Impacts of Personality on Herding in Financial

Decision-Making

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Experimental analyses have identified significant tendencies for individuals to follow herd decisions, a finding which has been explained using Bayesian principles of statistical inference. This paper outlines the results from a herding task designed to extend these analyses. Empirically, we estimate logistic functions using panel fixed effect estimation techniques to quantify the impact of herd decisions on individuals' decisions about whether or not to buy a financial asset. 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 such as gender, age and specific personality traits including impulsivity and venturesomeness.

Keywords: herding, social influence, financial decision making, personality *JEL codes:* D03, D81, C92, G14

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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 weaker conceptions of rationality: 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 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'.

Alternatively, herding tendencies may emerge as people copy and imitate the actions of others - not because they judge that others know more about the fundamental long-term values of goods and assets but because agreeing with a group bestows a utility that is independent of the information implicit in others' decisions. In this case, the impact of social information may reflect the impact of sociological and psychological forces. Sociological factors will 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. Psychological factors and individual heterogeneity will moderate susceptibility to social influence. For personality traits that predispose individuals to particular emotional responses, 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 way personal characteristics including gender, age and personality traits affect an individual's propensity to herd.

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, our experimental subjects were significantly more likely to agree with a herd than not. Also, we test competing explanations for this herding phenomenon in two stages. First, we estimate a model that is consistent with an objective, rational process of herding in which individuals are reasoning through some form of statistical inference (e.g. Bayesian updating) when making their choices. If herding is the outcome of such a reasoning process, then it will involve time-consuming deliberation and therefore we test the Bayesian hypotheses firstly by exploring whether or not

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herding is associated with longer decision times. In the second empirical stage, we test the impact of individual differences on herding tendencies and thereby allow a role for behavioural factors on propensities to herd. This also provides a second test of the hypothesis that herding is a rational process because, if it is rational to herd then this implies that herding is the outcome of an objective reasoning process in which case individual differences in non-cognitive personality traits (i.e. traits not associated with the ability to apply statistical principles), should not exert a systematic influence on propensities to herd.

To give a preview of our findings, our data do not fully support the predictions of the rational account of herding outlined above. For example, some of our empirical evidence suggests that herding is associated with <u>shorter</u> decision times. In addition, there are statistically significant individual differences in propensities to herd with herding more likely to be seen in younger, female, impulsive and/or venturesome individuals. Together these findings suggest that "one-size-fits-all" explanations of herding based on principles of statistical reasoning and inference should be expanded to include individual differences.

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. Here we focus on two main groups of explanation: rational learning explanations based around Bayesian updating assumptions, and explanations based on individual differences, drawing particularly on insights from sociology and psychology. It is important to emphasise that these explanations are not necessarily mutually exclusive.

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 decisionmaking. 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 100th person with a misleading private signal (favouring a "buy" decision) but is the first to decide. Then the group as a whole will 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 this neglect of relevant information by 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 will 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

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onto stable outcomes but often leading to convergence onto idiosyncratic and fragile outcomes (Chamley 2003).²

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 but without assessing the differential explanatory power of their Bayesian hypotheses against competing alternative hypotheses about why people herd. Others have extended this experimental evidence to distinguish between herding as a broad descriptive category of copying behaviours and 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). Following Avery and Zemsky (1998) Park and Sgori (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.

Mostly, the experimental literature establishes that there is a systematic pattern in herding behaviour though it does not establish that Bayesian belief-based explanations are superior to alternative explanations including those consistent with sociological and psychological analyses. One notable exception is Cipriani and Guarino (2005) who adapt Bayesian models to incorporate flexible prices in a model in which cascades cannot occur. They find that some subjects either do not use their private information, choosing either not to trade or to ignore private information but 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. This approach suggests that individuals' behaviours are essentially homogenous; different people will, on average at least, behave in the same way. But there is general evidence that decision-making is not just the outcome of statistical inference; furthermore, people are not necessarily competent in

² See also Kirman (1993) for a herding model based on different statistical assumptions.

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, there is 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 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.

