies that the agreement between the herd and the experimental subject is not a coincidence. We hypothesise that if people are being persuaded by a herd's decisions then this will lead to a significant increase in p_{buy} if the herd buys; if the herd rejects a stock then this leads to a significant decrease in p_{buy}. For the scenarios in which the herd made a clear choice to either buy or reject (i.e. the +4 and –4 scenarios), there are 4 possible combinations of subject and herd decisions, as follows:

		Herd's choice ↓	
		Buy	*Reject*
Experimental subject's choice →	*Buy*	Buy, Buy	Buy, Reject
	Reject	Reject, Buy	Reject, Reject

These four scenarios are mutually exclusive and exhaustive so the unconditional *a priori* likelihood that a subject will coincidentally agree with the herd decision is 50%, i.e. $\Pr(Agree = 1) = p_{agree} = 0.50$. We hypothesise that the probability of herding is higher than the unconditional probability of coincident subject and herd decisions, i.e. $p_{herd} > p_{agree}$ where $p_{agree} = 0.5$. The experimental data show a herding probability of 77.2%, which is statistically significantly larger than 0.50.[8] This is consistent with the hypotheses that herding is a form of social learning and/or that Bayesian reasoning is involved when social information is presented to experimental subjects.

5.1 Capturing revealed preferences: when do subjects buy?

For the first set of econometric estimations, logistic functions for a "buy" decision were estimated conditioned on revealed preferences for the 4 combinations of high /low

[8] $H_0 : p_{herd} = 0.50, H_1 : p_{herd} > 0.50, z = \dfrac{0.772 - 0.500}{\sqrt{\dfrac{0.50 \times 0.50}{2040}}} = 24.57, [p = 0.000]$

mean/variance stocks, whether herd decided to buy, and subject-specific fixed effects using a different dummy variable for each experimental subject. These dummies were included to capture individual differences in propensities to buy. Thus, for a given individual *i*, the probability of a "buy" decision is given by:

$$p_{buy,i} = f(\Omega_p, a_i) \qquad (2)$$

Where Ω_p is the private and social information made available to each experimental subject, as described above, and a_i is the subject specific fixed effect, capturing the differences across the experimental subjects in the predicted probabilities of a buy decision.

TABLE 2 - LOGISTIC ESTIMATION OF BUY DECISION
Panel fixed effects estimation

Dependent variable: SBUY(=1 if buys, =0 if rejects)
n = 2040

	Odds ratio	*z score*	*p value*
Herd buys	14.740	23.190	0.000***
High mean	1.411	3.020	0.003***
Low variance	1.768	4.960	0.000***
Subject-specific fixed effects:			
S2	1.108	0.320	0.749
S3	0.400	-2.860	0.004***
S4	0.571	-1.750	0.080*
S5	1.227	0.640	0.523
S6	0.280	-3.950	0.000***
S7	2.302	2.560	0.010***
S8	0.601	-1.590	0.111
S9	0.326	-3.480	0.000***
S10	0.633	-1.430	0.152
S11	0.601	-1.590	0.111
S12	1.859	1.920	0.055*
S13	0.491	-2.230	0.026**
S14	0.737	-0.960	0.339
S15	0.858	-0.480	0.632
S16	0.633	-1.430	0.152
S17	0.601	-1.590	0.111

Likelihood Ratio test: $\chi^2(19) = 786.06$ [p=0.000]
Log likelihood = -1019.4208

* Estimate significantly different from zero at 10% significance.
** Significantly different at 5%,
*** Significantly different at 1%.

The results reported in Table 2 confirm information from conditional probabilities above and the statistically significant [$p<0.01$] *z* scores on "high mean" and "low variance" show respectively that the experimental subjects are significantly more likely to choose high mean and/or low variance stocks. This suggests that, after controlling for the impact of the social information, the experimental subjects are choosing as predicted by mean-variance analysis, confirming the results from Table 1. In addition, the *z* scores on the subject specific fixed effects included to capture individual differences are significantly different from zero [$p<0.10$] for 7 of the experimental subjects indicating that there is considerable heterogeneity of preferences across the sample of experimental subjects. This is preliminary evidence that individual differences are important. The impact of the social information is also shown in Table 2. Confirming the conditional probabilities from Table 1, the *z* scores on "Herd Buys" shows that there is a statistically significant [$p=0.000$] increase in the tendency to buy when the herd buys; the odds ratio shows that the subjects are more than 14 times more likely to buy a stock when the herd buys relative to when the herd rejects. This result confirms evidence from previous studies showing that social information about others' choices changes people's decisions.

5.2 Why do subjects follow the herd?

To further analyse the propensity to herd conditioned on subject specific differences we next estimate the probability that a subject will agree with the herd.[9] We analyse econometrically the hypotheses about herding as outlined in section 3, i.e. that herding is the product of individual differences and non-economic factors such as personality traits, gender and age. Also, these factors might predispose experimental subjects to particular emotional responses that would encourage herd-copying behaviour and the impact of emotional factors is explored using neuroimaging evidence.

