A Closer Examination of Investment Manager Herding Behavior

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Utilising a unique database of the daily trades of institutional investors, we re-examine herding behaviour from a new perspective. We find active managers herd more substantially when selling stocks, trading in small and growth stocks, and across industry sectors. Broker participation results in a much higher level of herding. Brokers pass their best, most timely information to their largest clients first, and later disseminate the information to smaller clients. Consequently, larger broker institutional clients not only trade before, but also outperform smaller clients. We find evidence of leader-follower relationships. Active managers tend to follow those managers with higher past performance.

I. Introduction

"Remember that it is far better to follow well than to lead indifferently."

John G. Vance

Institutional investing has undergone substantial growth over the past decade, and institutional investors increasingly play a larger role in determining security prices. Critics have sometimes viewed fund managers as "herds" that charge into stocks without adequate or appropriate fundamental information justifying such actions. "Herding" occurs when active fund managers intentionally imitate or mimic the actions of competitors.[1] The financial community and media have paid increasing attention to potential herding behavior since the development and the subsequent bursting of the technology bubble at the turn of the millennium.[2] Commentators argue that fund manager incentives, and the need to protect reputational capital, are important motivations behind herding activity (see Sampson (2002)). These suggest that fund manager trading behavior is associated with controlling business risk and preserving aggregate funds under management. This paper is concerned with an empirical analysis of herding activity using a fine granularity dataset of the daily transactions of institutional equity managers. It includes information about the trade identities of brokers who execute fund manager decisions.

Wermers (1999) outlines four general theories as to why institutional investors may engage in herding behavior:

1) Institutions are subject to reputational risk when they act differently from the crowd, thus they may ignore private information to trade with the herd (Scharfstein and Stein (1990)).
2) Managers may infer that competing managers hold private information (due to their prior trades), resulting in the formation of informational cascades (Banerjee (1992), Bikhchandani *et al.* (1992), Avery and Zemsky (1998)).
3) Institutions may receive similar private information because they examine the same priced factors, causing them to arrive at similar conclusions regarding individual stocks (Froot *et al.* (1992), Hirshleifer et al. (1994)).
4) Institutions may exhibit similar aversions to stocks exhibiting particular characteristics, such as low liquidity, or low visibility (i.e. low analyst coverage) (Falkenstein (1996)).

The first two theories explain herding or *intentional* herding as defined above. The subsequent two theories are examples of *spurious* or *unintentional* herding, i.e. commonality in trading behavior arises from commonality in information or risk preferences.

One must question whether it is possible for active managers with a desire to herd, to achieve this objective. Hong, Kubik and Stein (2003) analyse the word-of-mouth effect in relation to the trades and holdings of mutual fund managers, and find managers are more likely to hold (or buy, or sell) a particular stock if other managers who are located in the same city are holding (or buying, or selling) that same stock. They conclude that this activity is due to investors spreading information about stocks to one another by word-of-mouth. Managers may also observe the trades of others due to an information leakage by brokers or the managers themselves (particularly after that manager's trade package is completed (Froot *et al.* (1992)). This is particularly relevant for Australia with its high concentration of trades amongst the top five brokers.[3] Bartholomeusz (*Sydney Morning Herald*, 2003) suggests that brokers divulge broker ID information to institutional clients, which may assist mimicking behavior.

In contrast to anecdotes and popular opinion, academic literature finds little empirical evidence of herding, particularly after controlling for common momentum strategies (Grinblatt *et al.* (1995) and Wermers (1999)). This lack of strong evidence of herding may be due to data constraints, where measuring herding has only been possible by using quarterly holdings to infer trades.[4] Low data frequency also leads Lakonishok, Shleifer and Vishny (1992) and subsequent researchers to examine herding by focusing on contemporaneous relationship between portfolio weight changes across managers. Another limitation of previous studies is the inability to differentiate between intentional and spurious herding, casting doubt over the validity of previous findings of even a limited amount of herding.

This paper is the first to study herding using daily transaction and monthly portfolio holdings data from a representative sample of Australian equity fund managers. It provides a more thorough representation of active managers' actual trading activities. With daily transaction data, it is possible to focus on the lead-lag effect implied by herding, in addition examining the contemporaneous relationship between the trades of fund managers. We also propose a new herding measure, based on whether fund managers lead or follow the trades of competitors, which avoids problems associated with the Lakonishok, Shleifer and Vishny (1992) herding measure. This breaks down with the employment of finer observation windows, as it becomes less likely that managers engage in trading contemporaneously. Our analysis provides important new insights into whether the herding level documented by previous studies is either intentional, or spurious. Finally, we bring a new perspective to the herding literature by examining the role of brokers in information transfer between fund managers. This is only possible because we area able to identify the broker conducting each fund manager trade.