Building on these insights, alternative explanations for herding can be grounded in principles of social psychology, particularly sociological analyses of the influence of crowds and group pressure as developed from le Bon's (1896) insights about mob psychology. Social psychology emphasises that situational influences have a significant impact on individual decisions, in the extreme provoking seemingly inappropriate levels of obedience to authority (Milgram 1963; Haney et al. 1973). 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. It is plausible that situational pressures operate in an economic and financial context too.³ It is difficult to establish whether wrong choices in Aschstyle tasks are the result of the subjects' perceptions of their own visual limitations and/or 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 will herd even when normative social influence is removed: they will follow decisions of a group of computers in much the same way that they will follow a human herd's decision. Experimental subjects tend to attribute their mistakes to their own physical limitations, such as poor eyesight. The operation of social influence even without

³See Bond and Smith 1996 for a survey of evidence on Asch-style tasks.

human face-to-face interactions can be interpreted as evidence that social conformity is a manifestation of information acquisition (Deutsch and Gerard 1955; Bikhchandani *et al.* 1992). On the other hand, theory of mind ("mind reading") explanations explain that herding operates even without face-to-face interactions if imagined peer pressure acts similarly to real peer pressure. So one theorist can argue that Asch's evidence does not disprove the rational herding hypothesis but another can equally argue that it does, depending on what is assumed about human cognition and emotion. Experimental evidence testing competing explanations has the power to resolve such impasses.

2.3 Reconciling Rational and Socio-Psychological Theories of Herding

In the preceding sections, we presented distinct explanations for herding drawing upon ideas from economics, sociology and psychology. The approaches are clearly not mutually exclusive: the sociological distinction between normative influences from wanting to conform versus the informational influences that emerge with learning from others' actions is a distinction which 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 social influence (Bernheim 1994). The limited nature of this literature in part reflects difficulties of effectively modelling social factors. One solution is to embed social factors (such as status and reputation) into individuals' preferences (Bernheim 1994; Scharfstein and Stein 1990).

Another possibility however is that apparently disparate approaches are not necessarily mutually exclusive. Real-world herding behaviour may be the outcome of interplays between rational/cognitive and instinctive/emotional processes as well as a reflection of sociological and psychological impacts emerging from situations and individual predispositions (Baddeley 2010). If decisions to herd are associated both with decision times and with individual differences then this would support models of behaviour which emphasise interactions between controlled, cognitive, automatic and affective processes in human economic and financial decision-making. When people are influenced by social information then this may reflect an interaction between a deliberative learning process and a more instinctive, affective, emotional response. This hybrid explanation would also be consistent with evolutionary principles. 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 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

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herding instincts may have evolved as a learning 'heuristic' or simple rule-of-thumb, enabling us to easily acquire important social information about the potential value of our acquisitions.

3. Experimental Hypotheses

To test the different models outlined above, we develop two broad hypotheses to contrast explanations based on objective factors versus subjective factors / individual differences:

3.1 Herding as the outcome of rational deliberationIf, following the microeconomic models described above, herding is a boundedly rational

phenomenon associated with deliberative, cognitive processes reflecting information gathering and processing, then it will involve the application of principles of statistical inference such as Bayes's Rule. If herding is a deliberative process, based on objective factors and requiring deliberation then people will need thinking time when they follow a herd. Individual differences, e.g. in personality traits, will have no systematic impact on the propensity to herd.

In experimentally capturing deliberative herding, we follow Reddi *et al.* (2003) and Reddi and Carpenter (2000) in using reaction times as a proxy for time-consuming deliberative thought.⁴ To justify this proxy we adopt the Schneider-Shiffrin separation of automatic versus controlled processes (Schneider and Shiffrin 1977; Kahneman 2003; Frederick *et al.* 2004, Camerer *et al.* 2004, 2005). Reasoning using methods of statistical inference involves objective decision-making and controlled cognitive processing. Cognition is the outcome of slower, more deliberative processes because it draws on higher-order, complex executive functions. On the other hand, affect is noncognitive, links directly with motivation and so operates very quickly. Cognitive processes will require more time and effort than automated emotional, affective, instinctive responses (Zajonc 1984). So if following the herd is a rational learning process founded upon principles of statistical inference such as Bayesian updating then it will be controlled, cognitive, effortful and timeconsuming and it will be associated with longer decision times.

3.2 Herding as the product of individual differences

If herding reflects individual differences rather than an objective process of information acquisition and processing then individual characteristics and heterogeneity amongst people will have a significant and systematic impact. Conversely, if the Bayesian explanation is complete, then some individual differences in age, gender and personality will have no significant systematic impact.⁵

⁴ Nonetheless, it is important to emphasise that decision times may be a limited measure of Bayesian reasoning processes. For example, Sgroi's (2003) experimental evidence from Bayesian herding games identifies associations between longer decision times and cognitive bias in reverse cascades suggesting that longer decision times may reflect general confusion rather than a systematic deliberative process.