As explained above, herding implies a non-random choice to copy what the herd is doing and so must necessarily capture something other than the probability of coincidentally agreeing with the herd. In estimating herding propensities, as for the previous estimations, we initially include fixed effects to capture individual differences – a_i but further estimations were also run in which herding probabilities were conditioned on the specific measures of

[9] Additional estimations showed that there was no statistically significant association between probability of buying and probability of herding.

individual differences.[10] The herding probabilities were estimated assuming that a combination of factors determines an individual's propensity to herd by adapting equation (1) as follows:

$$p_{herd} = \Pr(H \mid (\Omega_p, \Omega_h) = \frac{\exp(x\beta)}{1+\exp(x\beta)} \qquad (3)$$

where x —the vector of explanatory variables, includes either a_i (subject specific fixed effects) or individual differences measured using information about gender, age and personality traits.

The results from FE estimation to capture heterogeneity across the subjects are outlined in Table 3. These results show that private information about the type of stock (i.e. its mean and variance) is not significantly associated with propensities to herd. For 9 of the subjects the fixed effects capturing individual heterogeneity are strongly statistically significant [p<0.01] suggesting that there is a significant amount of heterogeneity across the subjects in terms of their propensity to herd.

TABLE 3 - LOGISTIC ESTIMATION: AGREEING WITH THE HERD
Panel fixed effects estimation
Dependent variable: AGREE (=1 if agree with herd to buy or reject, otherwise =0)
n = 1920[11]

	Odds ratio	*z score*	*p value*
High mean	0.864	-1.230	0.218
Low variance	1.002	0.020	0.984
S2	2.379	3.020	0.003***
S3	1.330	1.070	0.286
S4	40.801	5.030	0.000***
S5	2.379	3.020	0.003***
S6	1.549	1.610	0.107
S7	0.815	-0.780	0.434
S8	0.872	-0.520	0.601
S9	0.934	-0.260	0.793
S10	20.053	5.540	0.000***
S11	11.161	5.590	0.000***
S12	2.167	2.730	0.006***
S13	2.625	3.310	0.001***
S14	15.904	5.610	0.000***
S15	1.035	0.130	0.895
S17	82.298	4.320	0.000***

Likelihood Ratio test: $\chi^2(17) = 324.7$ [p=0.000]
Log likelihood = -895.952
*** Significant at 1%.

[10] The fixed effects cannot be included alongside these other measures of individual differences because this would create a problem of perfect multicollinearity between the fixed effects and the matrix of subject-specific characteristics.
[11] Subject 16 was excluded because of perfect multicollinearity; this subject always followed the herd.

In unravelling the sources of heterogeneity in different subjects' propensity to herd, explanatory variables were included to identify the impact of specific individual differences including age, gender and personality traits (as outlined in section 4.4). The private information variables to capture the impact of mean and variance were retained.

TABLE 4 - LOGISTIC ESTIMATION: AGREEING WITH THE HERD
Impact of individual differences

Dependent variable: AGREE (=1 if agree with herd to buy or reject, otherwise =0)
n=2040

	Odds ratio	*z score*	*p value*
High mean	0.874	-1.180	0.237
Low variance	1.002	0.020	0.985
Gender (M=1, F=0)	0.453	-3.860	0.000***
Age	0.948	-2.500	0.012**
Impulsivity	1.189	7.790	0.000***
Venturesomeness	1.251	9.670	0.000***
Empathy	1.047	2.150	0.032**
Sensitivity to reward	0.939	-3.100	0.002***
Sensitivity to punishment	0.831	-8.420	0.000***
Psychoticism (vs socialised)	0.821	-3.810	0.000***
Extraversion	0.745	-9.330	0.000***

Likelihood Ratio test: $\chi^2(11) = 166.98$ [p=0.000]
Log likelihood = -1006.6334

