Fund Manager Herding: A Test of the Accuracy of Empirical Results using UK Data

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Sam Wylie*
The Amos Tuck School

100 Tuck Hall, Tuck Drive
Hanover NH 03755
Email Samuel.Wylie@Dartmouth.Edu
Phone 603 646 2842
Fax 603 646 1308

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ABSTRACT

The portfolio holdings of 268 UK equity mutual funds are employed to test the accuracy of the Lakonishok, Shleifer and Vishny (LSV 1992a) measure of herding, and test for herding among UK mutual fund managers. Bootstrap re-sampling methods are developed to construct a large number of datasets that exhibit zero herding but retain the essential characteristics of the actual dataset. The LSV measure finds herding in those zero herding datasets. After adjusting for the positive bias in the LSV herding measure the results reveal a significant amount of fund manager herding in the largest and smallest UK stocks.

Why do we care whether fund managers 'herd' in their purchases and sales of financial assets? Empirical studies have sought to determine whether institutional investors, by trading in the same direction at the same time, affect the dynamics and formation of asset prices.[1] However, a separate motivation for studying herding is that findings of herding are evidence that the market can be clustered into groups of investors that are delineated by their different trading behavior.

There is growing evidence that financial asset markets are comprised of groups of investors that have fundamentally different incentives. Private and institutional investors are two such groups. The value of a mutual fund to its sponsoring investment management firm has been shown to increase as a non-linear function of the fund's excess-of-benchmark return.[2] In contrast, a private investor's pay-off from a self managed portfolio is simply the total increase in the portfolio's value. Not surprisingly differences in trading behavior between these groups are found; such as, positive feedback trading by mutual fund managers and negative feedback trading by private investors.[3] It is curious then that finance theory does not put more emphasis on the existence of groups of investors that differ in their investment and trading behavior. Consider, for example, the representative investor in the CAPM or the informed trader in the Kyle model of market microstructure. Clearly neither are institutional investors because their end of period wealth changes in direct proportion to the total return on the financial assets held.[4]

Groups of investors that have significantly different incentives can be expected to undertake net trade with each other to dynamically co-insure the different risks that they face. Understanding the interaction between those groups may be central to a better comprehension of the dynamic market equilibrium. In particular, a better understanding of differences in portfolio returns of institutional portfolio managers versus the market as a whole, or the causality of net trade between groups and serial correlation in stock prices. However, we first need to know how investors should be grouped on the basis of their trading behavior. In this context, the importance of empirical studies of herding in financial asset trading is that a test for herding by a group of investors constitutes a test of whether the group's trading behavior is significantly different from that of the rest of the market.[5]

Lakonishok, Shleifer and Vishny (1992a) present what has become a standard measure of herding by fund managers. It rests on the following proposition. In the absence of herding the expected number of managers who buy a stock in a period, as a proportion of those who trade that stock, has the same value for all stocks. If significant cross sectional variation in this proportion is found, then the null of no herding can be rejected. Most of the contemporary empirical studies of fund manager herding have employed the Lakonishok, Shleifer and Vishny (henceforth LSV) measure, including the recent studies of Wermers (1999) and Choe, Kyo and Stulz (1999).[6] Moreover, its use has expanded into studies of herding in other areas, including Jaffe and Mahoney's (1999) study of the performance of newsletters.

There is, however, reason to question the accuracy of the LSV measure. It rests on three assumptions that are not sustained in real datasets and are not obviously benign. Firstly, it is assumed that all managers may short sell all stocks.[7] Second, it is assumed that when a manager trades a particular stock, the ex ante probability of the manager buying rather than selling that stock (the propensity to buy) is not dependent on either the initial weight of the stock in the manager's portfolio or the amount of new money that the manager must invest because of investment flows. Third, that the error in estimating the managers' propensity to buy, in any particular period, can be ignored in finite datasets. These assumptions are made to arrive at an analytically tractable sampling distribution for the LSV measure; however, each of them causes the measure's assumed sampling distribution to differ from its actual sampling distribution, as explained in Section 1. The total effect of the invalid assumptions on hypothesis testing with the LSV measure has not been previously reported.

The purpose of this study is twofold. Firstly, to gauge whether the empirical herding literature is well founded by testing whether its principal measure of herding is accurate. That is, whether the LSV measure finds a statistically and economically significant level of herding where no herding exists. Or if herding does exist, whether the measure substantially overstates the level of herding present. Secondly, to broaden the generality of the empirical herding literature by testing for herding among a group of fund managers drawn from a market with institutional arrangements similar to those of the US; in this case UK equity mutual fund managers.[8]

Studies of fund manager herding are a large part of the empirical literature on herding, see Devenow and Welch (1996) for a discussion. In their 1992 study of herding among US equity pension fund managers LSV find evidence of herding, with more herding in small market capitalization stocks. Using the LSV measure, Grinblatt, Titman and

Wermers (GTW 1995) find stronger evidence of herding by US mutual fund managers in stocks that are traded by large numbers of managers in a period. Wermers (1999), applies the LSV measure to 20 years of US mutual fund data and finds substantial herding by US mutual funds, but little variation in the herding level with the number of managers trading the stock in a period.

Choe, Kho and Stulz (1999), again with the LSV measure, find surprisingly large levels of herding in the Korean equity market in 1997. Chang, Cheng and Khorana (1999) study herding by fund managers in the US, Hong Kong, Japan, South Korea and Japan. Building on the technique of Christie and Huang (1995) they measure temporal changes in herding as changes in the cross sectional dispersion of portfolio returns and find evidence of herding in South Korea and Taiwan but not elsewhere. Kodres and Pritsker (1995) examine herding in the futures market and find that institutional investors herd in their holdings of futures contracts, but the herding does not explain a large part of the changes in their positions. Nofsinger and Sias (1999) study herding by institutional investors at the asset allocation level using aggregate data on institutional stock ownership. They find a positive correlation between increases in total institutional ownership of US stocks and increases in stock prices, without establishing causality.

These studies demonstrate that mutual fund managers and pension fund managers are separate from the rest of the US equity market in terms of their trading behavior. Further, they reveal a relationship between fund manager herding and positive serial correlation in stock prices, the causality of which is unclear.[9] However, there remains the question of whether the results of the studies that employ the LSV measure of fund manager herding are valid.

This study employs a new dataset of the portfolio holdings of 268 UK equity mutual funds in the period January 1986 to December 1993. The LSV measure is first applied to the actual dataset, without adjustment for inaccuracy. The level of herding found in the trades of UK equity mutual fund managers is surprisingly similar that reported in the US studies of LSV and Wermers. The measured level of herding is higher for the smallest stocks, as was found by LSV and Wermers, but unlike those studies is also increasing with size in the very largest stocks. It is also strongly increasing in the number of managers who trade a stock in a particular period, again in accordance with US results. For the subset of the data where 20 or more UK equity fund managers traded a stock in a particular period the level of herding found is commensurate with an average of between 13 and 14 of the 20 managers trading on one side of the market.

Next, the question of whether these results are meaningful given the biases induced in the LSV measure by invalid assumptions is addressed. The sampling distribution of the measure is empirically estimated with and without the invalid assumptions in place. In each case an estimate of the required sampling distribution is built up by repeatedly re-sampling a new dataset from the original dataset and then applying the LSV measure to it. The bootstrap re-sampling techniques are designed to eliminate all systematic herding, but retain the essential characteristics of the actual dataset and at the same time control which of the invalid assumptions are in place.

These accuracy tests reveal that in measuring herding by fund managers who cannot all undertake short selling of all stocks, the LSV measure is not calibrated to zero. For stocks that lie between the largest and smallest stocks, by market capitalization, most of the herding found in the UK dataset can be attributed to the LSV assumption that all fund managers can sell stocks short. Moreover, about a third of the herding found in the smallest market capitalization stocks is attributable to the LSV short selling assumption. The assumption that managers do not vary in their propensity to buy stocks (despite differences in initial holdings of the stock and liquidity needs of their portfolios) is found to introduce only a very small negative bias in the LSV measure. The effect of the assumption that the propensity to buy can be estimated without error is tested and is found to introduce only a small bias even in small subsets of data.

The remainder of this paper proceeds as follows: Section I analyses the biases in the LSV measure; Section II introduces the UK equity mutual fund manager dataset and describes the UK mutual fund industry; Section III presents the results of the testing for herding among the UK fund managers, Section IV presents the methodology and results of the tests of accuracy of the LSV measure; and Section V concludes.

I. Methodology of Accuracy Tests

A. Explanations of Fund Manager Herding

Herding by a group of economic agents is generally taken to mean that individual agents do not act solely on the basis of their private information, but instead give some precedence in their decision-making to the choices of other members of the group, and consequently the members of the group act in concert.[10] A natural approach to the analysis of herding in asset markets is to begin with the individual investors' decisions to trade and then search for forces that align or polarize the actions of a subset of those investors to create the aggregate effect of herding. Since fund managers face a dynamic stochastic optimization problem in choosing their portfolio holdings through time, the alignment of managers' trading direction should arise from either similarities between their optimization problems or an interaction between the managers' separately solved problems. Several theoretical explanations of herding find application in the trading of fund managers and each can be understood in a portfolio choice framework.