When employing quarterly positions to measure herding, we find an average herding level of 2.70. This means that if 100 funds were trading in a particular stock then almost three more funds would be trading the same security on the same side of the market than would otherwise be expected if all managers traded in a random and independent manner. This is comparable with the US market, with an average level of herding of 3.40 (Wermers (1999)). However, when monthly positions are used, the mean herding level falls to 1.39. This suggests that there is less evidence of herding when researchers take a closer look at investment manager behavior. Its potential cause is a bias that arises from the aggregation of trades across periods. We find more pronounced herding on the sell-side, and amongst small and growth stocks. This is consistent with previous US findings. Our evidence also shows that herding is much greater at an industry level. Fund managers find it easier to both observe and mimic competitors at this level. Our results also indicate herding is more likely during the month of an index change, due to the common front-running strategies undertaken by managers.

When the new measure of herding activity is employed, which permits a closer examination of herding from trade activity at weekly intervals; we find that high performing investment managers lead other managers (where the lag is between three and four weeks). Often it takes fund managers a prolonged period in order to complete their trade package (Chan and Lakonishok (1995)). Consequently, it is not surprising that active managers have a greater ability to imitate others following completion of a trade package (due to the lower need for secrecy). We identify particular managers as leaders or followers. We do not find much evidence that poor performing managers are more likely to follow the market consensus, which is otherwise consistent with the theoretical model of Zweibel (1995). Indeed, median managers herd as opposed to poor performing managers who desire to conceal a lack of skill. Our findings are also consistent with Brown *et al.* (1996), who show that mid-year losers are more likely to deviate or increase risk, in order to increase the chance of performing well in a tournament environment where winners are highly rewarded.

We calculate the level of herding among active managers sharing the same brokers and find highly elevated levels of herding, providing evidence that there is either a significant leakage of information by brokers, or that information originating with brokers is passed on to multiple fund managers, resulting in commonality in trading. Brokers may pass either vague or non-specific information concerning the trades of clients in order to generate higher brokerage from trades. This activity is in line with recent research by Hong and Kubik (2003), who show that the rewards for broking analysts are for trade generation by promoting stocks rather than the accuracy of their predictions. These analyst's predictions have significantly positive predictive ability (Barber *et al.* 2001), where fund managers earn superior returns following analyst recommendations. We find that the higher trade value (more important) clients of brokers tend to lead the lower trade value (less important) clients, suggesting that brokers communicate their best and most timely information to larger clients first, and later disseminate information to smaller and less profitable clients. We demonstrate that these larger clients also generate higher returns for institutional investors, indicating that for the major clients at least, broker recommendations add value.

The remainder of this paper is organised as follows. Section I describes the data and the research design. Section III presents the empirical results. Finally, we conclude the paper and outline some suggestions for future research.

II. Data

A. Description of Databases

Data relating to investment manager trades has been scarce due to their highly sensitive and confidential nature. Prior studies employ U.S. fund managers' mandatory filings of quarterly portfolio holdings of in each period as a crude basis to infer trades. This is the first study, to our knowledge, that utilises actual daily trading data of active investment managers. Our sample comprises 30 active equity managers, sourced from the *Portfolio Analytics Database*. Individual managers provide daily trades' data and monthly holdings, together with identification of the broker, under strict confidentiality conditions. The period of this study is 2 January 1994 to 31 December 2001.

Construction of the database occurred on an invitation basis to the largest active[5] investment managers operating in Australia, based on total funds under management. We asked the investment managers to provide portfolio information for their largest[6] two institutional active Australian equities funds. For this study, 38 funds comprise the total sample, with benchmarking occurring against either the S&P/ASX200 or S&P/ASX300 accumulation indices.[7] This database provides a sample that is representative of the investment management industry and includes six of the largest ten managers, six from the next ten, four from those managers ranked 21-30 and 14 managers from outside the largest 30 (measured by funds under management as at 31 December 2001). The sample includes six boutique firms, which manage less than $A100m each.

Due to the data collection procedure, we need to assess data issues such as survivorship and selection bias. Funds have been included in the database only where they have continued to survive through until the collection date. Consequently, only data from 'successful funds' is included, hence potentially overstating performance. Similarly, selection bias may also be present, in that it is possible that managers who contributed data were generally more successful than non-contributors were. Studies including Grinblatt *et al.* (1995) show that funds that engage in herding tend to earn higher returns, thus, these biases may also overstate the level of herding. However, we have the opportunity to gain insight into these possible effects by comparing the fund returns of managers in our study relative to the returns for the population of investment managers (including non-surviving funds), sourced from Mercer Investment Consulting Manager Performance Analytics (MPA) database. Over the period of our study, the average manager across the entire industry outperformed the ASX 200 by 1.78 percent, with a standard deviation of 1.39 percent. The mean manager in our sample group outperformed the industry average by 0.35 percent.[8] The level of out performance for our sample is small compared with the performance dispersion of the industry, therefore we can conclude that survivorship and selection bias are unlikely to be significant problems for our study.

A number of funds in the sample invest in derivative securities. We calculate the effective exposures of options using the method outlined by Pinnuck (2003), where we calculate the delta of the option following the Black-Scholes option pricing model. We then add the effective exposures to the stock holdings value. We ignore index options and futures, as they do not affect the preference of the manager for particular stocks. Previous U.S. studies relying on portfolio holdings have been unable to adjust for options exposures due to the SEC 13F filings only requiring data on stock holdings. However, accounting for option exposures allows for a more accurate measure of portfolio holdings of investment managers.

