

Herding and Social Pressure in Trading Tasks: A
Behavioural Analysis

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Abstract

We extend the experimental literature on Bayesian herding using evidence from a financial decision-making experiment. We identify significant propensities to herd increasing with the degree of herd-consensus. We test various herding models to capture the differential impacts of Bayesian-style thinking versus behavioural factors. We find statistically significant associations between herding and individual characteristics such as age and personality traits. Overall, our evidence is consistent with explanations of herding as the outcome of social and behavioural factors. Suggestions for further research are outlined and include verifying these findings and identifying the neurological correlates of propensities to herd.

JEL classification: D7, D8, D81, D82, D83

Key words: Herding, Bayesian updating, social learning, social pressure

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1. Introduction

Herding is defined here as occurring when individuals mimic others, ignoring substantive private information (Scharfstein and Stein 1990, p.466). It occurs when the influence of private information on individual choices is overwhelmed by the influence of public information about the decisions of a herd or group. Evidence of herding in many economic and financial decisions is not inconsistent with weak assumptions about rationality. If we realise that our own judgement is fallible it may be rational to assume that others are better informed and so to follow them (Keynes 1937, p.214). If decision-making is Bayesian and probabilistic judgements are being updated systematically and logically using information about others' actions then a rational process of Bayesian updating will encourage information about others' choices to cascade through a group, generating herding and 'informational cascades' (Banerjee 1992, Bikhchandani *et al* 1992). Alternatively, herding tendencies may emerge as people copy and imitate the actions of others but 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 (Bernheim 1994).

In this paper, we present evidence that there are significant propensities to herd: our experimental subjects were significantly more likely to agree with a group than not and the likelihood of their agreement increased with the degree of consensus within the herd. Also, we separate the rational herding hypotheses from sociological explanations and show that, for our experimental subjects, both the Bayesian and the psychological hypotheses have some merit, with the main psychological findings being that there are significant positive associations between the propensity to herd, and conformity and extraversion; and significant negative associations between the propensity to herd and decision time, age, extraversion, empathy and venturesomeness.

2. Herding Theory

There are many explanations for herding behaviour.² Here we focus on two main groups of explanation: rational learning explanations, grounded in theories of Bayesian learning; and socio-psychological explanations, which draw particularly on insights from social psychology. We will also emphasise that these explanations are not necessarily mutually exclusive.

2.1 *Bayesian Learning and Informational Cascades*

Traditional economic and financial theory has focussed on such strong assumptions of rational expectations, efficient markets and independent, self-interested individuals. In response to the limitations of theories based on strong assumptions, more recent analyses have developed to take account of constraints on rationality imposed by imperfect information (Simon 1955, 1979). In a world of uncertainty, rational choices can be made following principles of statistical inference using Bayes's Theorem (Salop 1987). Bayesian explanations for herding lie in extensions of these principles of rational behaviour to scenarios in which different individuals' decisions are interdependent and reinforcing. Individuals may rationally judge that others' actions contain useful information (Keynes 1936, 1937). Thus they will discount useful private information in favour of information about the actions of the herd (Scharfstein and Stein 1990). Another important aspect of rational herding is that it is a convergent process and a stable solution will be reached (Bikhchandani *et al.* 1992, Chamley 2003). Putting these insights together, herding can be described as a Bayes rational response to imperfect information; Bayesian updating of *a priori* probabilities will draw upon an extensive set of information including social information coming from actions of others in a group or herd and the Bayes rational actions of individuals will generate convergence onto an outcome determined by social information about herd actions rather than private information.

² See Chamley (2003) and Baddeley (2007) for outlines of different approaches.

For example, Banerjee (1992) develops a herding model in which people look at what others are doing, e.g. in fertility choices, voting rights and in financial decisions, describing herding is the outcome of a rational but potentially misguided an information gathering process. He gives the example of restaurant choice. Restaurant A and Restaurant B are favoured *a priori* 51% and 49% respectively. A group of 100 people are making sequential decisions about which restaurant to choose. If 99 out of 100 people have private signals (e.g. this private signal may be an experience of another restaurant run by the same people) indicating that Restaurant B is better than restaurant A then, on the basis of the aggregate evidence, it could be assumed that Restaurant B should be preferred. But assume that Person 1 is the 100th person with a misleading private signal (favouring Restaurant A) but gets to choose first. Then the group as a whole will choose Restaurant A on the basis of this misleading evidence. The sequence of events that generates this outcome is as follows. Person 1 chooses Restaurant A on the basis of their (misleading) private signal. Person 2 is the next to choose. He knows the *a priori* probability (favouring restaurant A) and has a correct private signal favouring Restaurant B but also has social information about the prior actions of Person 1. Applying Bayes's rule and assuming that he weights these last two pieces of information equally, the information about Person 1's choice will cancel out Person 2's private signal. So Person 2 will rationally choose Restaurant A on the basis of prior probabilities (favouring Restaurant A by 51%). Similarly Person 3 will choose Restaurant A on the basis of Person 1 and 2's choices and so on – the impact of the incorrect signal will cascade through the herd. Overall, even though behaviour is Bayes rational, informative private information has no influence on choices; the herd will move towards Restaurant A when 99% of private signals favour Restaurant B. Banerjee emphasises that the herd's neglect of relevant private information may generate a negative 'herding externality' where important information is ignored in the aggregate.

Bikhanchandi, Hirschleifer and Welch (1992) develop a similar model of sequential decision-making in which informational cascades explain localised conformity emerging 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 and so private information becomes uninformative, potentially leading to convergence of behaviour onto idiosyncratic and fragile outcomes.