A.1. Linked Objective Functions, Information Cascades and Correlated Information Sets

Firstly, the objective functions of managers may be linked.[11] Positive correlation in the trading direction of fund managers can arise because the pay-off to a single manager depends on the decisions of other managers. Scharfstein and Stein (1990) argue that when the private signals of informed (product market) managers are more highly correlated than those of uninformed managers, then for the same pay-off to the principals, a consensus decision is taken to be a stronger signal of quality than a contrarian decision. Maug and Naik (1996) show that a manager whose pay-offs depend on returns that are measured relative to the return on assets held by other managers may choose to ignore some private information and herd with the other managers.

Secondly, managers infer information from each other's trades. Fund managers may augment their information sets with inferences from the trades of those other managers who are perceived to be informed. Bikhchandani, Hirshleifer and Welch (1992) provide the seminal ideas for herding theories based on local conformity. Banerjee (1992) applies these ideas to explain herding as an informational cascade.

Finally, the information sets of managers overlap. Models by Brennan (1990), Froot, Scharfstein and Stein (1992), Hirshleifer, Subrahmanyam and Titman (1994), and Dow and Gorton (1997) recognize that, when valuing private information, investors consider the probability that the information will be incorporated into the price of the asset within their investment horizon. This consideration may lead managers to research the same stocks and therefore derive their estimates of stock return moments from partially correlated private information sets. Further, fund managers may simply follow similar trading strategies based on public information, such as momentum or earnings surprise strategies.

A.2. Correlated Trading that is not Herding

Consideration of fund manager herding in a portfolio optimization framework highlights several other causes of positively correlated trading by fund managers that are not generally considered to be herding. Changes in the opportunity set faced by managers can induce them to trade in the same direction. For example, fund managers on average hold more than the market weight in larger stocks; so as small stocks get larger there is a net flow of ownership from private investors to institutional investors.[12] IPOs, SEOs, stock repurchases, delistings and other capital changes, also alter the opportunity sets of managers and thereby generate correlated trading that is an illusion of herding. Further, changes in the scale of the optimization problem faced by individual managers may lead to correlated trading. Fund managers who hold those stocks that realized high abnormal positive returns in the previous period, other things equal, receive more of the new money in the current period, and therefore have a liquidity need to buy. If these managers maintain their existing portfolio weights by investing the new money in stocks that they already hold, they will on average trade in the same direction. Useful measures of herding must control for these sources of correlation in fund manager trading that are not herding but simply artifacts of the optimization problems of fund managers.

B. The LSV Measure of Herding

The task in measuring fund manager herding is to test for independence of managers' portfolio changes whilst controlling for artifacts of portfolio optimization problems that are not herding; and if independence is rejected, then to summarize the degree of joint dependence between the trades of the managers in the group. The herding measure of LSV employs a non parametric method for this purpose. It starts with a portfolio holdings dataset that contains one panel for each date, with each panel recording the number of shares of each stock held by each fund manager's portfolio at that date. LSV difference the panels of portfolio holdings, and then transform the change in each manager's holding in each stock, over each period, to an ordered categorical variable that takes one of three outcomes; either *buy, hold* or *sell.* The basic unit of data is then a stock-period-manager observation, denoted here by X_{it}^j, that records whether stock *i*, in period *t*, was either bought, held or sold by manager *j*.

LSV further simplify by considering only those observations where the outcome is a *buy* or a *sell*. After this conditioning on the occurrence of a trade, the observed trading direction is the outcome of a Bernoulli trial with probability parameter p_{it}^j = Prob(X_{it}^j =

buy | X_{it}^{j} = *buy* or X_{it}^{j} = *sell*); where p_{it}^{j} is referred to as the propensity of manager *j* to buy stock *i* in period *t*. LSV assume that, in the absence of herding, the propensity to buy is invariant across managers and stocks in any period, so that $p_{it}^{j} = p_t$, $\forall$ *i, j*. Further, that each of the Bernoulli trials is independent of all other trials. Under these assumptions, if n_{it} is the number of managers who trade stock *i* in period *t*, and b_{it} is the number of managers who buy the stock, then b_{it} is the outcome of a random draw from a binomial distribution with probability parameter p_t and dimension n_{it}.

The null proposition in the LSV measure is that in the absence of herding the ratio of buys to trades has the same expected value, p_t, for all stocks in any one period. Deviations from this ratio that are larger than those expected by random fluctuation are evidence of herding. The herding in stock *i*, in period *t*, is measured as follows:

$$H_{it}^{lsv} = \left|\frac{b_{it}}{n_{it}} - \rho_t\right| - E\left[\left|\frac{b_{it}}{n_{it}} - \rho_t\right|\right], \qquad (1)$$

Where E is the expectation operator, and $\rho_t = \Sigma_t b_{it} / \Sigma_i n_{it}$ is the sample estimate of p_t, the managers' propensity to buy in period *t*. The value $|b_{it}/n_{it} - \rho_t|$ will be large if the trading of managers in stock *i*, in period *t*, is polarized in the direction of either buying or selling. The overall herding statistic H^{lsv} is the simple average of the measure over all stock-periods of interest.[13]

B.1. LSV Measure and the Principal Explanations of Herding

So how does the LSV measure relate to the theoretical explanations of herding discussed previously? If herding arises from 'linked objective functions' then the trading direction of individual managers should be positively correlated with the trading direction of other managers even after conditioning on overlapping information, as in equation 2: where z_{it}^{j} is a numeric representation of the trade direction that takes the values 1, 0, -1 when X_{it}^{j} takes the values *buy, hold* or *sell* respectively; z_{it}^{p} takes the value 1, 0, -1 if the most common action in the manager's peer group is *buy, hold* or *sell* respectively; and I_t is the overlapping information set shared by manager *j* with its peers, other than portfolio holdings data.[14]

Linked objective functions $$\text{corr}\left[z_{it}^{j}, z_{it}^{p} \middle| I_t\right] > 0 \qquad (2)$$

If herding arises solely from 'informational cascade' then positive conditional correlation in trading direction should be found only between individual managers and other managers that are perceived to be informed, as per equations 3a and 3b: where z_{it}^{I} takes the value 1, 0, -1 if the most common action among the subsets of managers that are perceived by manager *j* to be informed managers, is *buy, sell or hold* stock *i*, in period *t*; z_{it}^{u} is the equivalent variable for managers perceived to be uninformed.

Informational cascade $$\text{corr}\left[z_{it}^{j}, z_{it}^{I} \middle| I_t\right] > 0 \qquad (3a)$$

$$\text{corr}\left[z_{it}^{j}, z_{it}^{u} \middle| I_t, z_{it}^{I}\right] = 0 \qquad (3b)$$

If 'correlated information sets' is the sole explanation of herding, then the propensity of manager *j* to buy a stock *i* in period *t*, denoted p_{it}^{j}, is a function of information shared by the managers. Therefore trade directions of individual managers are correlated with the aggregate changes of the remaining managers, but after conditioning on the shared information, the correlation is zero, as per equations 4a and 4b.

Correlated information $$\mathrm{corr}\left[z_{it}^{j}, z_{it}^{p}\right] > 0 \qquad (4a)$$

$$\mathrm{corr}\left[z_{it}^{j}, z_{it}^{p} \middle| I_t\right] = 0 \qquad (4b)$$

The LSV measure has a positive expected value if the ‘linked objective function’ or ‘informational cascade’ explanations of herding are valid because the variance of b_{it} is then greater than $n_{it}p_{it}(1-p_{it})$, its variance under the null conditions, making extreme observations of b_{it}/n_{it} more likely. It also finds herding if the ‘correlated information’ explanation is valid because the expected value of b_{it}/n_{it} is shifted away from p_t by the arrival of shared information, again making extreme observations of this ratio more likely. Whilst the LSV measure captures herding arising from these three explanations it clearly cannot separate the explanations.

B.2. Affect of Invalid Assumptions

Unfortunately, the LSV measure should be expected to find a non zero level of herding, even where none exists, for three reasons. Firstly, if fund managers cannot undertake short sales, then the number of *sell* observations in a stock-period is constrained to be no more than the number of managers who had a position in the stock at the beginning of the period. In terms of the distribution of b_{it} a short sales constraint imposes a left truncation. In contrast, the LSV measure is calculated assuming a binomial distribution for b_{it}. Therefore, on real datasets drawn from groups of managers, few if any of whom can undertake short sales, the expected value of the LSV measure need not be zero. If none of the managers who trade in a stock-period initially hold the stock then all observed trades must be buys, so the measure must return a non-negative value. However, in other cases where some managers have positive initial holdings, the short sales constraint can lead to an expected value of the LSV measure that is negative in the absence of herding, because the truncation reduces the overall probability mass in the tails of the distribution of b_{it}.

Secondly, there are two other reasons that the distribution of b_{it} does not have the assumed binomial distribution, even in the absence of herding. Managers whose portfolio weight in a stock is already comparatively large at the beginning of the period are more likely to sell than other managers, other things equal, because of mean reversion in portfolio weights. Fund managers also differ in their liquidity needs to buy stocks because the flow of new money to mutual funds is unevenly distributed, with better performed funds receiving a disproportionate amount of the new money. It might therefore be expected that p_{it}^j, the probability that manager *j* buys rather than sells stock *i* in period *t*, is conditioned by both the size of the manager's initial holding in the stock and the manager's liquidity need to buy stocks. Tests of the UK equity mutual fund dataset, which is described in the next section, strongly reject a hypothesis of no variation in p_{it}^j by manager or initial holding.[15] When the propensity to buy, p_{it}^j, varies by initial holding and/or across managers, b_{it} is no longer binomially distributed. The variance of b_{it} will in most cases be smaller as a result of the variation in propensity to buy. Therefore, the variation in p_{it}^j by manager and initial holding should be expected to introduce a negative bias in the LSV measure.