In Table 1, Panel A, we present descriptive statistics for the monthly holdings on the *Portfolio Analytics Database*. In Panel B, the sample relating to fund sizes exhibits high variability, with a large number of small funds, but a concentration of investor assets amongst the largest few funds. Panel C shows the average number of stocks held by each fund is approximately 60. Consequently, funds in general would hold (and be overweight in) the largest stocks, but not a large number of small stocks. Panel D reveals that the active equity managers hold over 95 percent of portfolio assets in equities. In Table 1, Panel B, we present statistics for the daily trades. These display the number of buy and sell trades and the average size of these trades, as well as other statistics. In general, managers seem to engage in more buying than selling, consistent with growth in the level of investment funds under management.

(INSERT TABLE 1)

We supplement our database with stock price data sourced from the ASX Stock Exchange Automated Trading System (SEATS) in order to ensure pricing consistency. SEATS contains all trade information for stocks listed on the ASX, as well as stock specific data such as industry classification, market capitalisation, as well as public earnings announcements contained in the ASX Signal G Database. Index changes to the S&P/ASX 300 Index are also located in the SEATS Database.

B. Descriptive Statistics of the Australian Market

The Australian market is both small and developed, and provides a unique environment for examining herding activity. This is primarily due to the concentrated nature of both (a) stocks listed on the Australian Stock Exchange as well as (b) investment manager funds under management. The largest ten investment managers hold 58 percent of total assets under management ($A399.9 billion of $A688.9 billion). In terms of investments in Australian equities, there is a very pronounced level of concentration, where the largest ten investment managers control 69 percent of the total Australia equity assets. Statistics from ASSIRT (March 2002) are provided in Appendix A.

There is also a high level of concentration amongst stocks in the S&P/ASX300. The largest ten (fifty) stocks account for 48 percent (82 percent) of the index. We present the level of concentration, across both stocks and investment managers, in Figure 1.

(INSERT FIGURE 1)

This higher level of concentration in the Australian market may lead to a reduced level of herding. Active investment managers are required to hold a higher proportion of total funds in similar (cross-held) stocks. Institutional investors also trade more frequently than the average investor does. Thus in a concentrated market, managers are more likely to trade with fellow investment managers, reducing the level of herding that is possible. Intuitively, if the funds in our sample were to make up 100% of the market, then no herding could be possible, as for each buyer; there must also be a seller. Broker activity in Australia is also concentrated amongst the largest firms, leading to a convergence in information flow as the trades of competing managers are slowly revealed (whether intentionally or not) by the brokers employed.

III. Research Design

This study commences using the research design employed by previous studies to measure herding behavior by investment managers over a monthly and quarterly interval. For robustness, we also employ the measure of Sias (2004); however, we do not report these results. These traditional methodologies are not appropriate for higher frequency data. We develop a new measure that provides a different insight into herding behavior by observing whether leader-follower relationships are present and persistent across time.

A. LSV Measure

The fundamental research design employed by this study is the measure devised by Lakonishok, Shleifer and Vishny (1992) (hereafter LSV). We express the Herding Measure, $H_{i,t}$, (where i denotes stocks and t denotes periods) as follows:

$$(1) \qquad H_{i,t} = |p_{i,t} - E[p_{i,t}]| - E[|p_{i,t} - E[p_{i,t}]|],$$

where $p_{i,t}$ is the proportion of managers who had a net purchase in stock i during period t, and we only calculate $H_{i,t}$ for periods when five or more managers are trading in the same stock. For robustness, we calculate the level of herding using alternative minimum numbers of managers, yielding similar results (Appendix C). $E[p_{i,t}]$ is proxied by p_t, the proportion of all trades that are buys during period t, thereby staying constant across stocks, and changing only over time. This controls for market-wide net fund flows driving purchase decisions. The adjustment factor $E[|p_{i,t} - p_t|]$ is subtracted to account for random variation around the expected proportion of buyers under the assumption of independent trading decisions by investment managers. We employ a binomial distribution to calculate this factor. This herding measure computes the proportion of managers trading on one side of the market, above the random proportion. Values of $H_{i,t}$ that are significantly different from zero indicate evidence of herding behavior.

We divide this herding measure into buy-side herding (BH_{it}) and sell-side herding (SH_{it}), (that is, when more managers are buying (selling) than the average proportion of managers), expressed as:

(2) $$BH_{i,t} = H_{i,t} \mid p_{i,t} > E[p_{i,t}]$$

(3) $$SH_{i,t} = H_{i,t} \mid p_{i,t} < E[p_{i,t}]$$

Do certain managers with particular size and style characteristics herd more? To address these issues we also calculate the measure for a subset of funds with different size, investment styles, and during particular periods. Consequently our sample of 38 funds is equally divided into large and small managers, and also divided into two categories according to self-stated investment style (growth (four managers) and growth-at-a-reasonable-price (GARP) (12) are combined and compared to value managers (12)).