A large number of economic experiments have been conducted to test these theories of Bayes rational herding, starting with Anderson and Holt (1996, 1997). But these experiments merely establish that herding is consistent with Bayesian updating; they do not assess competing explanations for the same results. Also, early laboratory experiments generally focused on a discrete signal / action models. More recently, Çelen and Kariv (2004), Alevy *et al.* (2007) amongst many others have used 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. These experimental findings are generally broadly consistent with Bayes rational herding. In this literature, there is independent experimental evidence about herding in a financial context versus the impacts of cognitive limitations on herding (Sgroi 2003, Alevy *et al.* 2007) but there is no published evidence about the impacts of social influences and/or behavioural factors on propensities to herd.

2.2 *Insights from Social Psychology*

The Bayesian theories outlined above describe individual decision-making as the outcome of a mechanical algorithm in which information about group decisions is used to

update individuals' probabilistic judgements. In this, Bayesian theory suggests that individuals' behaviours are essentially homogenous; different people will, on average, behave in the same way. There is general evidence that decision-making is not just the outcome of the objective methods of statistical inference such as are set out in Bayes Theorem. People are not good at applying Bayesian principles of statistical inference in practice (Salop 1987, Tversky and Kahneman 1974, Baddeley *et al.* 2005). Cognitive biases limit rational behaviour in 'reverse cascades' – i.e. when incorrect decisions lead to information cascades down the wrong path (Sgroi 2003).

Also, there is evidence that decisions will change with changes in psychology. Fluctuations in emotions and mood, and heterogeneous personality traits will affect financial and economic decisions. For example Kamstra *et al.* (2003) and Hirschleifer *et al.* (2003) analyse the impact of weather and weather-related mood changes on financial markets. Lo *et al.* (2005) have identified roles for personality traits and fear/greed in the behaviour of day traders. Shiv *et al.* (2005), using lesion patient studies, have identified a relationship between impaired emotional response and risk-taking behaviour. These studies provide evidence 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, particularly socially focussed traits such as extraversion and conformity.

Building on these insights, alternative explanations can be built from principles of social psychology - focussing on the influence of crowds and group pressure and drawing on themes both from le Bon's (1896) analysis of mob psychology and the hypnotic influence of crowds. There is considerable evidence in social psychology that social pressure has a significant impact on individual decisions (Milgram 1963, and Haney *et al.* 1973) and it is plausible that this pressure operates in an economic and financial context too. Asch 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 persuaded to change their minds in the face of deliberately misleading decisions from experimental confederates (Asch 1951, 1955, 1956, 1958; Bond and Smith 1996). It is difficult to establish whether these wrong choices were the result of the subjects' perceptions of their own visual limitations and/or an attempt to avoid conflict. Either way, purely Bayesian accounts are difficult to reconcile with Asch's experimental evidence showing that people follow majority opinion even if private information signals strongly in favor of an alternative choice.

There is as yet no published experimental evidence about the psychological correlates of herding behaviour in a financial context and one of the aims of this paper is to fill this gap. If the psychological traits associated with sociability affect tendencies to herd, then this would add weight to socio-psychological theories of herding.

2.3 Reconciling Bayesian and Socio-Psychological Theories of Herding

In the preceding sections, we have presented two distinct explanations for herding. The approaches are not clearly mutually exclusive: the sociological distinction between normative influence versus informational influence is a distinction that surfaces in the (admittedly limited) economic literature on conformity (e.g. see Bernheim 1994, Becker and Murphy 2000). The limited nature of this literature in part reflects difficulties of effectively modelling social factors. Social learning theories such as Banerjee's model cannot account fully for the impact of social influence (Bernheim 1994). One approach is to embed social factors (such as status and reputation) into individuals' preferences (Bernheim 1994, Scharfstein and Stein 1990).

Scientifically, the problem remains that it is difficult systematically to test these explanations against each other. For example, some argue that Asch's evidence is consistent with a rational learning process because experimental subjects follow group decisions even

when normative social influence is removed, and experimental subjects tend to attribute their mistakes to their own physical limitations, such as poor eyesight. The operation of social influence even without face-to-face interactions is interpreted by some as evidence that social conformity is a manifestation of information acquisition (Deutsch and Gerard 1955, Bikhchandani *et al.* 1992, Shiller 1995). On the other hand, a theory of mind explanation could be invoked to explain the evidence that herding operates even without face-to-face interactions if imagined peer pressure generates similar behaviours as real peer pressure. So one theorist can argue that Asch's evidence does not disprove the Bayesian herding hypothesis but another could equally argue that it does, depending on what is assumed about human cognition and emotion. But another possibility is that these apparently distinct approaches are not necessarily mutually exclusive; real-world herding behaviour may be the outcome of interactions between a rational, cognitive learning and instinctive, emotional responses.

A 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 may have impulsive aspects, evolutionary pressure may have led to the evolution of these instincts as a social learning function: animals better able to monitor the actions of others will acquire social information about resource availability and mating potential (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.³ Resolving such questions means delving deeper into the motivators of behaviour better to understand the neurological black-box that generates human choice (Camerer 2007).

³ However human instincts are hard-wired processes that have not evolved recently enough to be specifically associated with modern behaviours (e.g. as has been established for the neurological origins of abilities to read and write). There is no reason that an ingrained instinct to herd should be useful in modern financial markets. Also, instincts that have evolved to increase chances of survival may be just that – instinctual and therefore not manifested as a deliberative Bayesian-style thought process.

3. Definitions, Hypotheses and Experimental Scenarios

3.1. Definitions and Hypotheses

Herding is a descriptive term defined by the *Concise Oxford English Dictionary* as ‘a large number of animals, feeding or travelling or kept together’. However, in the context of our analysis, this broad definition does not allow us to separate decisions that by coincidence match those of a group so, following Scharfstein and Stein (1990), we have defined herding as a state in which individuals ignore their own private judgements in favour of following decisions made by a group or herd.