Thirdly, H_{it} is calculated using the sample quantity ρ_t rather than its population counterpart p_t. Because of the absolute value operation in the LSV measure, the effects of positive and negative errors in estimating p_t, are not symmetric. Consequently, the expected value of the LSV measure is not zero, even in the absence of herding. LSV ignore this effect because estimation error is very small in their large dataset. However, this bias brings into question the suitability of the LSV measure on small datasets or small subsets of data from large datasets.

C. Methodology of Accuracy Tests

C.1. Bootstrapping Approach

To gauge the distortion that invalid assumptions introduce to hypothesis testing in the LSV measure an estimate of the actual, rather than assumed, sampling distribution of the measure under the null conditions is needed. To meet this requirement a cycle of re-sampling a new dataset, and then applying the LSV measure to it is repeatedly undertaken. This process builds up an empirical estimate of the sampling distribution of the LSV measure on data drawn from the fund managers of interest, but under conditions of no herding.

The LSV method transforms a dataset of portfolio holdings into one in which there is an observed trade direction, $X_{it}^j \in \{buy, sell, hold\}$, for each stock-period-manager combination. Each of these observations is a realization of its random variable, x_{it}^j, which has a trinomial distribution. To re-sample these observations the parameters of the trinomial distributions from which they were drawn must first be estimated. The first step is to form the observations from the actual dataset into groups of observations with similar characteristics such as stock size. A single trinomial distribution is then estimated for each group of observations, with $\Pr(X_{it}^j = buy)$ estimated by the proportion of *buy* observations in the group and likewise for *hold* and *sell* probabilities. In creating re-sampled datasets, each observation in a particular group is replaced with a draw from the trinomial distribution estimated from that group.

C.2. Eliminating Herding

The fundamental requirements of the re-sampling procedure are, firstly, that herding is eliminated, and secondly, that the re-sampling preserves the essential characteristics of the actual dataset that are not associated with herding. There are two sources of herding to eliminate – unconditional correlation between managers' trades and conditional correlation. Unconditional correlation, such as arises from 'linked objective functions' and 'informational cascade', is eliminated by independent re-sampling of observations. Conditional correlation in managers' trades is more problematic. It arises because managers' propensity to buy a stock *i*, in period *t*, is conditioned by information that is shared by the managers. This conditional correlation is not eliminated simply by the independence of the draws in the re-sampling of observations. Systematic herding will survive the re-sampling process if the trinomial distribution estimated from a group of observations is conditioned by information that is shared by managers. To eliminate herding the re-sampling must be from unconditional distributions, which requires that the conditioning information be averaged (integrated) out across the observations in each group.

C.3. Grouping Criteria

The observations in the actual dataset are first grouped by the period in which the observation was made, and then within each period group the observations are grouped into deciles by the market capitalization of the stock. Stocks that do not appear in the portfolio holdings dataset are ignored. These two levels of grouping, by period and stock size, ensure that the variation in the proportions of *buy*, *hold*, and *sell* observations by factors other than herding is similar in the re-sampled data to that in the actual dataset. In the test of the effect of the short sales constraint a further grouping criterion is imposed; which is whether the manager's beginning of period holding of the stock was zero, or alternatively, positive. This last grouping criterion ensures that re-sampled datasets exhibit no short selling. By re-sampling with and without this third grouping criterion imposed we can compare the sampling distribution of the LSV measure with and without short selling in the data, and hence estimate the level of bias induced in the sampling distribution by the short selling assumption.

C.4. Logit Estimation of Trinomial Distributions

To test the effect of the LSV assumption that a manager's propensity to buy, p_{it}^{j}, does not vary across the stock-period-manager combinations in a particular period, the level of variation in p_{it}^{j} that exists in the actual dataset must be retained in the re-sampled datasets. To that end, the observations of the actual dataset are first grouped by period, stock size and whether the initial holding is positive, or alternatively zero. Within each group the logit regression of equation 5 is undertake: where $X_{it}^{j} \in$ {*buy*, *hold*, *sell*} is the trade direction of an observation in the particular group; D_q is a dummy variable that takes the value 1 if the size of manager *j's* initial holding in stock *i*, in period *t*, is in the q^{th} quintile of all non zero holdings of stock *i*, in period *t*; and D_j is a dummy variable taking the value 1 for observations of manager *j's* trades, where there are J funds reporting in period t.

$$X_{it}^{j} = \text{Const} + \sum_{q=1}^{3} b_q D_q + \sum_{j=1}^{J-1} b_j D_j + e_{it}^{j} \qquad (5)$$

The fitted values from the logit estimation are estimates of the cumulative distribution of the random variable from which the dependent variable observation was drawn. Therefore, by estimating a logit regression within each group we get an estimated trinomial for each observation in the dataset, where the estimate is conditioned on the initial holding of the stock and the identity of the manager. Re-sampling from these individually estimated trinomials preserves in the re-sampled datasets the effect of the manager's liquidity need to trade and the size of the initial holding of the stock on the propensity to buy. By re-sampling with and without the logit estimation of trinomials the effect of the assumption of invariance in the propensity to buy by manager and initial holding can be estimated.

II. Data

A. UK Equity Mutual Fund Dataset

The primary data for this study is a record of the portfolio holdings of 268 UK equity mutual funds, taken from semi-annual reports to investors over the period January 31, 1986 to December 31, 1993.[16] The dataset was created by John Morrell and Associates of London. A sample of the source documents was examined to test for errors in the construction of the dataset and the error rate was found to be negligible. All other data required for the study, including asset prices and capital changes are taken from the London Business School's London Share Price Database (LSPD). Dimson and Marsh (1983) provides a detailed description of the LSPD.

At year end 1985 the total holding of UK listed equities by all UK mutual funds was £11 billion. By year end 1993 that total was £50 billion. The corresponding figures for the group of mutual funds covered by the dataset are £6.5 billion and £28 billion. Therefore the dataset is representative of UK equity mutual funds in that it records more than half of the UK equities held by UK mutual funds in the period January 1986 to December 1993. Moreover, some equities are held in mutual funds that have less than 90 percent of their assets in UK equities and therefore are not classified as UK equity mutual funds and hence not included in the dataset. Panel A of Table I shows the total market value of assets held by the funds at the end of the even years of the dataset, and the total number of unique stocks held in those funds. At any date the stocks represented in the dataset amount to about one half of the stocks listed on the London Stock Exchange.

[Table I about here]

The dataset contains semester data, meaning that for each full year during which a fund appears in the dataset, two snapshots of portfolio holdings are recorded. UK mutual fund managers choose the two calendar months in which they report to their investors each year, declaring their portfolio holdings on either a January - July cycle or a February - August cycle, etc. Panel B of Table I shows the number of mutual funds that reported in the first six months of the even years of the dataset period. On average 224 funds report in each six month period. The funds are nearly evenly distributed across the six reporting cycles with somewhat more in the March-September and April-October cycles.

Panel C shows the average market value of the assets of the funds. UK mutual funds are smaller than their US counterparts The average size of the funds is £93 million (approximately $150 million). The 268 funds (that is, 268 managers) are sponsored by 99 separate investment management firms. Panel D records the average number of stocks that the funds hold in their portfolios, broken down by investment management style groupings. Funds in the general category hold the most stocks with an average of 80, and growth funds the least with an average of 55. Over the period covered by the dataset UK mutual funds have increased the number of stocks held in their portfolios; particularly growth and small market capitalization funds.

The dataset is composed of 96 panels of data, being one for each month between January 1986 and December 1993 inclusive. The 96 data panels record 237,185 non-zero portfolio entries across all stocks, periods and managers. Of those records, 685 could not be matched to the LSPD dataset and were therefore excluded. There were 3,469 'cash' records that were deleted. The 95 records of stock holdings of less than 100 shares were deleted because they were unlikely to help extend our understanding of herding by UK fund managers. Next, the portfolios of each manager at sequential dates were differenced to determine whether a particular stock was *bought* (from an initial holding of zero), *increased* (from a positive initial holding), *held* (no change in an initially positive holding), *decreased* or *sold* (leaving a holding of zero).

In this process of determining the direction of trades, the dataset has been adjusted to ensure that basic changes to the opportunity set of fund managers, resulting from capital changes of stocks, are not measured as herding. Stock-periods that coincide with equity issues, stock buy-backs or capital payouts are deleted. Stock-periods that begin or end within six months of the birth or death of a stock are also removed. Finally, the effects of stock splits and scrip issues on prices and number of shares held are reversed. What remains are 234,689 observations comprised of 41,774 buys, 42,774 increases, 78,369 holds, 32,982 decreases, and 39,287 sells. These figures do not include the observations of a manager beginning and ending a period with a zero holding in a stock – the vast majority of observations.