** Significantly different from zero at 5%
*** Significantly different at 1%.

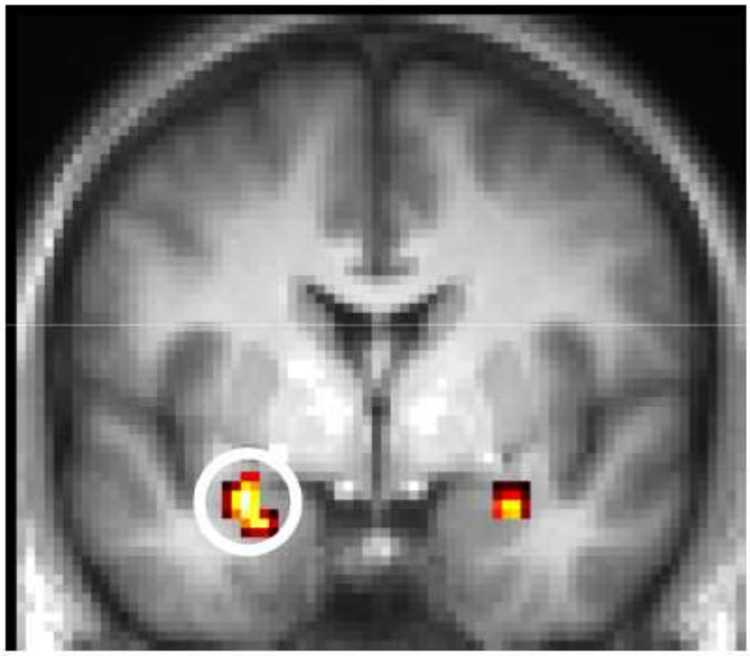
The estimations set out in Table 4 confirm the findings from FE estimation i.e. that private information about the mean and variance of a stock is not significantly associated with propensities to herd. On the other hand, individual differences are strongly significant. Male subjects were significantly less likely to herd [p=0.000]. Also, the older subjects were significantly less likely to herd across all scenarios 9 [p=0.012], confirming other research suggesting that older people are less susceptible to social pressure (Walker and Andrade 1996).

Empathetic individuals are more likely to herd and the effect is significant at a 5% significance level [p=0.032]. Individuals with higher scores on the psychoticism scale (i.e. the less socialised individuals) are less likely to herd and again the impact is strongly significant [p=0.000]. Empathy and psychoticism are, respectively, positively and negatively associated with sociability and so the impacts of these traits confirm the hypotheses outlined in section 3.2, *viz.* that herding is more likely amongst more sociable individuals and suggest that social awareness may increase a person's tendency to herd. Another facet of a sociable nature – extraversion, is highly significant but with a negative parameter suggesting that extraverts are less likely to herd [p=0.000]. This may reflect the fact that extraversion may be correlated with other personality traits which decrease herding tendencies e.g. it may link with confidence and confident individuals may be less willing to change their minds in response to social influence. Alternatively, extraversion corresponds at least partly to sensitivity to reward, which in turn correlates negatively with the propensity to herd (as explained below).

Other groups of personality traits also have a strong impact. Sensitivity to punishment and sensitivity to reward are both highly significant [p=0.000] and [p=0.002] respectively, and negatively correlated with herding. Traits associated with quick thought have an impact and herding tendencies are positively and significantly associated with venturesomeness [p=0.000] and impulsivity [p=0.000]. An explanation consistent with boundedly rational decision-making is that following the herd is a heuristic used by impulsive, venturesome people who want to make decisions quickly.

To establish the role of emotional processing in social learning, BOLD fMRI analysis (explained in section 4.4) reveals significant amygdala activation for the herd versus no herd contrast (left amygdala peak voxel (-24,-3,-24) z=2.162 [p=0.015], see also Fig. 2).

Fig. 2: Differential activation in the amygdala: herd-no herd contrast



Using the data on amygdala activations, a further set of econometric estimations was conducted to link together herding tendencies, individual differences and emotional responses – with the latter focussing on amygdala activations because its role in social decision-making has been established in previous studies, as outlined in section 3.3. The link between herding and amygdala activation was estimated first using a simple logistic estimation and the results from the econometric estimation summarised in Table 5A confirm that there is a strongly significant association between differential amygdala activation and the probability of agreeing with the herd [p=0.000].

TABLE 5 - AGREEING WITH THE HERD: NEUROECONOMIC EVIDENCE
fMRI analysis of amygdala activation
n=1800[12]

5A – Uncorrected estimation
Dependent variable: AGREE (=1 if agree with herd to buy or reject, =0 otherwise)

	Odds ratio	*z score*	*p value*
Amygdala activation	1.492	10.580	0.000***
Likelihood Ratio test: $\chi^2(1)$ = 123.96 [p=0.000]			
Log likelihood = -961.06			

5B – Two stage least squares (2SLS) estimation

Least squares estimation of predicted amygdala activation
Dependent variable: Amygdala activation when deciding whether or not to agree

	Parameter estimate	*t ratio*	*p value*
Gender (M=1)	-1.180	-5.970	0.000***
Age	-0.095	-8.240	0.000***
Impulsivity	0.288	22.810	0.000***
Venturesomeness	0.113	3.120	0.002***
Empathy	0.080	3.440	0.001***
Sensitivity to reward	0.042	2.670	0.008***
Sensitivity to punishment	-0.165	-6.850	0.000***
Psychoticism	-0.201	-3.890	0.000***
Extraversion	-0.279	-8.730	0.000***
Neuroticism	-0.128	-5.000	0.000***
Lie scale	-0.125	-2.810	0.005***
Constant	9.885	22.710	0.000***
R^2 = 0.2734	R^2 (adjusted) = 0.2690		
F test of explanatory power:	F(11,1788) = 61.18 [p=0.000]		