So far, there have been few academic investigations into the psychological correlates of herding in the economic / financial sphere and one aim of this paper is to separate the independent impacts of psychological factors such as personality and emotion versus Bayesian-style deliberation. In addition to constructing two competing sets of herding hypotheses, we allow that elements of Bayesian and psychological models may have independent explanatory power and adopt the encompassing principle to test the models against each other using a non-nested testing strategy (Cox 1961; Davidson and MacKinnon 1981, 1982; Mizon and Richard 1986), as explained below. This empirical strategy will allow us to verify either, both or neither set of hypotheses.

To summarise the hypotheses:

1. people’s economic / financial judgements are affected by social information about group decisions.

In explaining why this may occur we develop three further sets of hypotheses:

2. herding is largely deliberative and cognitive, consistent with Bayesian-style learning processes;
3. herding is largely motivated by emotive factors and specific personality traits;

4. herding is a combination of both 1. & 2., i.e. it is the outcome of interacting cognitive and emotional / affective processes.

As explained below, the herding task we analyse here is a binary choice task with social interaction. Such tasks give statistical models that are mathematically equivalent to logistic discrete choice (Brock and Durlauf 2000, Baddeley 2007). So in constructing the distribution of choices, we assume that the probability of agreeing with the herd is a random variable:

$$\Pr(\text{Agree} / Z_{k,i}) = \frac{1}{1 + \exp^{-(\alpha + \sum \beta_k Z_{k,i} + \varepsilon_i)}} \quad (1)$$

where $\Pr(\text{Agree})_i$ is the probability of agreeing with the herd each time for each choice – i (and $1 - \Pr(\text{Agree})_i$ is the probability of disagreeing). $Z_{k,i}$ is the matrix of explanatory variables and β_k is a vector of associated parameters and ε_i is a normally distributed, white noise stochastic error term with mean zero. It follows mathematically that the logistic function (the log of the odds ratio) takes the following linear functional form:

This basic logistic function is illustrated in Figure I.

$$\log \left[\frac{\Pr(\text{Agree})}{1 - \Pr(\text{Agree})} \right] = \alpha + \sum \beta_k Z_{k,i} + \varepsilon_i \quad (2)$$

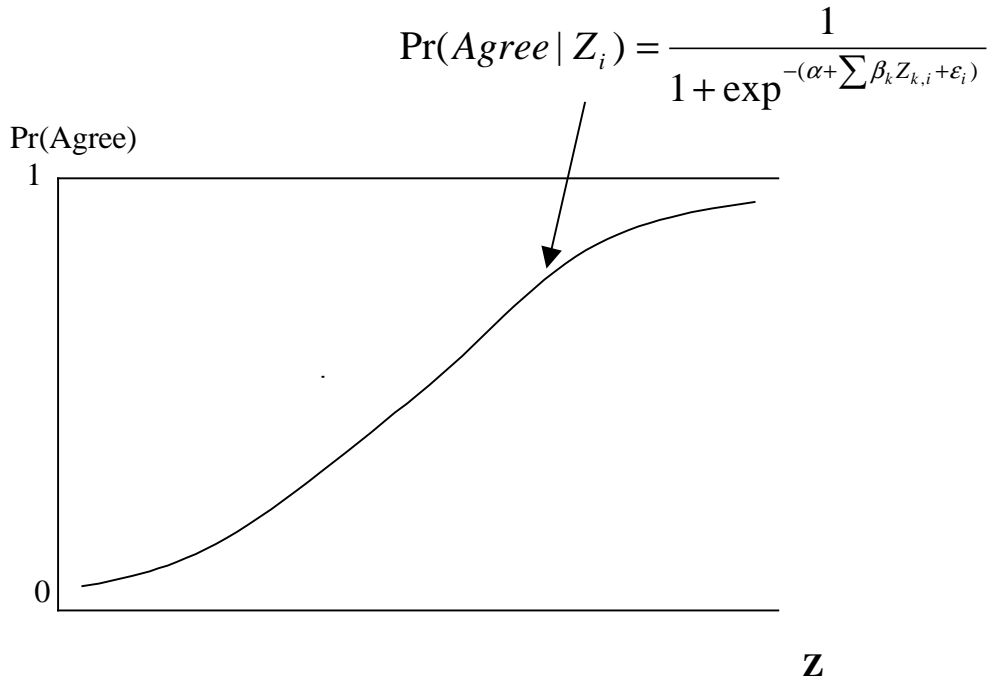


FIGURE I

Logistic Function for Herding Scenarios

3.2. Experimental Scenarios

The Control Scenario

As will be explained below, the experimental subjects are asked to make a binary choice between two financial stocks (Stock A or Stock B), given social information about a group or herd decisions when faced with the same binary choice. There are 4 possible combinations of subject and herd decisions:

| | | Herd's choice | |
|-------------------------------|---------|-----------------------|-----------------------|
| | | Stock B | Stock A |
| Experimental Subject's choice | Stock B | Subject: B Herd: B | Subject: B Herd: A |
| | Stock A | Subject: A Herd: B | Subject: A Herd: A |

In calculating the *a priori* likelihood of a subject's decision coinciding with a herd's decision (i.e. in a non-interactive situation in which no information about the herd is given), we can assume that the four possible scenarios are independent (so if there is no social

influence then any agreement with the herd will be a coincidence), mutually exclusive and so equiprobable. When the decisions of the herd and subject are independent, herd information will be irrelevant on average or completely ignored. The experimental subjects decide randomly and the logistic function described above will be ‘driven’ only by the stochastic error:

$$\Pr(Agree) = \frac{1}{1 + \exp^{-\varepsilon_i}} \tag{4}$$

Simulating this stochastic function by randomly generating normally distributed stochastic errors gives the logistic function depicted in Figure II.