⁵ Some personality traits may be correlated with cognitive ability, an issue addressed in section 6.

Decision times are not likely to be longer but may be shorter if herding is an automated, affective response. Furthermore, individual differences and shorter decision-times may interact if people with particular personality traits are predisposed to make quick, emotionally-driven decisions. We start by hypothesising that sociable, empathetic individuals are more responsive to social influence and so will be more likely to herd. In assessing the impact of visceral and/or emotional factors we also postulate that quickly-processed emotions may be implicated in herding in which case herding is more likely to be seen in impulsive and venturesome individuals. In addition, gender and age are included 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 A hybrid explanation

It is also possible that herding reflects an interaction of deliberative and affective factors. If social information plays some role in decision-making but is moderated by individual differences. For example, 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).

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 a functional magnetic resonance imaging (fMRI) analysis (see also Burke *et al.* 2009). 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 stock prices over the preceding month. 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*.

Stage 2: Subjects were then presented with social information about the herd choices – with the "herd" represented as 4 faces.⁶ 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 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. A herding control condition was used to capture the extent to which social information about herd decisions was being used as a real decision-making tool, by running the tasks with a herd represented by 4 chimpanzee faces. The experimental subjects were told that the chimps had no understanding of the task and did not care about money as a reward.

⁶ The face stimuli were kindly provided by Bruno Rossion of the Cognition & Development Research Unit, Université Catholique de Louvain, Belgium.

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

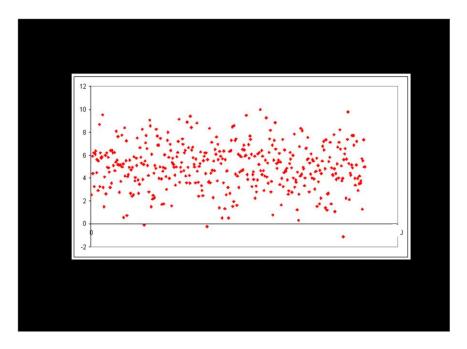
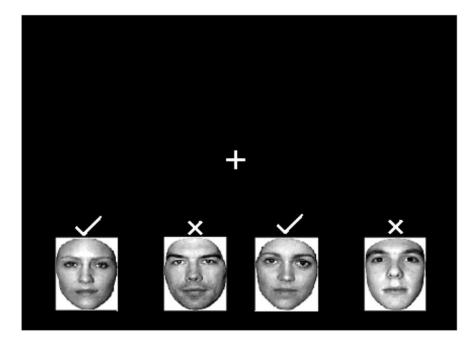


Fig. 1b: Stage 2 Social Information: Herd decisions revealed



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. Decisions and

decision times were collected at this stage. Decision times were collected because, as explained in section 3.1, we hypothesise that a decision to go with the herd reflects either a time-consuming deliberative reasoning process and/or individual characteristics affecting an individual's emotional susceptibility to social influence.

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

Each task scenario was used twice (once for a human herd and again for a chimp herd) with 12 repetitions for each of the 20 task scenarios so there were 480 trials per experimental subject. To 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 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, 1978; 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: $E(H|\Omega) = Pr(H=1|\Omega) = p_{herd}$

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 function⁷:

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

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.

		Subject buys	Subject herds	
Allscenarios		0.503	0.696	
Private informatio	n scenarios			
Share price chart:	High mean	0.574	0.695	
	Small variance	0.597	0.643	
	High mean, small variance	0.607	0.634	
	Scrambled	0.261	0.331	
Social information	scenarios			
Herd decision:	Buy	0.703	0.703	
	Reject	0.312	0.688	
	Split	0.530	n/a	
	No information	0.468	n/a	
	Human herd	0.516	0.774	

TABLE 1 - CONDITION AL PROBABILITIES

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

Panel fixed effect estimation techniques were 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. 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.

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 factors increase the probability that a person will follow the herd. The econometric analysis assesses these two 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 objective factors versus individual differences. This is done to separate explanations of herding that assume a rational, objective decision-making process from explanations that focus on individual differences and socio-psychological factors.