In order to measure the effect of various stock characteristics, the securities are partitioned into quintiles for size (market capitalisation), book-to-market ratio, earnings yield (earnings per share divided by market capitalisation), and momentum (prior six month return , following Jegadeesh and Titman (2001)). We calculate quintiles for book-to-market, earnings yield and momentum based on the largest 300 stocks, which account for over 90 percent of the total market capitalisation on ASX due to the concentration of trades executed in the largest stocks,. This provides an appropriate partitioning of stocks traded by investment managers, given that smaller and less liquid stocks are therefore not able to bias the composition of the quintiles. The size quintiles also balance the trading activities engaged in by the managers, where the largest 30 stocks comprise the first group, stocks 31-70 in the second group, the third group accounting for stocks ranked 71-120, the fourth group with stocks ranked 121-200 and, lastly, stocks greater than 200 represented in quintile five. This also resulted in a more balanced partitioning of trades amongst the five partitions.

Does herding occur more when measured in the context of industries rather than individual stocks? We aggregate the holdings in stocks of the same industry to determine the weight of the manager's portfolio in specific industries. If the manager's weight increases (decreases) in an industry, we conclude that the manager is a net buyer (seller) in that industry. Using the LSV measure, we then determine whether investment managers are herding at an industry level.[9] We also compute the LSV herding measure for the months when a firm makes an earnings announcement, when there is an index change in the S&P/ASX300 and during particular months of the year.

B. Alternative Measures of Herding

To take advantage of the finer granularity of the data this study also develops an alternative research design in order to measure leader-follower relationships. Firstly, in order to test whether brokers pass their best information to their largest clients before later disseminating the information to smaller (less profitable) clients, we rank each manager, in terms of dollar value of trades per quarter, for the largest six brokers[10], yielding a rank of importance. Next, during the months in which five or more managers traded using the same broker, we rank the managers in terms of the order in which they trade. We also rank managers by size (measured in terms of funds under management), since larger managers may have greater research capabilities and thus lead the trades of smaller managers. To determine whether more important managers for each individual broker follow less valuable managers, the order of trade rank (OTR) is regressed against the manager size rank variable (MS)[11], and the rank of importance (IR), where *a* denotes the individual manager, z is the specific broker and *t* is the time period:

(4) $$\mathrm{O}TR_{\mathrm{a,z,t}} = \beta_0 + \beta_1 \mathrm{M}S_{\mathrm{a,t}} + \beta_2 \mathrm{IR}_{\mathrm{a,z,t}} + \varepsilon_{\mathrm{a,t}}$$

Secondly, to test whether managers regarded as important to brokers generate higher returns, we regress a manager performance rank (where the highest performing managers over the prior three months receive the highest ranks, MPR) against the importance and size ranks.

(5) $$MPR_{\mathrm{a,t}} = \beta_0 + \beta_1 \mathrm{M}S_{\mathrm{a,t}} + \beta_2 \mathrm{IR}_{\mathrm{a,t}} + \varepsilon_{\mathrm{a,t}}$$

Thirdly, we analyse all the manager trades to determine if some managers were consistent leaders or followers. For each manager (denoted by *a*) the trades in a specific stock made in a certain period (week, fortnight, month or quarter (denoted by *t*)) are aggregated and then divided by the manager's holding in that stock at the beginning of the period.[12]

(6) $$\text{Proportional Trade}_{\mathrm{a,t}} = \frac{\sum (aggregated\_trades_{a,t})}{holding_{a,t-1}}$$

We rank stocks in deciles based on this measure. This means that we give stocks with the largest positive (negative) proportional change a ranking of ten (one).[13] We then calculate the average rank of all managers (except the manager being analysed) in each stock during each period. We also compute the correlation of individual manager ranks against the lagged, contemporaneous, and future average ranks of other managers to determine if specific managers follow or led the actions of competitors:

(7) $$\rho_{a,t,m} = Correl(Rank_{a,t}, AvgManagerRank_{-a,t-m})$$

where $m < 0$ for future average ranks, $m = 0$ for contemporaneous average ranks and $m > 0$ for lagged average ranks. We calculate this correlation across stocks for each time period, so that the proportion of a certain manager's trades, predicted by the trades of competing managers, can be determined.[14]

Intuitively, investment managers with little or no skill are more likely to imitate the actions of successful competitors. Therefore, we regress manager correlations against the prior three monthly relative returns as follows:

(8) $$\rho_{a,t,m} = \beta_m * r_{a,t} + \varepsilon_{a,t}$$

where $r_{a,t}$ = Manager Return – Average Manager Return during the prior three months

The beta estimates are analysed to ascertain the relationship between managers' prior performance and herding activity. This methodology extends the research design of LSV, enabling the identification of managers that lead or follow the actions of competitors, in addition to an analysis of whether these managers trade together.