Panel E of Table I shows the average number of *buy* (bought or increased) and *sell* (decreased or sold) occurrences for portfolios in the different sectors. There is not much variation year to year in the total number of trades. However, unreported results show that the UK equity mutual funds undertake more trades in the second half of each of the years than in the first half. That increase in trading in the second half of the year holds for each of the subsets of funds formed by investment style. There is also some variation across the sectors with more trades by the general sector funds that in part reflects the larger number of stocks held by those funds.

B. Log Deciles

In the re-sampling process of the accuracy tests of the LSV measure (presented in Section IV) the observations are grouped by stock size. The market value of UK stocks is heavily concentrated in the largest stocks and the number of trades is commensurately larger in those stocks. To even out the number of observed trades across the groups, from which the re-sampling trinomials are estimated, stocks are grouped into deciles by the log of the size rank of the stock. Each stock is ranked by market capitalization at the beginning of each six month period, with the largest stock assigned a rank of 1. The cut-off rank for each decile is determined as $10(S/10)^{(n-1)/9}$: where n is the decile and S is the total number of stocks listed at that date. This procedure ensures that the first decile contains the 10 largest stocks.

Panel F of Table I reports descriptive statistics for the size log-deciles that are employed in the accuracy tests of the LSV herding measure. The table entries demonstrate that the market value of UK listed stocks is heavily concentrated in the very largest stocks. The first log-decile contains 10 stocks by construction, the second contains 8 stocks on average, the fifth contains 48 stocks on average and the tenth contains an average of 941 stocks. The number of stocks in each of the log deciles is fairly stable over the period of the dataset.

III. LSV Measure Applied to the UK Dataset

A. Subsets Formed by Number of Managers Trading and Stock Size

Table II reports the results of applying the LSV herding measure to the dataset of 268 UK equity mutual fund managers. Results are reported for the entire dataset and subsets of the observations. The subsets are formed on the basis of the number of managers who trade in a stock-period and the market capitalization rank of the stock (where the largest stock at the beginning of the period has a rank equal to 1). For comparison, results are also reproduced from the LSV (1992a) and Wermers (1999) studies of US pension funds and US mutual funds respectively.

[Table II about here]

For the entire UK dataset the level of herding is 2.6 percent, as reported in Panel A. The herding figure rises with the number of managers trading to 9.0 percent when 25 or more managers trade the stock in a period. The increase in herding with the number of managers trading suggests that the events that cause a large proportion of managers to trade also causes them to herd. That finding is consistent with the portfolio optimization view that fund managers herd because their optimization problems are similar and/or linked. The total ratio of *buy* observations to *sell* observations in the dataset is 0.58, reflecting the strong flow of money into the funds over the period. When $p_t = 0.58$ and the number of managers trading is 25, a herding figure of 9.0 percent corresponds approximately to 19 of the managers buying or 15 managers selling.[17]

Where 10 or more managers trade a stock in a period, the level of herding found in the UK dataset is 3.3 percent; which is similar to Wermers' (1999) finding of 3.6 percent herding where 10 or more US equity mutual fund managers trade. This finding with UK data broadens the generality of previous results on herding in mutual funds. It is further evidence that the trading behavior of mutual fund managers differs from that of the rest of the market.

When interpreting results of the LSV measure across subsets where different numbers of managers trade it should be noted that the measure is intrinsically dependent on the number of managers trading. To illustrate, consider a dataset containing 100 managers who always buy or sell with the other managers if they choose to trade. If $p_t = 0.5$, then in a stock-period where all 100 managers trade the LSV measure is 46 percent. If only 10 of the 100 managers trade during the period then the figure is 37 percent, and if only 2 trade then the figure is 25 percent.[18] So for a given level of correlation among the trades of managers, some increase in the level of herding with the number of managers trading is expected. This means that the size of the dataset affects the mean as well as the variance of the sampling distribution of the LSV measure. By comparing the level of herding found in the actual dataset to an estimate of the empirical sampling distribution, this effect can be accounted for.

Panel B of Table II shows that the highest levels of herding are found in the largest stocks and the smallest stocks. Amongst the five largest stocks by market capitalization the level of herding is 4.1 percent. Amongst stocks outside the 1,000 largest, the level of herding found is 6.2 percent. LSV, in studying US pension fund managers' trades, find a level of herding of 6.1 percent among the quintile of smallest stocks. Wermers, finds a figure of 6.2 percent where 5 or more US equity mutual fund managers traded stocks in the smallest size quintile. LSV and Wermers do not find that herding is increasing with market capitalization in the largest stocks; however, they do not partition the data at a finer level than quintiles.

If herding results from relative performance evaluation, then among the stocks that make up a value weighted benchmark for a group of managers, we should expect to observe more herding by those managers in the larger stocks, simply because those stocks have greater weight in managers' optimization problems. Further, if herding is explained by managers acting on shared information then more herding in larger stocks should again be expected, because large stocks are followed by more analysts. However, there is little in the theoretical explanations of herding that predicts high levels of herding among the smallest stocks by market capitalization. It is curious therefore that a herding level of 6.1

or 6.2 percent is found in this study and the studies of LSV and Wermers among the smallest stocks.

B. Investment Style Groups

The remuneration of many UK mutual fund portfolio managers is dependent on their end of year ranking among their peer group of funds with the same investment style. Moreover, those fund managers have a similarly restricted set of assets to research and trade. If the 'linked objective functions' explanation of herding has explanatory power then more herding should be found among managers with the same investment style, than among the full set of managers, because the objective functions of managers within the same investment category are linked by relative performance evaluation.

Table III reports the results of testing for herding among managers within the same investment management sectors; that is, for herding within the general, growth and income groups of UK equity mutual funds. Herding is low within these categories for stock-periods where a small number of funds trade. Surprisingly, there is considerably more herding among income funds than among general or growth funds, which is the opposite of US results. Where the number of managers trading is 10 or more, the herding by funds within the same investment categories is higher than the overall level of herding. However, stock-periods where 10 or more managers within an investment group trade, are in many cases the same stock-periods where 20 or more managers in the full dataset trade - when measured level of herding is any case high. The general result is that the observed level of herding does not increase when the level of analysis is restricted to managers whose performance is measured against each other. These results do not support the 'linked objective function' explanation of fund manager herding.

[Table III about here]

C. Buy and Sell Herding

'Buy' herding stock-periods are those where $(b_{it}/n_{it}-\rho_t)>0$, and likewise 'sell' stock-periods are those where $(b_{it}/n_{it}-\rho_t)<0$. Several of the studies of fund manager herding that employ the LSV measure have divided the herding results into 'buy' herding and 'sell' herding. This practice can be highly misleading. Table IV presents figures for 'buy' and e UK dataset to illustrate the problem. Panel A shows that for the subset of stock periods where less than 5 managers trade H^{lsv}(buy) = 6.0 percent and H^{lsv}(sell) = 0.1 percent. Panel B shows that for stocks outside the 1000 largest, H^{lsv}(buy) = 12.1 percent and H^{lsv}(sell) = 1.2 percent.

[Table IV about here]

In other studies results such as these have been interpreted as meaning that in these subsets of the data managers are herding when buying but not when selling. However, much of this difference simply reflects the construction of the LSV measure. Consider for instance the case where just two managers trade a stock in a period – an event that is more common in small stocks than in large stocks. If p_t=0.58 then b_{it}/n_{it} can only take the values 0, 0.5 or 1; only the last of which is recorded as 'buy' herding. Consequently, when two managers trade but the there is zero systematic herding, the expected value of 'buy' herding is 13.7 percent and for 'sell' herding 7.0 percent.[19] The division of fund manager trading datasets into 'buy' and 'sell' stock-periods can create the misleading impression that most of the herding found arises from managers simultaneously buying stocks rather selling, or vice versa.[20]

The results of Tables II, III or IV indicate that herding is episodic in that it is strongly increasing in the number of managers trading. Further, that the herding by UK mutual fund managers, as measured by the LSV measure, is higher in the extremes of market capitalization, but relatively constant otherwise. These results demonstrate that the trading behavior of UK equity mutual fund managers is separate to that of the rest of the UK equity market.

IV. Results of the Accuracy Tests of the LSV Measure

The previous section's results on the level of herding among UK equity mutual fund managers cannot simply be taken at face value because the herding measure employed rests on assumptions that are not valid in the dataset. They are; the assumption that all managers can short sell all stocks, the assumed invariance of the propensity to buy, and the assumption that the propensity to buy is estimated without error. Under these assumptions the sampling distribution of the LSV measure is a normal distribution with a mean of zero and variance that can be calculated from the observations. The purpose of this section is to empirically estimate how the invalidity of each of these assumptions distorts the sampling distribution of the measure away from its assumed form.

For that purpose three sampling distributions are estimated. The first is an estimate of the sampling distribution of the LSV measure on the UK dataset, under conditions of no herding, but with error in estimating the propensity to buy, p_t, in each period. The second sampling distribution is estimated with both error in estimating p_t and no short selling. The third is estimated under those conditions but additionally with variation in the propensity to buy across managers and by the initial holding in the stock. In this way the incremental contribution of each assumption to inaccuracy in the herding measure can be estimated.