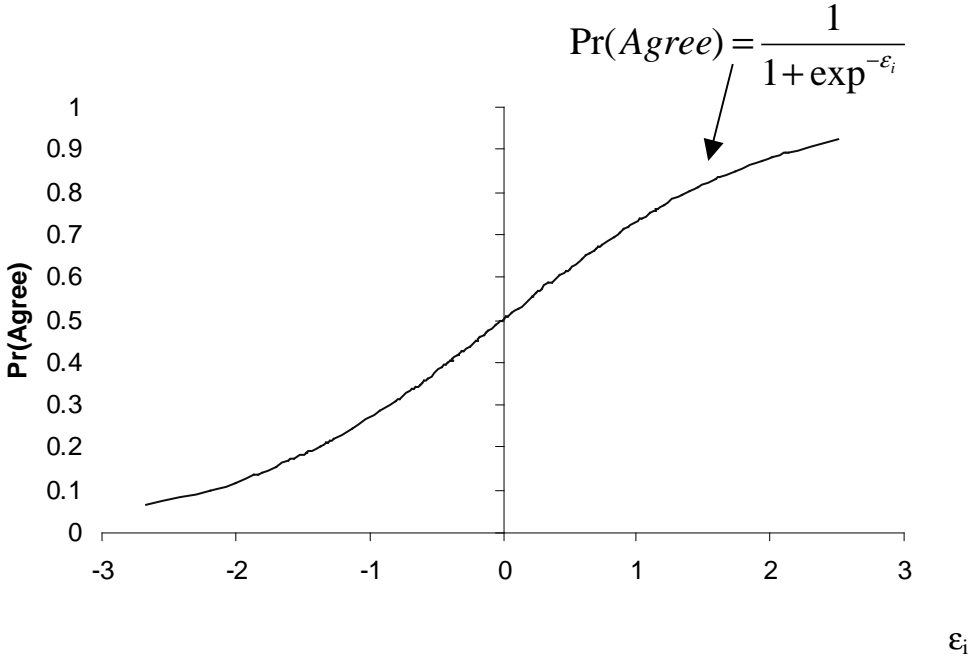


FIGURE II

The Stochastic Logistic Function

The point of inflexion for this stochastic logistic function is 50% reflecting the fact that the expected probability of choosing one of two stocks is 50%, as explained above. The random distribution around the average of 50% is consistent with a scenario in which there is

no objective reason systematically to prefer either one stock or the other. The control scenario allows us to assess the differential impact of herd information. If information about herd choices is affecting the subjects' choices then the point of inflexion will shift upwards if subjects are following the herd (and downwards if the subjects are acting in opposition to the herd). With herd information, the shape of the estimated logistic function will also be affected by the explanatory variables influencing tendencies to herd (or not) and these will vary according to our range of hypotheses – as described in more detail below.

In exploring the impact of herding information (and associated variables) on the shape and position of the estimated logistic function relative to the stochastic logistic function, we match the four hypotheses outlined in Section II.A. to their experimental scenarios.

Baseline Herding Model

Our first hypothesis is that herd decisions affect individuals' decision so we need to assess whether or not a herding signal significantly changes the probability of subject-herd agreement. To establish whether or not there is a significant tendency to herd versus not herd, we start by testing whether or not the proportion of subjects following the herd when presented with social information is significantly different from the *a priori* probability of 50%.

We also assess the differential impact of herding in assessing the insight that conformity levels will drop as herd consensus is broken (Asch 1952, 1955) and we construct a variable that increases as the degree of herd consensus increases. This is captured by introducing a herd unanimity variable (HERD) which measures grades of herding, with the grades varying positively with the degree of herd unanimity – i.e. 6-0, 5-1 and 4-2). Our hypothesis is that a stronger herding signal will be associated with an increased likelihood of subject-herd agreement, in which case $\text{Pr}(\text{Agree})$ will be a positive function of HERD.

Overall, we estimate the following logistic function:

$$\log \left[\frac{\Pr(Agree)}{1 - \Pr(Agree)} \right] = \alpha + \beta_1 HERD_i + \varepsilon_i \quad (5)$$

We use z and likelihood ratio tests to test $H_0 : \beta_1 = 0$.

Bayesian Herding Model

In capturing Bayesian-style thinking, we introduce the Schneider-Shiffrin separation of automatic versus controlled processes, (Schneider and Shiffrin 1977, Kahneman 2003, Loewenstein and O'Donoghue 2004). Standard tools of economics are assumed to be the outcome of controlled processes (Camerer *et al.* 2005). Bayesian reasoning would be similar in nature to these standard tools. In Camerer et al.'s (2005) categorisation of controlled, automatic, affective and cognitive processes, affect links directly with motivation and so operates quickly; cognition is the outcome of a slower, more deliberative process because it draws on higher-order, complex executive functions. Assuming this primacy of affect (Camerer *et al.* 2005) cognitive processes will require more time and effort than a purely emotional or instinctive response. So if following the herd is a rational learning heuristic and herding is controlled and cognitive rather than automatic and affective, then it will be associated with longer decision times because it is relatively effortful and time-consuming. Following Reddi et al. (2003) and Reddi and Carpenter (2000) and assuming that Bayesian updating is relatively time consuming, reaction times are used as a proxy for deliberative thought. Building upon these insights we constructed the following logistic function to capture the Bayesian reasoning approach:

$$H_0 : \beta_1 = 0 \left[\log \left[\frac{\Pr(\text{Agree})}{1 - \Pr(\text{Agree})} \right] = \alpha + \beta_1 \text{HERD}_i + \beta_2 D_i + \varepsilon_i \right] \quad (6)$$

where D=decision time. The herd consensus variable was retained in this and subsequent models to avoid model misspecification errors from omitted variable bias. We use a z test independently to test $H_0 : \beta_1 = 0$ and $H_0 : \beta_2 = 0$ and a likelihood ratio test to test $H_0 : \beta_1 = \beta_2 = 0$.