Table 1 shows the conditional probabilities of buying and herding in the various experimental scenarios, including both chimp and human scenarios. Assuming no social or private information is available, the baseline probability that a person will buy a stock is $Pr(Buy = 1) = p_{buy} = 0.50$ because

there is no reason to expect the person to favour a buy versus reject decision. The results in Table 1 confirm that the unconditional p_{buy} for subjects in our sample is 0.50. Experimental subjects were more likely to buy stocks with a high mean and/or a small variance which is consistent with the behaviour predicted by mean-variance analysis.

As explained in section 2, the concept of herding implies that the agreement of the herd and the experimental subject is not a coincidence. 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			
		\downarrow			
		Buy	Reject		
Experimental	Buy	Buy, Buy	Buy, Reject		
subject's choice \rightarrow	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 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} . 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 70%, which is statistically significantly larger than 0.50.⁸ The likelihood of human herding, i.e. following the human herd as opposed to the chimp herd is 77%, which is also statistically significantly higher than the overall probability of herding indicating that the experimental subjects are taking the human herd decisions more seriously than the chimp herd decisions. 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 in two stages to mirror the stages of the experimental subjects' decision-making and also to overcome

⁸ H₀:
$$p_{herd} = 0.50$$
, H₁: $p_{herd} > 0.50$, $z = \frac{0.703 - 0.50}{\sqrt{\frac{0.50 \times 0.50}{8160}}} = 36.68 \ [p=0.000].$

potential econometric problems of endogeneity. In the first stage revealed preferences for the 4 combinations of high /low mean/variance stocks were analysed, conditioned on 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:

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

where Ω_p is the private information made available to each experimental subject in the form of a stock chart, as described above, and a_i is the fixed effect for each subject capturing the differences across the experimental subjects in the predicted probabilities of a buy decision.

In the second stage, to capture the differential impact of herd information, the predicted probabilities from the first stage were used in the estimation of the probability of a buy decision conditioned on social information about herd decisions:

$$p_{buy,i} = f(\hat{p}_{buy,i}, \Omega_{herd})$$
(3)

where $\hat{p}_{buy,i}$ is the predicted probability from the first stage and Ω_{herd} is the social information about herd decisions.

The results from these two estimation stages are shown in Table 2. The results summarised in Table 2A were used to get predicted probabilities of a buy decision given private information. These predicted probabilities were then included in the estimation outlined in Table 2B, to capture the additional impact on buy probabilities of social information about herd decisions.

TABLE 2 – LOGIT ESTIMATION: BUY DECISION

Dependent variable: SBUY (=1 if buys, =0 if rejects) n=8160

2A - As function of private information

	Odds			
	ratio	Std. error	z score	p value
High mean	1.488	0.047	8.420	0.000
Low variance	1.804	0.047	12.480	0.000
Subject-specific fi	ixed effects (a _i):		
Subject 1	1.442	0.191	2.770	0.006
Subject 2	0.629	0.084	-3.490	0.000
Subject 3	0.543	0.073	-4.560	0.000
Subject 4	1.148	0.151	1.050	0.293
Subject 5	1.481	0.196	2.960	0.003

Subject 6	0.991	0.130	-0.070	0.948
Subject 7	0.574	0.077	-4.160	0.000
Subject 8	2.153	0.293	5.640	0.000
Subject 9	1.100	0.145	0.720	0.470
Subject 10	1.009	0.132	0.070	0.948
Subject 11	0.590	0.079	-3.960	0.000
Subject 12	1.119	0.147	0.850	0.393
Subject 13	1.220	0.161	1.510	0.131
Subject 14	1.179	0.155	1.250	0.212
Subject 15	0.950	0.125	-0.390	0.694
Subject 16	0.917	0.121	-0.660	0.511
Subject 17	1.442	0.191	2.770	0.006
$LR \square^2(df=18) = 5$	03.31 [p=0.000]			

Log likelihood = -5404.25

2B - As function of social information

	Odds	Std.				
	ratio	error	z, score	p value		
Predicted <i>p</i> _{buy}						
(from 2A above)	1.032	0.015	2.080	0.037		
Herd buys	2.382	0.138	15.040	0.000		
Herd rejects	0.455	0.026	-13.790	0.000		
LR $\chi^2(df=3)=648.07 [p=0.000]$						
Log likelihood = -5331.868						

The results reported in Table 2A confirm information from conditional probabilities above and the statistically significant [p=0.000] 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. As noted above, this suggests that they are behaving as predicted in mean-variance analysis. In addition, the *z* scores on the dummy variables included to capture individual differences are significantly different from zero [p<0.05] for 8 of the experimental subjects. This is preliminary evidence that individual differences are important and that individuals' decisions are not

the outcome of purely objective, economic factors. Table 2B shows the impact of social information on individuals' decisions. Confirming the conditional probabilities from Table 1, the *z* scores on "Herd Buys" and "Herd Rejects" show that there is a statistically significant [p=0.000] increase in the tendency to buy when the herd buys; and a statistically significant [p=0.000] decrease in the tendency to buy when the herd rejects (baseline scenarios are that the herd is split 2-2 or that there is no herd information).