A. Benchmark Test

For each stock-period-manager combination in the UK equity mutual fund dataset there is an observed trade direction {*buy*, *hold* or *sell*}. The full set of stock-period-manager combinations in the dataset is divided into 150 groups. Firstly, observations whose reporting period commenced between 31 January 1986 and 30 June 1986 inclusive form one groups of observations. Those observations whose period commenced between 31 July 1986 and 31 December 1986 for a second group and so on to form 15 groups by reporting period. Then each of those groups is divided into 10 deciles by the log of the size rank of the stock at the beginning of the reporting period. The proportion of *buy*, *hold* and *sell* observations in each group are the estimated probability weights of the trade direction trinomial for that group. For each stock-period-manager combination in the group the trade direction observation is replaced by a separate draw from the group's trinomial. In that way each observation in the dataset is re-sampled. The process is repeated to create 1000 re-sampled datasets and the LSV measure is applied to each dataset, and subsets of each dataset, to build up estimated sampling distributions of the LSV measure on the dataset and its subsets. The summary statistics of those estimated sampling distributions are reported in Table V.

The expected value of the LSV measure is not zero, even in this simple benchmark estimation of the sampling distribution, for the following reason. The value of ρ_t in equation 1 is an estimate of p_t. That estimate is unbiased but contains errors. The effect of those errors on the expected value of the LSV measure is systematic because of the absolute value operations in the LSV herding measure. It might expected that this effect will be small in large datasets and that expectation is born out in the Table V results. The bias caused by systematic errors in estimating p_t is small for all subsets of the stock-periods. For the stock-periods where a large number of managers trade, and for the smallest stocks, the 95th percentile of the sampling distribution exceeds 1 percent.

[Table V about here]

Another possible source of this (small) bias is migration of stocks between the size deciles over time. The illusion of herding that can result from small cap managers selling in unison stocks that become too large for their portfolios is not eliminated when stock-periods are grouped by size. However, that effect is not considered to be herding, so in a test like this it is desirable that it be captured in the mean of the sampling distribution in the absence of herding.

B. Effect of the Short Selling Assumption

The period and size grouping criteria generate 150 groups. These criteria are intended to preserve characteristics of the actual dataset that are not associated with herding. The third criterion is that all observations in which the initial holding of the stock is zero are placed in a separate group. The trinomials estimated from the zero-initial-holding groups have an estimated probability of ‘sell’ observations that is zero by construction.

Therefore the re-sampled data does not exhibit any short selling. Therefore, the invalid assumption that all managers undertake short selling is relaxed. The zero herding sampling distribution is estimated with and without this third grouping into positive and zero initial holdings. This control of the presence of the assumption permits an estimate of the effect of the short selling assumption on the accuracy of the LSV herding measure.

Table VI shows the effect of relaxing the short selling assumption. The results indicate that a significant amount of the herding found in certain subsets of the stock-periods is a result of the LSV assumption that managers can short sell. For stock-periods where the number of managers trading during the period is less than 10, the mean of the sampling distribution is a substantial fraction of the amount of herding found in that subset of the actual dataset. For the subset of observations where less than 5 managers trade, the measured level herding in the actual dataset is 2.6 percent, but the estimated bias in the measure for this subset is 1.7 percent.

[Table VI about here]

For stocks outside the largest and smallest stocks, where size rank is between 20 and 100, the mean of the sampling distribution is more than one half of the herding measured on actual datasets (as shown in table II). For stocks with a market capitalization rank of more than 1,000 (the smallest stocks), the mean of the sampling distribution under simulated conditions of zero herding is more than one third of the herding measured in the actual dataset.

C. Effect of Variation in Propensity to Buy

The effect of the invariance assumption is tested by preserving in the re-sampled data the variation in p_{it}^{j}, by manager and initial holding, that exists in the actual dataset. This requires that the trade direction of each stock-period-manager combination is re-sampled from a trinomial distribution that is conditioned by the identity of the manager and the manager's initial portfolio weight in that stock. An estimate of a trinomial distribution specific to each stock-period-manager combination is achieved by undertaking the logit regression of Equation 5 for each grouping of observations by the criteria of period, size and whether the initial is positive. For groups in which the initial holding is zero, the initial holding quintile dummy variables are dropped from the logit regression. The fitted values of the logit regression are the values of the cumulative distribution function of the individual trinomial distributions. For computational tractability only the 5 log-deciles of largest stocks are considered (which equates roughly to the 100 largest stocks). The summary statistics of the sampling distribution of subsets of the stock-periods of 1,000 re-sampled datasets are reported in Table VII.

[Table VII about here]

The main result is that the effect of variation in the propensity to buy across observations in a period is small. When variation in p_{it}^{j} is included in the trinomials from which the observations are redrawn, the effect is to slightly reduce the mean and 95th percentile values of the re-sampling distribution under conditions of zero herding. This implies that the variation in p_{it}^{j} induces a negative bias in the measure, which is expected because in most stock-periods that variation reduces the variance of b_{it} below the assumed variance of a binomial distribution.

However, for one subset the bias is increased by the invariance assumption. Where fewer than 5 managers trade the mean of the sampling distribution under conditions of no herding rises to 2.4 percent when the variation in p_{it}^{j} is preserved.

D. Comparison of UK Dataset Results and Estimated Sampling Distribution

In table VIII the results of measuring the actual dataset with the LSV (from Table II) are compared with the results of estimating the sampling distribution of the LSV measure under conditions of no herding, but with the essential characteristics of the actual dataset preserved (from Tables VI and VII). In Table VIII the *adjusted* LSV measure is simply the LSV measure on the actual dataset less the estimated bias in each subset of the data. In making this subtraction the assumption is the bias in the absence of herding is a good estimate for the bias at the 'true' level of herding.

[Table VIII about here]

The LSV measure adjusted for bias shows that the level of herding is strongly increasing in the number of managers trading the stock. For stock-periods where the number of managers trading is less than 5 the level of herding measured does not exceed the 95th percentile of the estimated sampling distribution under conditions of no herding and therefore the null of no herding in this subset cannot be rejected. For higher numbers of managers trading the level of herding increases substantially.

In the adjusted LSV results the effect of stock size is considerably more pronounced than for the unadjusted figures. Among the largest stocks the adjusted level of herding increases from 0.8 percent for 50 largest stocks to 3.7 percent for the 5 largest stocks.

About one half of the level of herding found in the mid-cap stocks is explained by the identified biases in the LSV measure. When those biases are adjusted for, the level of herding in the largest and smallest stocks is relatively higher. However, about one third of the herding found in the stocks outside the 1000 largest is explained by the invalid assumptions in the LSV measure.

V. Concluding Remarks

The results of this study extend the generality of the empirical literature on fund manager herding. Herding is found among mutual fund managers in data drawn from a country that has an investment management industry comparable to that of the US; in this case the UK. Further, the foundation of the empirical herding literature is strengthened because the sampling distribution of the herding measure, under the null assumption of no herding, is estimated empirically.

A new dataset of the portfolio holdings of 268 UK equity mutual funds is employed to test for herding among UK mutual fund managers using the herding measure of Lakonishok, Shleifer and Vishny (LSV 1992a). The measured herding by the fund managers is increasing in the number of managers trading a particular stock over a period. For the full dataset the percentage of managers trading on one side of the market is 2.6 percent more than would be expected by chance in the absence of herding. Where approximately one half of the managers trade a stock in a period that figure rises to 9 percent. The measured herding is larger for the smallest and the largest stocks. The level of herding found is similar to that reported in studies of US mutual fund and pension fund managers.

The LSV measure of fund manager herding, which has delivered much of the empirical literature's fund manager herding results, rests on three assumptions that are not sustained in real datasets. To gauge the effect of these invalid assumptions on the accuracy of the LSV measure, the sampling distribution of the measure is estimated both with and without the assumptions in place. The LSV measure applied, without adjustment, to the UK dataset indicates significant herding in stocks where less than 5 managers trade in a period. However, the accuracy tests reveal that essentially all of that herding arises because of the invalid assumption that all managers can short sell all stocks. A third of the herding level found in the smallest stocks is likewise simply a result of that invalid assumption. The other invalid assumptions are, firstly, that the ex ante probability of any trade being a *buy* rather than a *sell* is invariant across managers or with a manager's initial holding in the stock, and secondly, that the ex-ante probability of a *buy* observation can be estimated without error. The effect of these assumptions is shown to be small.

The results of the accuracy tests show that the LSV measure of herding is not suitable for measuring herding where only a small number of managers trade. Moreover, it is shown here that when the herding found in individual stocks is taken as the starting point for further analysis then great care must be taken. Ranking stocks by the level of herding in those stocks in a particular period, or averaging over stocks in which *buy herding* occurs are not in general valid procedures. However, these restrictions aside the LSV measure is shown to be suitable for measuring herding.

It is common in the finance literature for researchers to develop a metric and then to reason that under null conditions the expected value of the metric is zero. In the investment management literature this is the standard approach for measures of herding, fund manager performance, performance persistence and the like. When computing power was limited this was the necessary approach. But now, for most measures in investment management, researchers should be able to estimate the distribution of their measures under simulated null conditions to better determine whether the measure is properly calibrated. That is the approach taken in this study. The data is restructured to eliminate the phenomenon that is being measured, whilst retaining the essential characteristics of the dataset that are not related to that phenomenon. Repeated random replication of the data and application of the measure allows a sampling distribution to be estimated. In this study re-sampling techniques can be nested such that the effect of individual assumptions is revealed.