Behavioural Model of Herding

In redressing the neglect of behavioural evidence in the economics experiments discussed in Section II.A., the behavioural analysis presented here involves a comprehensive analysis of the relationships between the psychological characteristics of our experimental participants and their tendency to herd in various scenarios. The focus will be on assessing whether or not psychological traits associated (positively or negatively) with sociability have an impact on herding tendencies. In outlining the dimensions of social awareness, we use the DSM-IV-TR (2000) / ICD-10 (1994) classifications of an anti-social / dissocial personality along the dimensions of non-conformity, recklessness, disregard for others, impulsivity and risk-seeking. So assuming that sociable individuals are more responsive to social influence, social pressure will operate more strongly in conformist, empathetic and extraverted individuals; and will operate less strongly in impulsive, venturesome individuals. The herding impact variable is retained in the model to avoid omitted variable bias and the intercept is included to capture fixed factors. 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 in women (Milgram 1963).

Overall the behavioural hypotheses are captured within the following model:

$$\log\left[\frac{\Pr(\text{Agree})}{1-\Pr(\text{Agree})}\right] = \alpha + \beta_1 \text{HERD}_i + \beta_3 A_i + \beta_4 G_i + \beta_5 C_i + \beta_9 I_i + \beta_6 V_i + \beta_7 E_i + \beta_8 X_i + \varepsilon_i \quad (7)$$

where A is age, G is gender, C is conformity, I is impulsivity, V is venturesomeness, E is empathy, and X is extraversion. These psychological traits are measured using published psychometric tests. Impulsivity, venturesomeness and empathy are measured using Eysenck's Impulsivity, Venturesomeness and Empathy (IVE) questionnaire (Eysenck and Eysenck 1978). Extraversion is measured using Eysenck's Personality Revised Questionnaire – EPQR (Eysenck and Eysenck 1975, Eysenck *et al.* 1985). Conformity is measured using the Goldsmith questionnaire (Goldsmith et al. 2005).

Age and gender are not included in the Bayesian-style estimation because the Bayesian approach focuses on homogeneity of behaviour and so age / gender would not have an independent impact outside a behavioural approach.

Again, we use z tests to test the independent explanatory power of each explanatory variable (i.e. to test $H_0 : \beta_k = 0$) and we use a likelihood ratio test to test the overall explanatory power i.e. $H_0 : \beta_1 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = 0$.

Encompassing Model

In addition to estimating models that capture competing hypotheses we also estimate an 'encompassing' model containing all the variables from the competing models:

$$\log \left[\frac{\Pr(Agree)}{1 - \Pr(Agree)} \right] = \alpha + \beta_1 HERD_i + \beta_2 D_i + \beta_3 A_i + \beta_4 G_i + \beta_5 C_i + \beta_6 I_i + \beta_7 V_i + \beta_8 E_i + \beta_9 X_i + \varepsilon_i$$

(8)

As before, we use a z test to establish the independent explanatory power of each explanatory variable and a likelihood ratio test to test the overall explanatory power i.e.

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = 0.$$

We estimate this model for two reasons, firstly to escape the dichotomous distinction between the rational and non-rational. We are adopting insights from neuroeconomics about interactions with and between controlled, cognitive, automatic and affective processes. When people are influenced by social information, it may reflect an interaction between a deliberative learning process and a more instinctive, emotional response. An encompassing model captures both sets of explanations.

The second (not unrelated) reason to estimate the encompassing model is econometric – encompassing models can be used to establish whether or not different models have independent explanatory power. In this we use non-nested tests (NNTs) because standard variable deletion hypothesis tests must be extended for models that are not fully nested within each other, such as our Bayesian and Behavioural models. The NNT strategy emerges from Cox (1961, 1962) who formulated an LR test to test the statistical contributions of individual sets of hypotheses within encompassing models and Mizon and Richard (1986) who formulated the Wald Encompassing Test (WET). To overcome specification problems with these tests, Davidson & McKinnon (1981, 1982) developed the J test in which fitted values from one model were introduced as an explanatory variable into a competing model, using a t test to test the null that the coefficient on those fitted values is equal to zero. All these tests rest on the insight that if one model can encompass the results of another, then the latter

model has no independent explanatory power and therefore can be rejected on the grounds of parsimony. Non-nested tests allow that either, neither or both models can be rejected.⁴

Here we use this non-nested testing strategy artificially to create a model nesting both specifications thus allowing model comparison. The problem is non-linearity in the models—the non-nested tests outlined above were developed for models that are linear in the parameters. So here we use a non-linear equivalent of Davidson and MacKinnon’s J test by testing that parameter on fitted values is insignificantly different from zero using Wald and LR tests (rather than a t test). Also following Horowitz and McAleer (1988) we conduct a comparison of the log-likelihoods from the two models. Finally, we compare the models’ Akaike Information Criteria and Schwartz Bayesian Criteria (Pagan and Wickens 1989).

4. Task Design

4.1. General setting

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 (analysed in detail in Kahneman *et al.* 1982, Thaler 1991, Kahneman and Tversky 2000), the task and its context have been simplified in a number of ways. First, to avoid the complications introduced by loss aversion, the subjects were not faced with choices that would involve them losing money. Second, the task was designed so that there were two clear, independent and mutually exclusive choices neither of which was objectively better or worse than the other; in this way, we could establish the clear *a priori* probability of 50%, as explained above.