To summarise findings from these first estimations of buy probabilities: subjects are on average more likely to buy high mean, low variance stocks. Information about herd decisions has a significant impact with the experimental subjects more likely to buy a stock when the herd is buying it, thus confirming previous evidence that herd information 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 in two stages. To recap: the competing explanations for herding are first – that herding is the outcome of an objective, rational decision-making process in which social information about group/herd decisions is processed systematically alongside private information; and second – that herding is the product of individual differences and non-economic factors such as personality traits, gender and age. These factors might predispose experimental subjects to particular emotional responses that would encourage herd-copying behaviour.

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 effect dummies to capture individual differences – a_i but further estimations were also run in which herding probabilities were conditioned on the specific measures of individual differences.¹⁰ The herding probabilities were estimated assuming that a combination of factors determining an individual's propensity to herd adapting equation (1) as follows:

$$p_{herd} = \Pr(H \mid (\Omega_p, \Omega_h) = \frac{\exp(x\beta)}{1 + \exp(x\beta)}$$
(4)

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

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.

where *x* —the vector of explanatory variables includes *d* — decision time and either a_i or specific measures of individual characteristics including gender, age and personality traits. In the Bayesian herding models decision-makers are discounting potentially meaningful private information (Ω_p) and favouring social information about the herd's decisions (Ω_h). The rational herding hypothesis is tested using *d*, included to capture the extent to which herding is a deliberative decision, consistent with models of rational herding in which people are applying principles of statistical inference. As explained in section 3, if individual characteristics are significant then this would suggest that herding is the outcome of individual, possibly subjective, factors and so is not necessarily strictly rational in the sense that it is driven by objective factors.

The results from estimations including only private information and decision-time are outlined in Table 3.Some private information about the type of stock is significantly associated with propensities to herd: the experimental subjects were significantly more likely to herd when offered a high variance stock; they were also significantly more likely to herd when social information was from a human herd, suggesting that herding does reflect a genuine attempt to decipher meaningful information. The decision time variable is negatively associated with decisions to herd [p=0.045] but the impact is very small. This may undermine theories of herding which suggest that herding is a strategy associated with deliberation and the rational application of principles of statistical inference because, as explained above, we could expect that such deliberation should take more time rather than less. However, this does not necessarily prove that cognition is not implicated in herding decisions: reasoning processes can become automated through practice (Kahneman 2003) and if Bayesian herding is not controlled, slow and time-consuming does not necessarily mean that they are free of reasoning and deliberation.

TABLE 3:

Is herding moderated by private information?

Dependent variable: H (=1 if agree with herd; =0 otherwise)n=4080

	Std.					
	Odds ratio	Err.	Ζ	P > z		
High mean	0.913	0.072	-1.160	0.247		
Low variance	0.543	0.043	-7.700	0.000		
Scrambled signal	0.572	0.059	-5.380	0.000		
Human herd	2.148	0.151	10.850	0.000		
Decision time	1.000	0.000	-2.000	0.045		
LR χ^2 (5)= 189.16 [p=0.000]						

Log likelihood = -2411.9802

The results shown in Table 3 also capture the extent to which the quality of private information affects propensities to herd. This can be seen by comparing the subjects' responses to three different types of private information: relatively clear signals for high versus low mean scenarios; differentially ambiguous signals for the low variance versus high variance scenarios; and the meaningless "scramble" signal in which the private information was conveying no information at all (the presented stock chart was completely random). The subjects were relatively more likely to follow the herd in high variance scenarios and less likely to follow the herd in the "Low variance" scenarios. Initially assuming no individual differences in the propensities to herd given high variance stocks, then the increased tendency to herd with high variance stocks may indicate that herd information is being used as a quick decision-making rule, i.e. as a heuristic, when information is widely dispersed and imprecise. The statistical insignificance of the high mean / low mean variable is not inconsistent with this explanation because whether or not the subjects are being asked to choose a a high mean versus low mean stock is relatively easy to discern; the clarity of private information is reflected in its variance whether it is a high mean or a low mean stock. This may explain the negative, though statistically insignificant, paramater on "high mean" - for 50% of trials, the herd was seen foolishly to be buying either a low mean stock or rejecting a high mean stock and in this case the experimental subjects, on average and wisely, decided to ignore the herd signal hence the negative parameter on "high mean". The experimental subjects were not tricked into selecting a low