Herding by a group of investors manifests itself as net trade between that group and all other investors. The flip side of this notion is that a finding of herding by a group of investors is evidence that the group is separate to the rest of the market in its trading behavior. Studies of herding may therefore have an important empirical input into understanding the equilibrium in asset markets in which traders are not homogenous in their trading behavior. Accurate herding measures can help to identify the separate groups. In the UK equity market mutual fund managers are separate to the rest of the market in their trading behavior.

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Footnotes

1. See Lakonishok, Shleifer and Vishny (1992a), Grinblatt, Titman and Wermers (1995), Wermers (1999), Nofsinger and Sias (1999), Choe, Kyo and Stulz (1999).

2. See Orphanides (1996), Khorana (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998). Fund manager pay-offs are non-linear in the excess-to-benchmark return of their portfolio, because even though total management fees generally increase linearly with the size of the fund, there is a non-linear relationship between a fund's excess-to-benchmark return and the flow of new money to the fund.

3. See Grinblatt, Titman and Wermers (1995), Wermers (1997) and Nofsinger and Sias (1999), regarding institutional investors and Heisler (1996) and Odean (1998, 1999) regarding private investors.

4. Brennan (1993) addresses this issue in the CAPM framework.

5. Brown and Goetzmann (1997) form US mutual fund managers into 'style' groups by a method that is analogous to k-means cluster analysis.

6. Empirical studies of the existence of fund manager herding began with the Friend, Blume and Crockett (1970) study of mutual funds that found, for the brief period studied, that managers buy stocks that were previously bought by successful managers. Kraus and Stoll (1972) examined the monthly trades of 229 institutional investors between January 1968 and September 1969. They reported large monthly net trade, in some stocks, between the group of institutional investors and the rest of the market. Klemkosky (1977) examined the relationship between the net trades of a group of large institutional investors and the returns of securities before and after the measured period. He found evidence of herding by institutional investors that was consistent with 'overshooting' of stock prices; the herding was manifested in net buying of stocks that had recently risen in price and net selling of stocks that had recently peaked in price.

7. UK mutual fund managers are prohibited from undertaking short sales. US mutual funds are technically neither forbidden nor allowed to undertake short sales. Section 12(a) of the Investment Companies Act 1940 prohibits short sales by registered mutual funds in contravention of SEC rules. However, the SEC has not issued rules under Section 12(a). As a result few US mutual funds undertake any short selling.

8. The UK analog of the US mutual fund is known as a unit trust. For simplicity, UK unit trusts are referred to as mutual funds in this paper.

9. See Wermers (1999) and Nofsinger and Sias (1999).

10. There is a large theoretical herding and social learning literature that seeks to explain why agents choose to imitate or conform to the decisions of others. See Devenow and Welch (1996) for a survey.

11. Devenow and Welch (1996) provide a similar categorization of studies.

12. See Lakonishok, Shleifer, and Vishny (1992b)

13. The LSV measure would be more efficient if it weighted the contribution of each stock period by the inverse of its variance. Under its null conditions, the variance of the LSV measure in a particular stock-period is approximately inversely related to the number of managers trading in that stock-period.

14. It is appropriate to treat each of the peer managers equally in characterizing the effect of ‘linked objective functions’ because managers are typically remunerated on the basis of their rank by total return among funds in the same investment style group without consideration of the relative size of funds in the peer group.

15. To test for variation in p_{it}^{j} across managers, the proportion of each manager’s trades that are *buys* is calculated for each period in which the manager is active. The null hypothesis that all managers have the same propensity to buy in any particular period is rejected at the 95 percent significance level in χ^2 tests in all but two of 90 periods. To test for variation in p_{it}^{j} by the initial holding of managers, stock-period-manager observations for which the initial holding of the stock is positive are grouped by stock-periods. For each such group, the observations are formed into quintiles by the initial weight of the stock in the corresponding

manager's portfolio. Retaining the quintile marker, the full set of observations are regrouped into the 90 reporting periods and the ratio of *buy* observations to trades is calculated for each quintile in each period. The null hypothesis of no variation in propensity to buy by initial holding in the stock is rejected at the 95 percent significance level in χ^2 tests in all 90 periods.

16. The dataset was created in 1992 and includes only UK equity mutual funds that survived the period 1986-1992. It is conceivable that studying only the survivors creates an illusion of herding because the survivors are more likely to have avoided strategies that led to termination or merger of other funds. An early version of Wermers' (1999) reports tests for herding with the LSV measure on a dataset of portfolio holdings of 274 US equity mutual funds over a 10 year period. Wermers finds that the herding results are much the same whether or not the dataset includes only funds that survived the entire period. It therefore appears that survivorship bias is not an important issue in studies of herding by mutual fund managers.

17. Where p_t=0.58 and 25 managers trade, the LSV measure is 6.0 percent if 18 managers buy (14 sell) and 10.0 percent if 19 managers buy (15 sell).

18. The LSV measure for one stock period is $H_{it}^{lsv} = \left|\frac{b_{it}}{n_{it}} - r_t\right| - E\left|\frac{b_{it}}{n_{it}} - r_t\right|$. For a given value of b_{it}/n_{it}, the second term in this equation is decreasing in n_{it}.

19. Wermers only examines stock-periods where 5 or more managers trade, but there is still a problem. Where n=5 and p_t=0.58 the figures are H^{lsv}(buy) = -4.0 percent and Hlsv(sell) = 7.2 in the absence of herding. Where n=10 the figures are H^{lsv}(buy) = -1.7 percent and H^{lsv}(sell) = 2.5 percent in the absence of herding.

20. Using the LSV measure to rank stock-periods is also misleading. In Wermers (1999) all stock-periods in which 5 or more managers trade are formed into deciles by the value returned by the LSV measure. The abnormal returns to equally weighted decile portfolios are calculated for periods before and after the herding period. However, the variance of the LSV measure is decreasing in the number of managers that trade in the period. So a ranking of stock periods by the LSV measure reflects the number of managers trading more than the

level of herding. For example, where n_{it} =5, p_t=0.58, and there is no systematic herding, prob(H_{it} > 10.0 percent) = 0.17, whereas if n_{it}=25 and p_t=0.58 then prob(H_{it} > 10.0 percent) = 0.04.

21. In each stock period the number of managers with a positive initial holding is an integer into which 5 can be divided R times with a remainder of S. Then the qth quintile contains R observations, except the third quintile which contains R+S observations.

22. See the 1996 *Fund Management Survey* Institutional Fund Managers Association, 1996, , (London).

Table I

Summary Statistics for UK Equity Mutual Fund Holdings Dataset

Descriptive statistics of the dataset of portfolio holdings of UK equity mutual funds are provided below. The data was collected from the bi-annual reports to fund shareholders in the period January 1986-December 1993. The funds report to shareholders on a six month cycle. Characteristics of the 268 funds are reported for the first half of the even years of the dataset. Panel A gives aggregate data on the total value of assets held by funds in the dataset and the total number of unique stocks held. Panel B records how many funds reported in each cycle. Panel C reports the average size of funds in the four major fund investment style categories. Panel D shows the average number of stocks held in the funds. Panel E records the average number of buy and sell trades undertaken by funds of different investment style categories. Panel F shows the market value and number of stocks in each size decile of the London Stock Exchange. The market value of stocks listed in London is concentrated in the largest stocks. Consequently, grouping by size here is into deciles by the log of the stock's size rank at the beginning of the period of interest. The cut off for decile *n* is calculated as $10(S/10)^{(n-1)/9}$, where S is the total number of stocks listed at that date.

	Year				
	1986	1988	1990	1992	Average
Panel A. Total Value and Number of Stocks					
Total assets of funds (£bn)	6.5	13.5	18.3	21.5	17.3
Total unique stocks held	924	1,068	1,207	1,210	1,140
Panel B. Number of Funds Reporting					
Total	133	206	253	258	224
Jan-July	15	22	31	32	27
Feb-Aug	21	30	40	44	37
Mar-Sep	27	47	56	57	49
Apr-Oct	33	44	49	49	45
May-Nov	21	37	42	40	36
Jun-Dec	16	26	35	36	30
Panel C. Average Fund Asset Value					
General (£mn)	69	113	147	168	142
Growth	35	41	43	52	47
Income	48	60	63	67	65
Small Cap	16	30	22	30	28

		1986	1988	1990	1992	Average
	Panel D.	**Average Number of Stocks Held**				
General		72	83	79	80	80
Growth		49	51	54	58	55
Income		63	63	58	60	61
Small Cap		51	68	54	61	63
	Panel E.	**Average number of trades**				
General	Buy	29	29	26	31	29
	Sell	18	25	25	28	24
Growth	Buy	20	20	22	23	21
	Sell	17	20	18	23	20
Income	Buy	26	25	23	28	26
	Sell	17	21	19	22	20
Small Cap	Buy	23	27	15	20	21
	Sell	18	21	20	16	19
	Panel F.	**Log Deciles**				
Stock size decile						
1	# of stocks	10	10	10	10	
	Market Cap(£bn)	(58.2)	(82.6)	(103.7)	(138.0)	
2		8	8	8	8	
		(21.4)	(31.0)	(38.1)	(61.7)	
3		15	15	15	14	
		(26.7)	(38.9)	(47.3)	(69.7)	
4		26	26	27	27	
		(29.5)	(45.8)	(52.0)	(70.3)	
5		48	49	50	46	
		(33.5)	(53.3)	(56.5)	(67.7)	
6		87	87	90	85	
		(28.9)	(47.0)	(45.5)	(63.2)	
7		157	158	165	152	
		(24.0)	(38.3)	(36.0)	(47.4)	
8		284	286	300	275	