IV. Empirical Results

A. Overall Levels of Investment Manager Herding

In Table 2 we present the overall levels of herding using the LSV measure.[15] The overall level of herding calculated using monthly holdings is 1.39 percent, indicating that if 100 funds are trading in a particular stock, then approximately one more funds would be trading on the same side of the market than would be expected if all managers traded in a random and independent manner. The scores for buy-side and sell-side herding are 0.95 percent and 1.85 percent, respectively. This indicates that managers display greater levels of herding when selling. This is consistent with the findings of Wermers (1999), but is in contrast to the findings of Grinblatt *et al.* (1995) who found greater levels of herding on the buy-side. This suggests that active managers are more likely to sell rather than buy in herds. This result may be due to active managers having a greater propensity to imitate competitors when they are concerned about a fall in a stock's price, or that active managers adopt strategies on the sell side with persistent timing differences.

(INSERT TABLE 2)

B. Comparison with Results using Quarterly and Monthly Portfolio Holdings

In previous studies, such as Lakonishok *et al.* (1992) and Grinblatt *et al.* (1995), the level of herding activity is calculated using inferred trades from the quarterly portfolio holdings of U.S. mutual fund managers. Wermers (1999) completes the most detailed study of herding using this measure and finds the level of herding to be 3.40 percent. In Panel A of Table 2, the level of herding calculated in this study using quarterly portfolio positions is 2.70 percent. The difference may be sample and/or time period specific, or due to different factors (such as the high level of stock and manager concentration) affecting the Australian market. When the interval is considered over monthly periods, our paper shows the level of herding is lower (1.39 percent) than at quarterly snapshots. The differential may arise due to a divergence in manager behavior when measured over a shorter time period. However, when we aggregate trades over a longer time period, it is harder to identify differences in the trading behavior of managers. This reveals the likely aggregation error caused when using quarterly rather than monthly portfolio holdings to infer trades.

C. Herding Partitioned by Stock Characteristics

In order to investigate the potential drivers of herding activity engaged in by institutional investors, we examine the level of herding in subgroups of stocks exhibiting certain characteristics. We study factors such as size (proxied by market capitalisation), book to market ratio, earnings yield and momentum (proxied by six month prior return) so that we can determine whether synchronous trading is associated with risk factors that have been well documented in the literature. Stocks are divided into quintiles based on these characteristics (as explained in the research design), and the results for each characteristic are presented in Panels B-E of Table 2. We present averages for the herding measure for each partition, including the averages for both buy and sell-side herding.

Most theories predict that herding is greater amongst small growth stocks, as the precision of information concerning these stocks is likely to be lower (Wermers (1999)). Consequently, active managers are more likely to acquire information by observing the actions of competing managers. In support of these theories, our most compelling evidence of herding occurs in Panel B in the sell-side of the S1 category (10.02). This indicates that managers are more likely to follow the consensus when there seems to be a flight from the smallest category of stocks.

The book-to-market ratio for stocks proxy the degree to which a stock's value relates to its current tangible assets, compared to its future growth potential (Panel C). Accordingly, growth (value) stocks have a low (high) book-to-market ratio, indicating a large (small) percentage of firm value is due to that firm's growth potential. The book-to-market factor is clearly important. Fortunately, managers do classify their investment process in a manner that enables investors to predict likely style biases in portfolios. The level of herding is more severe in the lowest quintile, which may be due to the lower levels of transparency and surety in terms of information relating to high growth stocks. Our findings for our earnings yield quintiles (Panel D) also support this result.

The past return of stocks (i.e. price momentum) appears not to significantly affect the level of herding. This is in contrast to previous studies, which found that managers herded into momentum stocks. This could be due to Australia having a less pronounced momentum effect.

D. Herding Partitioned by Investment Manager Characteristics

Particular manager characteristics, such as investment manager size or style may also influence the level of herding. Sawicki (2000) presents Australian evidence showing that fund flows relate to past performance. Given the significance of the performance-flow relationship, as well as evidence that money flows for poor performers is relatively ‘sticky’, it follows that managers with good past returns should experience fund inflows, and that poor performers experience fund outflows. Depending on the relative size of funds under management, as well as the fact that managers understand the relationship between fund size and fund profitability, it follows that managers will seek to maximise fund size. Our analysis examines herding behavior with respect to fund size, given the potential differences in behavior. However, by partitioning the sample into large and small manager categories in Table 3, the herding level is similar for both large and small managers.

(INSERT TABLE 3)

In Table 3, we also partition managers into growth, growth at a reasonable price (GARP), value, style neutral and other. These are determined on the self-stated classifications provided by the managers. We combine the growth and GARP managers to compare with value managers. Our results of elevated levels of herding show that managers tend to mimic the strategies of other managers with similar strategies. This lends support to the reputational argument for herding. Appendix B (Panels B-E) presents a three-way classification of herding, which we partition by manager size and style, stock characteristics, and trade direction (i.e., buy and sell-side). These results are generally consistent with Table 2, although due to the small sample size in the lowest categories, we cannot make strong statistical inferences from the results.