mean stock just because the herd was selecting it. The scramble variable is negatively and significantly associated with the propensity to herd, i.e. herding is less likely with a scrambled chart. This suggests that the subjects were only following the herd when the information was unclear rather than completely scrambled: subjects were using the herd information more often when the signals were ambiguous, i.e. in the high variance scenarios, but were not persuaded to follow the herd when their private signal was pure noise.

Overall, these results may reflect a rational response to the poor, ambiguous quality of the information. In the high variance case, it is harder to discern whether or not the stock was high mean or low mean and the herd information may have been allowing the subjects a quick decision-making rule to help them when their private information was unclear.

Individual differences were captured in the estimations summarised in Table 4. As for the estimations of buying probabilities above, individual differences were included using dummy variables to capture subject-specific fixed effects. For 10 of the subjects the dummy variables capturing individual differences are significant. Also, these results partially confirm the results from Table 3, indicating that there is a negative association between propensities to herd and decision-times but the association is now statistically insignificant [p=0.873]. This may reflect the fact that differences in decision-times are being captured by individual differences across the subjects.

TABLE 4: Is herding captured by individual differences?

Dependent variable: H (=1 if agree with herd; =0 otherwise)n=4080

	Odds	Std.		
	Ratio	Err.	Z	P > z
High mean	0.906	0.074	-1.220	0.223
Low variance	0.524	0.043	-7.900	0.000
Scrambled signal	0.548	0.059	-5.600	0.000
Human herd	2.261	0.165	11.170	0.000
Decision time	1.000	0.000	0.160	0.873
Subject specific fixed effect	ts (a _i):			
Subject 2	2.212	0.442	3.970	0.000
Subject 3	1.267	0.242	1.240	0.215
Subject 4	4.262	0.938	6.590	0.000
Subject 5	2.991	0.622	5.270	0.000
Subject 6	1.189	0.234	0.880	0.379
Subject 7	5.176	1.186	7.170	0.000
Subject 8	1.692	0.332	2.690	0.007
Subject 9	0.948	0.179	-0.280	0.776
Subject 10	0.999	0.189	-0.010	0.994
Subject 11	5.016	1.145	7.060	0.000
Subject 12	1.070	0.205	0.350	0.723
Subject 13	3.463	0.748	5.750	0.000
Subject 14	2.839	0.584	5.070	0.000
Subject 15	1.852	0.370	3.080	0.002
Subject 16	1.584	0.308	2.370	0.018
Subject 17	4.129	0.904	6.480	0.000

LR χ^2 (21)= 444.50 [p=0.000]

Log likelihood = -2284.3101

In Table 5 some of the elements of those individual differences are explored in more detail using the specific measures of individual differences. The male subjects were significantly less likely to herd. Also, the older subjects were significantly less likely to herd across all scenarios, confirming

other research suggesting that older people are less susceptible to social pressure (Walker and Andrade 1996).

TABLE 5

Do particular characteristics increase the likelihood of

herding?

Dependent variable: H (=1 if agree with herd; =0 otherwise)n=4080

	Odds	Std.		
	Ratio	Err.	Ζ	P> z
High mean	0.912	0.072	-1.160	0.244
Low variance	0.537	0.043	-7.770	0.000
Scrambled signal	0.567	0.059	-5.410	0.000
Human herd	2.179	0.155	10.940	0.000
Decision time	0.999	0.000	-2.150	0.032
Gender (M=1)	0.516	0.052	-6.570	0.000
Age	0.976	0.011	-2.110	0.035
Psychotic (vs.				
Socialised)	0.989	0.030	-0.380	0.703
Extraversion	0.915	0.014	-5.660	0.000
Impulsiveness	1.034	0.011	2.990	0.003
Venturesomeness	1.070	0.013	5.440	0.000
Empathy	0.967	0.012	-2.590	0.010
LR χ^2 (12)=259.76 [p=0.000]				

Log likelihood = -2376.6829

In terms of personality traits, herding is statistically significantly less likely amongst extraverted and/or empathetic individuals. There is no significant impact of psychoticism/socialisation, even though extraversion and empathy are associated with more sociable natures. This does not imply however that social influence is unimportant; it may be that socialised individuals are less susceptible to social influence and peer pressure. Also statistically, if there is multicollinearity between measures of extraversion, empathy and socialisation, then the power of the z test on the socialisation variable will be reduced.