	(17.6)	(29.7)	(25.5)	(31.7)
9	514	518	545	495
	(10.8)	(19.8)	(15.2)	(6.4)
10	930	939	994	892
	(4.6)	(9.0)	(6.8)	(5.9)

Table II
Herding Levels in UK Mutual Funds by LSV Measure of Herding

Results from applying the LSV measure to the UK mutual fund holdings dataset are reported in this table. The LSV measure calculates the herding in stock *i* in period *t* as $H_{it}=| b_{it}/n_{it}-\rho_t | - E| b_{it}/n_{it}-\rho_t |$; where n_{it} is the number of observed trades, b_{it} is the number of those trades which are *buys*, and ρ_t is the proportion of all trades in period *t*, across all stocks, that are *buys.* Subsets of the dataset's stock-period combinations are formed by the number of managers who trade in the stock-period and by the size rank of the stock. Each stock is allocated a size rank by market capitalization at the beginning of each period, with the largest stock having a rank of 1. H^{lsv} is the simple average of H_{it} across a subset of stock-periods of interest. The number of stock-periods in each subset is shown below the herding value.

Panel A. Number of managers trading in the period

	n≥2	**n≥5**	**n≥10**	**n≥15**	**n≥20**	**n≥25**
H^{lsv}	0.026	0.025	0.033	0.043	0.069	0.090
stock-periods	27,014	10,522	3,342	1,007	302	101
t-value	25.4	23.5	22.8	19.5	19.5	16.0
	2≤n<5	**5≤n<10**	**10≤n<15**	**15≤n<20**	**20≤n<25**	
H^{lsv}	0.026	0.021	0.028	0.032	0.059	
stock-periods	16,492	7,180	2,335	705	201	
t-value	17.4	15.1	15.5	11.6	13.6	

Panel B. Size rank of stock

	r≤5	**r≤10**	**r≤20**	**r≤50**	**r≤100**
H^{lsv}	0.041	0.028	0.023	0.020	0.021
stock-periods	466	890	1,690	3,991	7,682
t-value	9.7	8.9	9.2	11.0	15.5
	r>100	**r>200**	**r>500**	**r>1000**	
H^{lsv}	0.027	0.032	0.044	0.062	
stock-periods	19,332	14,031	6,004	1,247	
t-value	21.0	19.5	16.6	10.1	

Panel C. Comparative results from US studies

	US Pension Funds*			**US Mutual Funds****		
	n>1	**n>10**	**n>20**	**n>5**	**n>10**	**n>20**
H^{lsv}	0.027	0.020	0.021	0.034	0.036	0.034
stock-periods	na	na	na	109,486	67,252	34,704

* *US pension fund data is from Lakonishok, Shleifer and Vishny (1992a)*

** *US mutual fund data is from Wermers (1999)*

Table III
Herding Levels in UK Mutual Fund Sectors by LSV Measure

Results from applying the LSV measure to the UK mutual fund holdings dataset are reported in this table. The LSV measure calculates the herding in stock *i* in period *t* as $H_{it}=| b_{it}/n_{it}-\rho_t | - E| b_{it}/n_{it}-\rho_t |$; where n_{it} is the number of observed trades, b_{it} is the number of those trades which are *buys*, and ρ_t is the proportion of all trades in period *t*, across all stocks, that are *buys*. Subsets of the dataset's stock-period combinations are formed by the number of managers who trade in the stock-period and by the size rank of the stock. Each stock is allocated a size rank by market capitalization at the beginning of each period, with the largest stock having a rank of 1. H^{lsv} is the simple average of H_{it} across a subset of stock-periods of interest. The number of stock-periods in each subset is shown below the herding value.

	Number of managers trading in the period			**Size rank of stock**			
	n≥2	**n≥5**	**n≥10**	**r≤20**	**r≤100**	**r>100**	**r>200**
		Panel A Funds in the 'general' sector					
H^{lsv}	0.013	0.022	0.076	0.017	0.012	0.027	0.027
stock-periods	10,704	2,055	55	1,496	5,877	4,827	2,170
t-value	7.5	8.3	6.2	4.5	5.7	5.0	6.0
		Panel B Funds in the 'growth' sector					
H^{lsv}	0.013	0.018	0.045	0.009	0.010	0.016	0.024
stock-periods	10,776	1,719	62	1,462	5,473	5,303	2959
t-value	7.0	6.4	3.9	2.4	4.3	5.6	6.1
		Panel C Funds in the 'income' sector					
H^{lsv}	0.033	0.043	0.059	0.043	0.034	0.033	0.037
stock-periods	9,852	2,137	166	984	4,173	5,679	3310
t-value	18.2	17.1	8.5	9.1	13.1	13.0	10.6

Table IV
Buy and Sell Herding Levels by LSV Measure of Herding

Results from applying the LSV measure to the UK mutual fund holdings dataset are reported in this table. The LSV measure calculates the herding in stock *i* in period *t* as $H_{it}=| b_{it}/n_{it}-\rho_t | - E| b_{it}/n_{it}-\rho_t |$; where n_{it} is the number of observed trades, b_{it} is the number of those trades which are *buys*, and ρ_t is the proportion of all trades in period *t*, across all stocks, that are *buys*. 'Buy' herding stock-periods are those where $(b_{it}/n_{it}-\rho_t)>0$, and likewise 'sell' stock-periods are those where $(b_{it}/n_{it}-\rho_t)<0$. Subsets of the dataset's stock-period combinations are formed by the number of managers who trade in the stock-period and by the size rank of the stock. Each stock is allocated a size rank by market capitalization at the beginning of each period, with the largest stock having a rank of 1. H^{lsv} is the simple average of H_{it} across a subset of stock-periods of interest. The number of stock-periods in each subset is shown below the herding value.

Panel A. Number of managers trading in the period

	n≥2	**n≥5**	**n≥10**	**n≥15**	**n≥20**	**n≥25**
H^{lsv}(buy)	0.044	0.022	0.038	0.048	0.068	0.095
stock-periods	12,566	5,486	1,840	591	191	66
t-value	34.9	15.3	19.6	16.8	15.2	13.7
H^{lsv}(sell)	0.010	0.027	0.026	0.036	0.072	0.080
stock-periods	14,448	5,036	1,502	416	111	35
t-value	7.1	18.1	12.3	10.3	12.2	8.4
	2≤n<5	**5≤n<10**	**10≤n<15**	**15≤n<20**	**20≤n<25**	
H^{lsv}(buy)	0.060	0.014	0.033	0.039	0.053	
stock-periods	7,080	3,646	1,249	400	125	
t-value	26.7	7.3	13.2	10.6	9.3	
H^{lsv}(sell)	0.001	0.028	0.023	0.023	0.068	
stock-periods	9,412	3,534	1,086	305	76	
t-value	0.4	14.2	8.6	5.4	9.2	

Panel B. Size rank of stock

	r≤5	**r≤10**	**r≤20**	**r≤50**	**r≤100**
H^{lsv}(buy)	0.045	0.035	0.030	0.027	0.025
stock-periods	267	496	953	2,081	3,899
t-value	8.2	8.5	9.2	11.5	13.5
H^{lsv}(sell)	0.036	0.020	0.015	0.011	0.017
stock-periods	199	394	737	1,910	3,783
t-value	5.4	4.0	3.7	4.2	8.6
	r>100	**r>200**	**r>500**	**r>1000**	
H^{lsv}(buy)	0.052	0.063	0.087	0.121	
stock-periods	8,667	6,203	2,695	570	
t-value	27.6	26.7	22.5	13.5	
H^{lsv}(sell)	0.007	0.007	0.009	0.012	
stock-periods	10,665	7,828	3,309	677	
t-value	4.2	3.0	2.5	1.5	

Table V
Summary Statistics of Estimated LSV Sampling Distribution with Resampling Groups Formed by Period and Size

The sampling distribution of the LSV measure is empirically estimated and the summary statistics are reported here. Corresponding summary statistics are reported for subsets of the data that are formed on the basis of the number of managers trading in a stock-period and the size rank of the stock, where the largest stock by market capitalization has a rank of 1. The observations of trade direction for all the dataset's stock-period-manager combinations is divided into 15 groups by reporting period, which are then each divided into deciles by the log of the market capitalization of the stocks at the beginning of the period. In each of the resulting 150 groups the proportions of *buys*, *holds* and *sells* are the estimates of the probability of those outcomes in the trinomial distribution from which the observations in the group were drawn. A new dataset is created by replacing each observation with a draw (*buy, hold, sell*) from its estimated trinomial. 1000 such zero herding datasets are created and the LSV measure is applied to each dataset to build up an empirical estimate of the sampling distribution of the LSV measure under null conditions.