E. Herding During Specific Periods of the Year

The literature has previously been unable to observe particular periods when the inclination for active managers to trade together is the strongest. The finer granularity of our dataset enables us to provide valuable new insights into investment manager trading activities, and the motivations that might lead them to herd. Earnings announcements (which greatly affect stock price movement, Ederington and Lee (1993)) are one such example, as managers are able to observe the actions of other managers in response to a particular announcement by observing their trading activity. It is likely that trades by managers following such announcements are due to information-based reasons. Therefore, this period allows an enhanced study of information based herding. We present results for this period in Panel A of Table 4, showing that the level of herding is no greater for this period. These results provide no evidence that active managers herd for informational reasons, in contrast to the predictions of theoretical research.

(INSERT TABLE 4)

During index changes, active managers who engage in ‘front running’ may also experience commonality in trading.[16] An abnormal positive (negative) return occurs after an index inclusion (exclusion) from the index (Harris and Gurel (1986) and Beneish and Whaley (2002)). By purchasing (selling) stocks that are about to be or have just have been included in (excluded from) the index, managers can make short-term gains from index managers who are forced, (by mandates dictating replication of the index) to purchase (sell) these newly included (excluded) stocks (Chan and Howard (2002)). In Panel B of Table 4, the level of herding in the month of index changes is substantially higher at 17.75 percent, showing that managers do engage in similar strategies during these periods. However, this represents an example of spurious herding, as managers are not necessarily imitating others but are only being responsive to changes in index constituents. These results show the importance of clearly specifying periods when commonality in trading is likely to arise, and not necessarily the result of true herding behavior.

The calendar or financial year-end is a prospective time for herding, due to managers engaging in common strategies during those periods, such as window dressing (Haugen and Lakonishok (1988)) or tax-loss selling.[17] However, Panels C and D of Table 4 show that the levels of herding during the months of December, January, June and July are not substantially greater than average.

F. Industry Herding

It may be easier for managers to both observe and mimic the strategies of competitors at an industry rather than an individual stock level. Intuitively, in the case of smaller and illiquid stocks, herding in sectors would provide a better measure of the true level of herding. For example, if one manager is to purchase a large quantity of stock in a small firm, then it may not be practically possible for other managers to mimic exactly this strategy, however, by purchasing another small firm, following managers are able to expose themselves to similar factors affecting the first manager. In Panel E of Table 4, the average level of herding calculated across industries is 6.16. In this measure, if a manager increases (decreases) the weight of the portfolio in a particular industry, the manager has therefore purchased (sold) stocks within that industry. This is substantially more than the level of herding documented when herding is measured according to individual stocks (1.39), indicating that managers exhibit a higher propensity to herd at the industry level. However, this may be due to the aggregation of trading within narrower boundaries, or, alternatively, that fund managers can more easily identify and/or imitate the actions of competitors at this level.

G. Herding due to Broker Involvement

We present the level of herding calculated for trades completed by the six most active (or frequently used) brokers[18] in Table 5. The average LSV herding measure is 16.86, which is far greater than the general level of herding. This provides evidence that broker activity creates a significant level of commonality in behavior.

(INSERT TABLE 5)

Three explanations are possible. Firstly, fund managers may receive broker IDs attached to trades and copy the trades of other large clients of their own broker. They might also copy the trades of large clients of other brokers, but we would not pick this up in our measure of broker-client herding unless the manager places his copycat trades with these other brokers. It is not obvious why they would mainly want to copy trades of other clients of their own broker. Hence, this very indirect means of communication via display of broker IDs is not very likely. Secondly, brokers may pass either vague or non-specific information concerning the trades of clients to others in order to generate higher trade volume and increased brokerage commissions. This follows Hong and Kubik (2003) who show that rewards for broker analysts occur for trade generation rather than for the accuracy of recommendations. Thirdly, and perhaps most plausibly, brokers may provide similar information to their clients, which may lead to similar trading decisions. These analyst recommendations have significantly positive predictive ability (Barber *et al.* 2001), so managers can earn superior returns by following broker recommendations. This is consistent with the findings of Sias (2004) who shows that managers herd for informational reasons and that these trading decisions positively relate to future returns.[19]

We expect brokers to provide their best information to their largest clients first, given the profit motive, and later disseminate the information to smaller clients. This is consistent with the finding by Aitken *et al.* (1995) that Australian brokers provide upstairs facilitation for large, long-term clients but charge them more for agency trades. Higher brokerage fees are a means of rewarding superior brokerage recommendations, as well as better trade execution. In order to test this, we regress the order that trades are completed (OTR) with the same broker against the importance of the manager to the broker (where the importance of a manager is measured by the quantity of trades completed by the broker on behalf of the manager, IR).[20] We find significant results where less profitable managers indeed follow the trades of more important (i.e., profitable to the broker) managers using the same broker, where the coefficient on the importance rank is 0.0076 (which is significant at the 1% level, *t*-statistics are presented in parentheses). We include an additional variable to ascertain whether it is the larger managers that move first (MS, calculated by ranking managers based on funds under management), rather than those managers who receive broker information. The results show the MS variable is also statistically significant, even though the overall explanatory power of the regression is low.[21] We conclude that, as expected, larger managers, transact before smaller managers, after accounting for the manager's level of importance to their brokers:

(4) $$OTR_{a,z,t} = 3.3531 + 0.0034 * MS_{a,t} + 0.0076 * IR_{a,z,t} + \varepsilon_{a,t}$$

(101.14) (4.54) (5.58) (Sample size = 26,212; R^2 = 0.002)

Intuitively, trading first should have a positive influence on an investment manager's performance if the information conveyed by the broker is of value. In order to test this, we regress calendar year manager performance (expressed as a rank compared with other managers, MPR) against the manager's average importance rank with the six largest brokers. We also include a manager-size-rank variable (MS) in order to control for the potential effect of manager size upon performance. We find significant results with a positive beta of 0.6975 for the Importance Rank Variable (IR) which is significant at the 1% level (sample size=312). Consequently, we conclude that managers regarded as important by their brokers in terms of generating larger brokerage commission, yield higher returns for fund investors. Moreover, conditional on broker importance, smaller managers outperform larger managers:

(5) $$MPR_{a,t} = 15.5906 - 0.2096 * MS_{a,t} + 0.6975 * IR_{a,t} + \varepsilon_{a,t}.$$
(18.30) (-5.82) (5.35) (Sample size = 378; R^2 = 0.11)

In Appendix D, we calculate the general level of herding after excluding periods of spurious herding (periods when five managers trade using the same broker and when there are index changes). We find herding is reduced but significant at 1.03, leaving our conclusions unchanged.

H. Leader-Follower Relationships

Table 6 presents the correlations for the largest 50 stocks against the average equity manager.[22] Quarterly, monthly, fortnightly, and weekly periods are indicated in Panels A, B, C, and D, respectively. The data suggests some managers are more likely to be either leaders or followers. For example, the data suggests manager 19 is a follower, as his proportional trades positively correlates with to that of the lagged average manager. In addition, manager 19's lagged proportional trades negatively correlates with the average manager. Therefore, when competing managers' trade, this manager generally makes the same trades in future periods. However, after the manager trades, the consensus appears to do the opposite, suggesting the manager is not a leader. This holds for quarterly, monthly, fortnightly, and weekly positions. Manager 23's trades seem to be highly correlated with the trades of other managers, but does not identify as either a leader or a follower, due to a high correlation for both leads and lags. There is strong evidence that this manager engages in herding behavior, shown by the high correlation at zero lags for all periods of accumulation. Manager 30's trades have low correlations, with even negative correlations at various lags. This shows that manager 30 does not seem to herd. In aggregate, the results suggest that some managers are more likely to lead, herd with, or follow competing managers. However, this does not provide conclusive evidence of herding, as these relationships may be coincidental or spurious.

(INSERT TABLE 6)

We would expect active managers to be more likely to imitate the trades of more successful rivals. In order to test this hypothesis, we perform a regression on these correlations against the prior three-month relative return of the active managers in our sample. Intuitively, the prior relative return should positively correlate with the leader correlations, and should negatively relate to the follower correlations. This is because others are more likely to mimic managers who performed well in the past three months, and managers who performed poorly are more likely to imitate the strategies of their more successful competitors. We present the results for the regression in Table 7. They provide significant evidence that this proposition is indeed the case. Using fortnightly and weekly-accumulated (packaged) trades in Panels C and D, the coefficients for leaders are significant at the one and two lag level for fortnightly trades, and at the three and four lag level for weekly trades.

(INSERT TABLE 7)

Two explanations are possible for these results. Firstly, Gallagher and Looi (2003) show that completion occurs for almost 42 percent of the value of manager trades within two to ten days of the start of the trade package. After this period, details of the trade package are more likely to be passed on to other managers by the manager themselves (following the intuition of Froot *et al.* (1992) who propose that managers require rival managers to possess similar information in order to profit from their trades). Alternatively, given the role that brokers play in terms of influencing the behavior of fund managers, our results could indicate that brokers pass information to larger clients far sooner than smaller clients. The delay could be as long as three weeks. Consequently, other active managers are more likely to imitate the strategies of the leader after a period of two-to-three weeks. This suggests that active managers who perform well in the prior three months are more likely to lead other managers.

When the follower correlations are analysed, there is almost no evidence to suggest that managers who perform poorly are more likely to imitate the consensus. The coefficient at three lags for the weekly interval is significant at the ten percent level, but there is no support from unreported results for the largest 20 stocks. This is consistent with two explanations: Zweibel (1995) argues that it is median managers, in terms of performance, who should herd. Moreover, poorly performing managers would intentionally deviate from the benchmark to conceal skill deficiency. Brown *et al.* (1996) propose that poor performing managers at mid-year will increase volatility in order to maximise the probability of achieving a better tournament outcome. Neither of these two models predicts a negative relationship between past return and the level of herding.[23] These measures cannot prove conclusively whether managers herd, as two conclusions are possible: Firstly, low-performing managers have less skill and thus seem to imitate high-performing managers. However, they might just receive information late and thus trading later, or react more slowly to the information they do receive. Another possibility is that both higher-performing and average fund managers implement momentum strategies, such that stocks that they purchase stocks that have appreciated in price, and sell those that have depreciated. However, more skilful (or highly performing) fund managers react more quickly to these price changes and earn a higher return.