2SLS Logistic estimation using predicted amygdala activations
Dependent variable: AGREE (=1 if agree with herd to buy or reject, =0 otherwise)

	Odds ratio	*z score*	*p value*
Predicted amydala activation	1.352	4.480	0.000***
Likelihood Ratio test: $\chi^2(1)$ = 20.03 [p=0.000]			
Log likelihood = -1013.02			

*** Significantly different from zero at 1%

[12] Two subjects were excluded from the imaging results because always or almost always herded and so fMRI contrasts could not be calculated.

Next, Table 5B shows the results from the two stage least squares (2SLS) estimation of herding and amygdala response. 2SLS was used first to correct problems of endogeneity and also to capture the mediating impact of individual differences. In the first stage of 2SLS, amygdala activation is predicted using individual differences as instruments with additional personality traits – neuroticism and lie scale scores – included because these may correlate with potential sources of endogeneity, particularly measurement error. Then the predicted values from the first stage were used in the final 2SLS estimations. The results from the first stage of 2SLS show that all the individual differences correlate significantly with amygdala activation (all parameters significant at $p<0.01$) and, with the exception of sensitivity to reward, in the same direction as in the estimations outlined in Table 4. In the second stage of the 2SLS estimations, the predicted amygdala activation variable is again strongly significant [$p=0.000$] with a similar odds ratio, indicating that the endogeneity from using uncorrected amygdala activations did not create a large degree of bias. Moreover, the fact that individual differences largely correlate with amygdala activations with the same direction and significance as they correlate with propensity to herd, suggests that individual differences may play a role in emotional processing: individual characteristics affect differential amygdala activations which in turn affect the propensity to herd.

6. Implications and Conclusions

Herding affects a wide range of human behavior, and this study has focussed specifically on financial herding. Understanding herding in financial markets is an important issue because herding has such destabilising impacts on the financial sector - particularly as herding, by definition, reflects a neglect of important non-social information. Financial instability will be exacerbated by herding tendencies and, given the dependence of real activity on finance, impacts will spread to investment, employment and output. Thus it is important to understand the phenomenon of financial herding because it raises some crucial policy challenges especially in the context of recent financial crises.

The experimental results presented here indicate that subjects' financial choices are affected by herd decisions and that the propensity to herd is not homogenous but varies by gender/age and across personality types. In addition, the findings outlined in this paper suggest that herding can be explained in terms of individual differences and herding is associated with some of the traits specifically linked to a socialised personality. Herding is also positively associated with personality traits including impulsivity and venturesomeness. This may indicate that it is an acquired, automated decision-making heuristic that enables people to decide quickly in uncertain situations. This analysis also identifies a significant relationship between herding and amygdala activation and this may reflect the fact that the amygdala plays a role in social learning and decision-making.

Further investigations of individual differences could uncover other behavioural / psychological correlates of herding. Other studies suggest that intelligence is positively associated with empathy, extraversion and socialisation, but negatively associated with impulsivity (Eysenck and Eysenck 1976)[13] and so further research could explore the impacts of cognitive ability, impulsivity and herding. This might also help to explain the greater reliance on herd information amongst more impulsive individuals.[14] A negative correlation between herding and cognitive ability might also explain the negative parameters on extraversion identified in this study: if the essential characteristic is cognitive ability, then the extraversion variable could be acting as proxies for cognitive ability in this analysis.

The evidence about the links between propensities to herd, individual differences and differential amygdala activation may enable the development of herding models which clarify the role played by emotional processing, thus reconciling theories about rational and emotional / affective influences on behaviour (Camerer *et al.* 2004, 2005). This could involve the development of neuroeconomic behavioural models in which dual processing and consilience are emphasised, drawing together inductions from different disciplines including economics, experimental psychology and neuroscience (Kahneman 2003, Glimcher and Rustichini 2004, Camerer 2007). Resolving questions about whether herding is being generated by cognitive and/or affective processes does require deeper delving into the motivators of behaviour so better to understand the neural black-box that underlies human decision-making. One approach could be to develop studies on non-standard discount functions and time inconsistency (see Frederick *et al.* 2002 for a survey) to explore links with impulsivity, cognition and discounting parameters. McClure *et al.* (2004) present neuroeconomic evidence suggesting that time inconsistency reflects the interaction of separate neural systems valuing immediate versus delay rewards and, given the link between impulsivity and herding identified in this analysis, similar neural interactions may affect decisions to herd.

[13] Though Zeidner (1995) highlights the inconsistent and contradictory evidence about the link between extraversion and intelligence.
[14]See also Dohmen et al (2007) on risk aversion and impatience.

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