The general experimental situation and design of the task is described in Pillas (2006). The task was designed using MATLAB 7.0 and the use of a computer-based design was

⁴ See McAleer and Pesaran (1986) for a survey of non-nested tests.

justified on the basis of evidence that experimental subjects are affected in similar ways by both virtual and real experimental confederates (Reysen 2005, Pillas 2006). In the presentation of the information, the task adopts some design features from Berns *et al.*'s exploration of the impact of social conformity in mental rotation tasks (Berns *et al.* 2005).

Two sets of information were presented: information about the two stocks – A and B; and social information about the herd's choices. Fig. III shows the visual format of the information presented, where Stock A is on the right-hand side of the screen and Stock B is on the left-hand side. As explained in the results section, there was no evidence of right-hand / left-hand bias.

4.2. *Herd Information*

The members of the herd were represented using photos selected from a databank of 100 faces; in this databank, faces are shown without hair because including different hairstyles is distracting. To minimise the chances of selection bias, the attractiveness of the faces was ranked before the experiment and the six faces used (3 male, 3 female) were chosen from a subset of faces ranked as being similarly attractive.

To capture the impact of herd consensus, different grades of herd agreement were used, i.e. 6-0 (all the herd agree), 5-1 (one dissenter), and 4-2 (relative ambivalence). For the control trials, the faces were still shown but no information was given about the herd's choices.



FIGURE III

Example of an image shown to experimental subjects under control conditions

4.3. *Stock Price Information*

Participants were presented with charts conveying information about the daily price of two stocks over 30 days. The choice was presented as randomised pairs of stocks, with each pair ranked according to performance (low, medium and high). Thirty different stocks were used to prevent familiarisation with the stock patterns and the stock positions (left versus right) were allocated randomly.

The stock charts were simulated and, within each performance category, had the same statistical characteristics in terms of mean and variance. This reflected two considerations. First, when an experimental subject agrees with the herd, this may be just a coincidence, i.e. not a reflection of any social influence. Second, separating the influence of herd consensus from other variables under various scenarios of correct and incorrect decisions would have

made it difficult to assess the independent impacts of objective factors versus social information. So effectively to control for the differential impact of information about herd choices on subjects' decisions, the task was designed so that there was no 'right' or 'wrong' answer: experimental subjects were asked to choose between two stocks from the same performance category with the same distributional moments and neither alternative was objectively correct or incorrect thus we would expect subjects to pick each stock 50% of the time on average, as explained above.

4.4. *Task Context and Schedule*

The task was undertaken by 34 Cambridgeshire residents (students and non-students) aged 18 to 35, including 16 males and 18 females, with varying degrees of economic / financial knowledge and experience.⁵ The subjects were paid for performing the task and were instructed that their payment would vary positively with their performance. Each subject performed the task 15 times under control conditions (in which no herding information was provided) and 45 times under herding conditions.

Participants were presented with the visual representation of simulated historical share price performance for 3 seconds (3s). Then, the choices made by the herd (represented by four facial photos) were displayed for 2s. Then participants chose one of the two stocks by pressing a button. The subjects' decision-times were collected. Inter-trial intervals averaged 4s and overall each trial lasted 10s. Similar timings were used for the control trials.

4.5. *Statistical Analysis*

As explained above, the logistic function (the log of the odds ratio) was estimated as a linear function of the explanatory variables using binary choice techniques viz logit, to

⁵ Ethical approval granted by the Cambridge Psychology Research Ethics Committee, 2006.

capture the determinants of the probability that a subject's choice coincides with the herd's choice. Using EViews 4 logit maximum likelihood estimation option, the four forms of the logistic function were estimated: the baseline model (equation 5); the Bayesian model (equation 6); the behavioural model (equation 7); and an encompassing model with the separate models 'nested' within it (equation 8). The empirical results presented are based on the trials in which herding information was presented giving a sample size of $n=1530$, (34 subjects x 45 choices). The results from the estimations of these models are summarised in Table I.

5. Discussion of Results

Pillas (2006) presents an initial assessment of the data set, reporting a 50.39% probability of choosing stock A and a 49.61% probability of choosing stock B. The difference between these two proportions is insignificantly different from zero. These results verify firstly, that there was no right or left-hand bias in selections, and secondly, that the subjects' choices were random under controlled conditions (Pillas 2006). After establishing that choices were random under controlled conditions, data was analysed from the trials in which the experimental subjects made choices 45 times conditioned on the degree of herd consensus.