That said, other groups of traits appear to have a stronger influence, e.g. the traits associated with risk-taking. Herding tendencies are positively and significantly associated with venturesomeness and

impulsivity. This is consistent with the assertion that herding and faster decision times are both more likely in individuals with particular personality traits that predispose them to risk-seeking behaviour i.e. the venturesome and/or impulsive personalities.

The decision time variable is again significant (at a 5% significance level) but the again the impact of decision-time is small. In exploring the link between personality and decision times, correlations were calculated between decision times and other personality traits (see Table 6).

	Decision	Gender						
	time	M=1	Age	Psychotic	Extravert	Impulsive	Venturesome	Empathetic
Decision time	1							
Gender (M=1)	-0.05	1						
Age	-0.01	-0.26	1					
Psychotic	-0.13	-0.20	0.38	1				
Extravert	-0.23	-0.48	0.24	0.35	1			
Impulsive	-0.24	-0.10	0.53	0.23	0.31	1		
Venturesome	-0.05	0.08	0.04	0.44	0.27	0.11	1	
Empathetic	0.30	-0.09	0.21	-0.06	-0.35	-0.01	0.16	1

 Table 6: CORRELATION MATRIX: Decision times versus individual

 characteristics

Overall, the only personality trait that is positively associated with decision times is empathy which may suggest that empathetic responses are reasoned rather than impulsive, emotional responses. So if herding is an instinctive impulsive response then, contrary to our initial hypotheses outlined in section 3.2, it would be less likely amongst empathetic individuals.

Other estimations revealed that venturesome and impulsive individuals were not only significantly more likely than others to herd; they were also more likely to buy high variance stocks.¹¹ This clarifies the evidence from Table 3A about herding being more likely with high variance stocks and suggests that herd information is not being used objectively and systematically by all agents when information is unclear but is instead associated with risk-taking personality traits. This is consistent with the idea that herding is not simply an objectively driven heuristic to enable decision-making in uncertain environments; it may also be the outcome of emotionally-driven, risk-seeking impulses.

6. Implications and Conclusions

The results presented here indicate that experimental 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

¹¹ Additional linear estimation results indicate significantly negative associations between venturesomeness and decision times [p=0.001] and between impulsivity and decision times [p=0.000]. Spearman's Rank correlation coefficient between venturesomeness and probability of buying a high variance stock is +0.20.

explained in terms of individual differences but herding does not appear to be specifically associated with a socialised personalities; in fact, the evidence presented here suggests that characteristics associated with sociability (e.g. extraversion and empathy) are negatively associated with herding tendencies. More importantly, herding is positively associated with personality traits associated with risk-taking, including impulsivity and venturesomeness. This may mean that it is an acquired, automated decision-making heuristic to enabling impulsive people to decide quickly in uncertain situations.

Overall, these findings lend support to socio-psychological models which explain economic and financial decision-making as the outcome of subjective factors and individual differences. This does not completely exclude explanations of herding as a rational, objective reasoning process; in this sample, herding is seen with high variance stock price information suggesting that it may be a decision-making device used when private information is unclear and, if this is the case, then herding may have rational, reasoning elements.

There are important qualifications. The results presented represent just one limited sample of data. More work is needed in verifying the findings. For this experimental design in particular, it would be important to identify other proxies, apart from decision times, for deliberative thought and/or Bayesian reasoning. A fuller investigation of individual differences could uncover other behavioural / psychological correlates of herding. Other studies suggest that intelligence is positively associated with empathy, extraversion and socialisation and negatively associated with impulsivity (Eysenck and Eysenck 1976)¹² and so further research could explore the links between herding, cognitive ability and discounting parameters to test the idea that impulsivity is associated with lower cognitive ability and/or impatience. This might also help to explain the greater reliance on herd information amongst more impulsive individuals.¹³ A negative correlation between herding and cognitive ability might also explain the negative parameters on extraversion and empathy: if the essential characteristic is cognitive ability, then the empathy and extraversion variables are acting as proxies for cognitive ability in this analysis.