Panel A: Number of managers trading in the period

	$n \geq 2$	$n \geq 5$	$n \geq 10$	$n \geq 15$	$n \geq 20$	$n \geq 25$
Mean	0.001	0.002	0.003	0.006	0.010	0.011
Std Dev	0.001	0.002	0.002	0.006	0.005	0.012
95 pct	0.003	0.004	0.006	0.011	0.018	0.030
Stock-periods	28,826	9,632	2,626	664	169	31

	$2 \leq n < 5$	$5 \leq n < 10$	$10 \leq n < 15$	$15 \leq n < 20$	$20 \leq n < 25$
Mean	0.001	0.001	0.002	0.005	0.009
Std Dev	0.001	0.001	0.002	0.003	0.006
95 pct	0.003	0.003	0.006	0.011	0.019
Stock-periods	19,194	7,006	1,962	494	139

Panel B: Size rank of stock

	$r \leq 5$	$r \leq 10$	$r \leq 20$	$r \leq 50$	$r \leq 100$
Mean	0.006	0.005	0.006	0.003	0.002
Std Dev	0.004	0.003	0.002	0.002	0.001
95 pct	0.013	0.010	0.010	0.006	0.004
Stock-periods	443	871	1,703	4,137	8,071

	$r > 100$	$r > 200$	$r > 500$	$r > 1000$
Mean	0.001	0.001	0.001	0.001
Std Dev	0.001	0.002	0.003	0.007
95 pct	0.003	0.004	0.006	0.012
Stock-periods	20,753	14,266	5,340	1,046

Table VI
Summary Statistics of Estimated LSV Sampling Distribution with Resampling Groups formed by Period, Size and Initial Holding

The sampling distribution of the LSV measure is empirically estimated, where short selling is prohibited, and the summary statistics are reported here. Corresponding summary statistics are reported for subsets of the data that are formed on the basis of the number of managers trading in a stock-period and the size rank of the stock, where the largest stock by market capitalization has a rank of 1. The set of observations of trade direction for all the dataset's stock-period-manager combinations is divided into 15 groups by reporting period, which are then each divided into deciles by the log of the market capitalization of the stocks at the beginning of the period. Those groups are in turn divided into two groups by whether the manager's holding of the stock was positive or zero at the beginning of the period. In each of the resulting 300 groups the proportions of *buys*, *holds* and *sells* are the estimates of the probability of those outcomes in the trinomial distribution from which the observations in the group were drawn. A new dataset is created by replacing each observation with a draw (*buy, hold, sell*) from its estimated trinomial. 1000 such zero herding datasets are created and the LSV measure is applied to each dataset, and various subsets, to build up an empirical estimate of the sampling distribution of the LSV measure under null conditions.

Panel A. Number of managers trading in the period

	n≥2	**n≥5**	**n≥10**	**n≥15**	**n≥20**	**n≥25**
Mean	0.015	0.013	0.010	0.010	0.011	0.013
Std Dev	0.001	0.001	0.002	0.003	0.004	0.007
95 pct	0.017	0.015	0.013	0.015	0.018	0.025
Stock-periods	27,741	9,937	3,011	854	249	73

	2≤n<5	**5≤n<10**	**10≤n<15**	**15≤n<20**	**20≤n<25**
Mean	0.017	0.014	0.010	0.010	0.010
Std Dev	0.001	0.001	0.002	0.003	0.005
95 pct	0.019	0.016	0.013	0.016	0.020
Stock-periods	17,804	6,926	2156	605	176

Panel B. Size rank of stock

	r≤5	**r≤10**	**r≤20**	**r≤50**	**r≤100**
Mean	0.008	0.010	0.013	0.014	0.013
Std Dev	0.004	0.003	0.003	0.002	0.001
95 pct	0.015	0.016	0.017	0.016	0.015
Stock-periods	444	869	1,687	4,072	7,919

	r>100	**r>200**	**r>500**	**r>1000**
Mean	0.016	0.015	0.015	0.022
Std Dev	0.001	0.002	0.003	0.007
95 pct	0.019	0.018	0.019	0.033
Stock-periods	19,812	13,904	5,543	998

Table VII

Summary Statistics of LSV Sampling Distribution with Re-sampling from Trinomials Estimated by Logit Regression in each Period-Size-Initial Holding Group

The sampling distribution of the LSV measure is empirically estimated, under conditions of no short selling, but with variance in the propensity to buy across observations in a period. The summary statistics are reported here. Corresponding summary statistics are reported for subsets of the data that are formed on the basis of the number of managers trading in a stock-period and the size rank of the stock, where the largest stock by market capitalization has a rank of 1. The set of observations of trade direction for all the dataset's stock-period-manager combinations is divided into 15 groups by date, which are then each divided into deciles by the log of the market capitalization of the stocks at the beginning of the period. The first five deciles, roughly corresponding to the 100 largest stocks are then retained. The resulting groups of observations are each in turn divided into two groups by whether the manager's holding of the stock was positive or zero at the beginning of the period. In each of the 150 resulting groups a logit estimation of the following equations is undertaken. $X_{it}^{j} = \text{Const} + \sum_{q=1}^{4}\beta_q D_q + \sum_{j=1}^{J-1}\beta_j D_j + \varepsilon_{it}^{j}$ where $X_{it}^{j} \in \{buy, hold, sell\}$ is the trade direction of an observation in the particular group; D_q is a dummy variable that takes the value 1 if the size of manager *j's* initial holding in stock *i*, in period *t*, is in the q^{th} quintile of all non zero holdings of stock *i*, in period *t*; and D_j is a dummy variable taking the value 1 for observations of that manager's trades. The fitted values of the logit are the parameters of a trinomial for each individual stock-period-manager observation. A new dataset is created by replacing each observation with a draw (*buy, hold, sell*) from its estimated trinomial. 1000 such zero herding datasets are created and the LSV measure is applied to each dataset, and various subsets, to build up an empirical estimate of the sampling distribution of the LSV measure under null conditions.

Panel A. Number of managers trading in the period

	n≥2	n≥5	n≥10	n≥15	n≥20	n≥25
Mean	0.013	0.010	0.008	0.008	0.008	0.010
Std Dev	0.001	0.001	0.002	0.002	0.002	0.007
95 pct	0.015	0.012	0.011	0.012	0.015	0.021
Stock-periods	8,610	6,857	2,986	933	273	80

	2≤n<5	5≤n<10	10≤n<15	15≤n<20	20≤n<25
Mean	0.024	0.012	0.008	0.008	0.008
Std Dev	0.004	0.002	0.002	0.003	0.005
95 pct	0.030	0.015	0.011	0.013	0.016
Stock-periods	1,752	3,871	2,053	660	193

Panel B: Size rank of stock

	r≤5	r≤10	r≤20	r≤50	r≤100
Mean	0.004	0.006	0.010	0.012	0.012
Std Dev	0.004	0.003	0.002	0.002	0.001
95 pct	0.011	0.011	0.014	0.015	0.014
Stock-periods	444	870	1,695	4,112	8,027

Table VIII
Comparison of Measured Level of Herding and Estimated Sampling Distribution

The level of herding in the UK equity mutual fund dataset, H^{lsv}, is compared to the mean and 95th percentile of the empirically estimated sampling distribution of the LSV measure. The comparison is also made for subsets of the datasets which are formed on the basis of the number of managers trading in a stock-period and the size rank of stock. The H^{lsv} values are the measured values from the actual dataset as reported in Table II. The sampling mean and 95th percentile figures in Panels A and B are estimated with re-sampling from the logit estimate of trade direction trinomials as reported in Table VII. The corresponding data in Panel C are estimates based on re-sampling from simple period and size grouping as reported in Table VI

Panel A. Number of managers trading in the period

	n≥2	**n≥5**	**n≥10**	**n≥15**	**n≥20**	**n≥25**
H^{lsv}	0.026	0.025	0.033	0.043	0.069	0.090
95th percentile	0.015	0.012	0.011	0.012	0.015	0.021
Sampling mean	0.013	0.010	0.008	0.008	0.008	0.010
Adjusted H^{lsv}	0.013	0.014	0.025	0.035	0.061	0.080
	2≤n<5	**5≤n<10**	**10≤n<15**	**15≤n<20**	**20≤n<25**	
H^{lsv}	0.026	0.021	0.028	0.032	0.059	
95th percentile	0.030	0.015	0.011	0.013	0.016	
Sampling mean	0.024	0.012	0.008	0.008	0.008	
Adjusted H^{lsv}	0.003	0.009	0.020	0.024	0.051	

Panel B. Size rank of stock

	r≤5	**r≤10**	**r≤20**	**r≤50**	**r≤100**
H^{lsv}	0.041	0.028	0.023	0.020	0.021
95th percentile	0.011	0.011	0.014	0.015	0.014
Sampling mean	0.004	0.006	0.010	0.012	0.012
Adjusted H^{lsv}	0.037	0.022	0.013	0.008	0.009

Panel C. Size rank of stock

	r>100	**r>200**	**r>500**	**r>1000**
H^{lsv}	0.027	0.032	0.044	0.062
95th percentile	0.019	0.018	0.019	0.033
Sampling mean	0.016	0.015	0.015	0.022
Adjusted H^{lsv}	0.011	0.016	0.029	0.040