TABLE I
ESTIMATION RESULTS FROM HERDING MODELS

| <i>Dependent variable: Herd Agreement (Agree with herd = 1, Disagree with herd = 0)</i> | | | | | | |
|---|---------------------------|----------|----------|-------------------------------------|-------------------|---------------------|
| <i>Maximum likelihood estimation - Binary Logit (EViews 4)</i> | | | | | | |
| No. of observations | | n=1530 | | Mean dependent variable: 0.720 | | |
| | | | | Restricted log likelihood: -907.785 | | |
| | | A | B | C | D | E |
| | | Baseline | Bayesian | Behavioural | | Encompassing |
| | | Herd | Model | Model | | model |
| | | Impact | | <i>Unrestricted</i> | <i>Restricted</i> | <i>Unrestricted</i> |
| Intercept | Parameter estimate | 0.070 | 0.265 | 2.236 | 2.514 | 2.320 |
| | z statistic | 0.199 | 0.733 | 3.595 | 4.453 | 3.681 |
| | p value | 0.843 | 0.464 | 0.000 | 0.000 | 0.000 |
| Herd Consensus (HERD) | Parameter estimate | 1.053 | 0.979 | 1.139 | 1.138 | 1.110 |
| | z statistic | 2.506 | 2.319 | 2.605 | 2.604 | 2.531 |
| | p value | 0.012 | 0.020 | 0.009 | 0.009 | 0.011 |
| Decision time (D) | Parameter estimate | ... | -0.045 | ... | ... | -0.019 |
| | z statistic | ... | -2.244 | ... | ... | -0.900 |
| | p value | ... | 0.025 | ... | ... | 0.368 |
| Age (A) | Parameter estimate | ... | ... | -0.056 | -0.053 | -0.055 |
| | z statistic | ... | ... | -3.711 | -3.743 | -3.697 |
| | p value | ... | ... | 0.000 | 0.000 | 0.000 |
| Gender (G) | Parameter estimate | ... | ... | 0.146 | ... | 0.137 |
| | z statistic | ... | ... | 1.133 | ... | 1.057 |
| | p value | ... | ... | 0.257 | ... | 0.291 |
| Conformity (C) | Parameter estimate | ... | ... | 0.074 | 0.071 | 0.075 |
| | z statistic | ... | ... | 4.601 | 5.171 | 4.654 |
| | p value | ... | ... | 0.000 | 0.000 | 0.000 |
| Venturesomeness (V) | Parameter estimate | ... | ... | -0.169 | -0.169 | -0.165 |
| | z statistic | ... | ... | -8.447 | -8.641 | -8.097 |
| | p value | ... | ... | 0.000 | 0.000 | 0.000 |
| Empathy (E) | Parameter estimate | ... | ... | -0.044 | -0.047 | -0.046 |
| | z statistic | ... | ... | -2.258 | -2.543 | -2.348 |
| | p value | ... | ... | 0.024 | 0.011 | 0.019 |
| Extraversion (X) | Parameter estimate | ... | ... | 0.117 | 0.108 | 0.115 |
| | z statistic | ... | ... | 3.754 | 3.701 | 3.665 |
| | p value | ... | ... | 0.000 | 0.000 | 0.000 |
| Impulsivity (I) | Parameter estimate | ... | ... | -0.0003 | ... | 0.001 |
| | z statistic | ... | ... | -0.018 | ... | 0.059 |
| | p value | ... | ... | 0.986 | ... | 0.953 |
| Log likelihood | | -904.6 | -902.2 | -845.7 | -846.3 | -845.3 |
| Likelihood Ratio (LR) statistic (df=1) | | 6.31 | 11.22 | 124.16 | 122.87 | 124.96 |

When social information about herd decisions was presented, the probability of agreeing

with the herd increased to 72%. This reflects 429 decisions conflicting and 1101 coinciding

with herd decisions (Pillas 2006).

5.1. *Herding Impacts*

The results from the estimation of the baseline herding model (equation 5) are recorded in Table I, column A. A one-tailed z test of whether or not the observed probability of agreement with the herd (72%) was significantly different from $H_0: \Pr(\text{Agree})=0.5$ gives $z=17.214$ and therefore we reject the null and conclude that the proportion of subjects herding is significantly greater than would be expected with no social influence.

The results from the estimation of the logistic function confirm this finding - social information has a strong, positive and statistically significant impact on the probability of herding – as the grade of herding increases (i.e. with more group consensus), the probability of herding increases accordingly.

5.2. *Bayesian Model*

The results from the estimation of the Bayesian model (equation 6) are recorded in Table I, column B. For the Bayesian model, decision time is also significant but negatively correlated with the probability of herding. The fact that a decision to follow a group is associated with less thinking time rather than more suggests that herding is not the outcome of a time-consuming deliberative process. This finding may undermine the assertion that herding is a Bayesian learning process and would be more consistent with the assertion that herding may be an instinctive affective process rather than a controlled cognitive process. However, the possibility that herding is a cognitive reasoning process is not necessarily ruled out. Cognitive reasoning processes can become automated through practice (Kahneman 2003) and if Bayesian learning heuristics become automatic at an early age, then the fact that they are not controlled, slow and time-consuming does not necessarily mean that they are not reasoning and deliberative.

5.3. *Behavioural Model*

The results from the estimation of the behavioural model (equation 7) are recorded in Table I, columns C (unrestricted model) and D (restricted model). In the behavioural model, gender and impulsivity have no significant impact on the tendency to herd. The grade of herding still exerts a strong, positive and statistically significant impact on the likelihood of herding. The association with age confirms other research suggesting that older people are less susceptible to social pressure (Walker and Andrade 1996). There was a negative association between empathy and herding, which suggests that not all aspects of sociability intensify propensities to herding. In a broader context, it is possible that interactions between empathy, selflessness and altruism complicate people's motivations in financial decision-making because the hypothetical context is a zero-sum game between buyer and seller.

Conformity and extraversion are associated with a significantly higher tendency to herd and venturesomeness is associated with a significantly lower tendency to herd. With the exception of the anomalous finding that the propensity to herd is relatively low in the empathetic subjects, overall the results from the psychometric analysis support the idea that the tendency to herd is a function of sociability, giving preliminary evidence that the interactions between conformity and sociability extends beyond the purely social contexts and into economic and financial decision-making. Also, the association between venturesomeness and a decreasing propensity to herd is indirect evidence confirming Keynes (1936, 1937) insights about herding as a risk-avoidance strategy when reputation matters (see also Bernheim 1994 and Scharfstein and Stein 1990).

5.4. *Encompassing Model and Non-nested Tests*

The results from the estimation of the unrestricted encompassing model (equation 8) are reported in Table I, column E (note that the restricted version of the encompassing model is just the restricted version of the behavioural model).