Overall, if herding reflects an interaction of Bayesian and socio-psychological factors then herding models could be developed to identify the role played by emotional processing, thus reconciling rational and emotional / affective influences on behaviour. This could involve the development of neuroeconomic behavioural models in which dual processing and consilience are emphasised, drawing together inductions from different areas (Kahneman 2003, Glimcher and

¹² Though Zeidner (1995) highlights the inconsistent and contradictory evidence about the link between extraversion and intelligence

¹³See also Dohmen et al (2007) on risk aversion and impatience.

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 as to better understand the neurological black-box that generates human choice. So whilst this paper has focussed on distinct explanations for herding – first, as a deliberative form of social learning in which it is assumed that others have more or better information; and second, as an instinctive or impulsive emotional responses, these explanations are not necessarily mutually exclusive.

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APPENDIX I: Experimental Instructions (presented in Powerpoint)

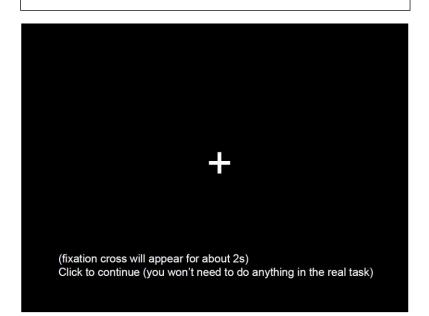
In this task you will be choosing whether or not to invest in different stocks.

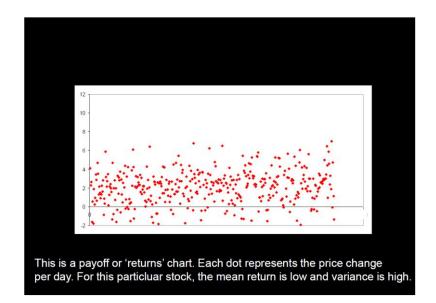
The experiment will run for about 60 minutes and we will record 480 Investment decisions from you.

At first you will see a 'fixation' cross for a few seconds.

You will then be presented with a 'returns' chart for the stock (more on next Slide). If you are unfamiliar with any of the instructions, please ask one of The researchers.

Click the mouse to see what this will look like.





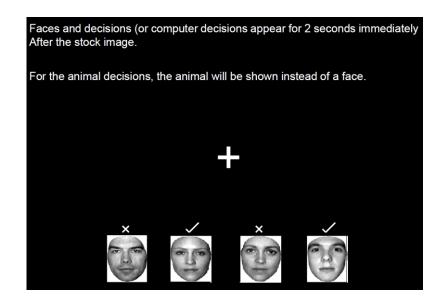
You will see the stock chart for 2 seconds. This is very short, so you'll have to concentrate.

You will then see a screen with some extra information. This information Is in the form of other decisions for the same stock.

The decisions are either real human recorded decisions, or decisions that an Untrained animal has made.

The human decisions come from a previous pilot experiment with Cambridge Graduate students. You will be able to see the faces of these previous Decision makers, along with their decisions.

Click the mouse to see what this will look like.



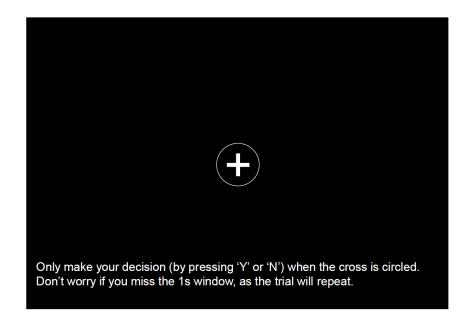
After 2 seconds the decision information will disappear and you will have One second to make your decision. This is denoted by a circle around the Fixation cross.

It is very important that you only make your decision when the fixation cross Circled.

Press 'Y' to invest in the stock and 'N' to pass.

f you don't make a decision, the trial will repeat. If you miss the decision, wait Until the fixation cross is circled before pressing 'Y' or 'N'.

Click the mouse to see what this will look like.



After your decision is made, the final price of the stock is determined and Logged. The total of all your winnings and losses is computed at the end.

There are four different 'types' of stock. High mean, high variance; high mean Low variance; low mean, high variance; low mean, low variance. In addition to These, sometimes a 'scrambled' stock will appear; in this situation, you don't know what stock it is, but still have to make a decision.

Half of all stocks will decrease in value and half will increase in value. If you Fail to choose wisely and simply invest in every single stock, you won't make any money.

Click the mouse to see next slide