The fitted values from the estimation of the logistic function from the encompassing model are depicted in Figure IV and this gives a visual impression of how social influence has shifted the logistic function relative to the stochastic logistic function depicted in Figure II. A comparison of these graphs reveals that the point of inflexion of the estimated logistic function has moved upwards from an average probability of 0.5 to an average of 0.72

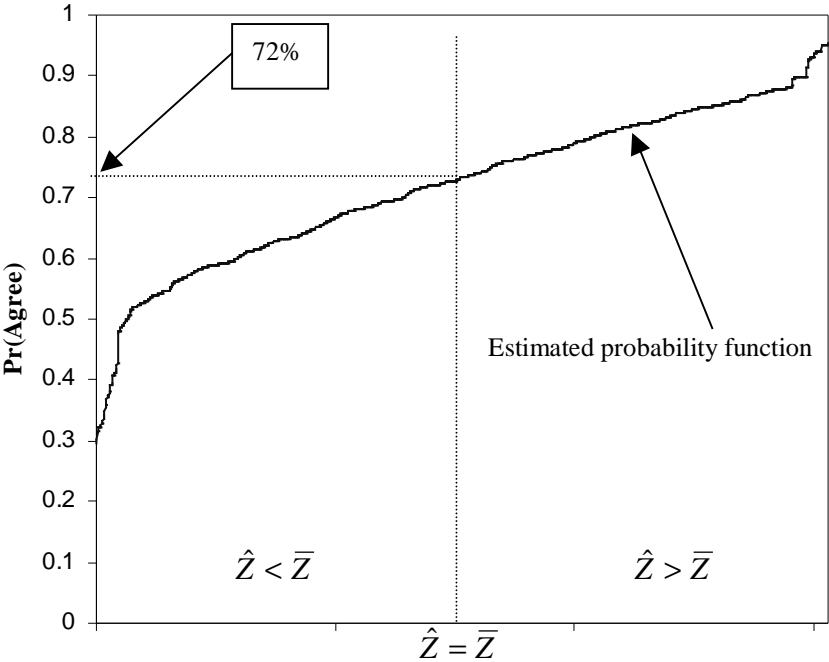


FIGURE IV

Estimated Logistic Function – Encompassing Model

In the encompassing model, the parameter on decision time is insignificantly different from zero – in contrast to the result from the estimation of the Bayesian model. This may

reflect multicollinearity between decision time and personality traits, in which case further work is needed to establish whether or not quick thinking time is related to specific personality traits. Nonetheless, this finding does again appear to undermine the Bayesian model as constructed here.

To give a more robust test of the relative power of the Bayesian versus behavioural models, non-nested tests (NNTs) were employed, as described above. The results from these model comparison tests are reported in Table II and indicate that, for all the tests used, the Behavioural model strongly outperforms the Bayesian model in terms of explanatory power.

TABLE II
Model Comparison Tests

| | Bayesian Model | Behavioural Model | Test favors: |
|--|--------------------|-------------------|-------------------|
| Non-nested Tests | | | |
| LR test | 2.088 | 113.742 | Behavioural model |
| - against encompassing model | p=0.3520 | p=0.000 | |
| LR test | 1.912 | 28.257 p=0.000 | Behavioural model |
| - fitted values from alternative model | p=0.1670 | | |
| Wald test | 0.632 | 108.884 | Behavioural model |
| - fitted values from alternative model | p=0.427 | p=0.000 | |
| Model Selection Criteria | | | |
| Akaike Information Criterion | 1.115 | 1.183 | Behavioural model |
| Schwartz Criterion | 1.140 | 1.194 | Behavioural model |
| Horowitz & McAleer (1988) LR test | 111.650 p=0.000 | | Behavioural model |

As explained above NNTs do allow either, neither or both of two competing models independently to capture the data so the fact that these NNTs unequivocally favor the behavioural model suggest that the Bayesian model (as constructed here) has no independent explanatory power. Also, the significant associations between personality traits and propensities to herd are difficult to reconcile with Bayesian herding theories focusing on systematic, methodical decision making processes by homogenous agents.

But it is important to emphasise that decision times may be an inadequate 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. Also (and as emphasized above) it is possible that the two sets of motivators (behavioural and Bayesian) are interacting. Further insights into this question would require a deeper analysis of the neurological correlates of herding, and some research strategies are suggested in the concluding section.

6. Concluding Remarks

The results presented here suggest that financial choices are affected by social influence and that the propensity to herd is not homogenous but varies across personality types and by age. There is no evidence here to confirm Bayesian theories of herding when decision-time is used as a proxy for Bayesian-style deliberation. The heterogeneity in propensities to herd across personality types also suggests that models of behaviour implying that all people adopt the same systematic and methodical Bayesian reasoning process are incomplete.

There are important caveats. The results presented represent just one limited sample of data. More work is needed in verifying and replicating the findings. For this experimental design in particular, further work does need to be done in identifying a good proxy for deliberative thought.

More broadly, in understanding some of the processes underlying propensities to herd and in developing the hypothesis of cognitive interaction, further research could build upon these findings using neuroeconomic techniques and models in supporting a general theory of human behaviour that emphasises consilience and draws together inductions from different areas (see Glimcher and Rustichini 2004). Tools such as fMRI could be used to establish links between herding behaviour and differential brain activation, exploiting parallels with research

in economics, experimental psychology and neuroscience and building upon existing fMRI research into financial decision making (e.g. Kuhnen and Knutson 2005). In addition to providing new research tools, neuroeconomics may offer new theoretical approaches that blend insights from different economic models and escape the binary classification of herding into rational versus non-rational. If herding reflects an interaction of social learning and socialised impulses then neuroeconomics may offer a new way of conceptualising herding as the outcome of an interaction of different thought processes (Baddeley 2007), linking into neuroeconomic insights about the interaction of the cognitive, controlled, emotional and automatic responses (Camerer 2007, Camerer et al 2004, 2005, and Cohen 2005).

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 non-information seeking outcome of sociability and/or response to group pressure - the estimation of the encompassing model reflects a recognition that these explanations are not necessarily mutually exclusive.

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