V. Conclusions and Suggestions for Future Research

Using traditional measures to identify common trading behavior, this study supports previous research showing evidence of active manager herding behavior. We find stronger evidence for herding on the sell-side, which might be due to active managers being more likely to imitate others when concerned about a fall in the stock price. Managers might also adopt sell-side strategies with persistent timing differences, or the concentrated nature of the Australian market explains the strength of the sell-side phenomena. We also find that fund manager herding is more prevalent among small and growth stocks, where these stocks exhibit lower levels of information transparency, as well as more concentrated share ownership by institutions. We also identify higher levels of herding when measured across industry sectors, due to the aggregated nature of observing and/or imitating the actions of competing managers at the sector level.

We contribute by showing how information flows between brokers and investment managers facilitates herding. This is due to our ability to identify the brokers utilized by each investment manager. Managers that execute trades using the same broker are far more likely to herd. Brokers revealing either vague or non-specific information concerning the trades of the clients could cause this. Our results, to the contrary, reveal that brokers communicate their best information to their most valuable clients (in terms of market value of securities traded), and later disseminate this information to remaining clients. As a result, managers that make a lower contribution to broker revenue follow the trades of those investment managers that execute larger orders. In addition, we find clients who are more valuable to brokers obtain higher investment returns on behalf of fund investors. The most active managers, who contribute the greatest brokerage revenue, outperform managers who provide their broker with less business. We show that valuable broker research is bundled with trading fees paid by fund managers. This method of paying for broker research promotes both herding due to broker commonality and active trading by managers.

Our utilization of daily trading behavior for the first time enables a closer examination of herding behavior, and provides evidence that active funds follow the trades of better performing managers (at an interval of approximately three weeks). Since managers, particularly large managers, require up to a few weeks in order to complete a trade package (Chan and Lakonishok, 1995), this elevated level of mimicking could result from a lower concern for secrecy after a trade package is completed. Our findings also identify certain managers as being leaders or followers and others as having a higher level of general herding. These findings support previous U.S. research, as well as media commentary suggesting managers mimic one another's behavior. The effect of this behavior on markets, whether destabilising or in fact speeding the price discovery process, is unknown and represents an important area available for future research. Consequently, regulators will wish to know whether herding leads to market destabilisation, and if so, the appropriate regulatory adjustments which might need to be implemented to avoid such problems.

An important caveat is the inability to prove conclusively that active managers consciously engage in trade imitation strategies. Further analysis of information signals is required to be able to say unequivocally that leader-follower activity is genuine herding. For example, the existence of leader-follower relationships does not rule out the possibility that one fund manager is systematically faster at processing public information signals than other managers that simply appear to be herding. Future research should also examine leader-follower relationships with respect to the investment style of managers as well as the characteristics of individual stocks affected. It may be possible to discover whether value (growth) managers lead in value (growth) stocks. It may also be possible to discover whether managers follow competitors that also implement the same investment style.

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Table 1

Descriptive Statistics on the Portfolio Analytics Database

Panel A – Holdings Database

	1994	1995	1996	1997	1998	1999	2000	2001
Panel A1: No. of Funds								
As at End of Year	10	12	15	19	26	29	36	36
Panel A2: Fund Size								
Average ($millions)	146.7	164.4	281.9	339.4	380.0	493.4	544.4	645.1
Standard Deviation ($millions)	235.4	244.6	339.2	412.6	515.0	651.6	796.3	990.8
Median ($millions)	49.7	52.6	72.2	167.9	212.4	257.4	171.4	235.6
Minimum ($millions)	0.5	1.8	3.4	7.6	7.1	6.3	14.4	19.0
Maximum ($millions)	775.5	837.3	985.7	1307.0	1725.7	2286.8	3134.5	4721.3
Panel A3: No. Stocks Held per Fund								
Average	70.1	59.6	52.9	54.2	56.6	59.0	60.1	58.8
Standard Deviation	49.3	37.6	24.6	29.2	29.7	27.0	29.8	26.8
Median	50.0	49.5	43.0	45.0	50.5	54.0	54.0	54.0
Minimum	24.0	18.0	19.0	19.0	22.0	18.0	28.0	28.0
Maximum	176.0	140.0	109.0	122.0	128.0	122.0	143.0	155.0
Panel A4: Composition of Portfolio								
Equity (%)	95.84	95.82	96.41	96.86	96.19	97.16	96.82	97.02
Cash (%)	1.87	3.21	1.50	1.24	0.79	1.21	1.09	1.19
Futures (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Options (%)	0.00	0.00	0.00	0.00	0.02	0.01	0.01	0.01
Other (%)	2.29	0.98	2.10	1.90	3.00	1.61	2.08	1.78

Panel B – Trades Database

Daily Trade Statistics	**Total**	**Mean**	**Std. Dev**	**Median**
Dollar Value of all buy trades ($A millions)	10,623	272	493	60
Dollar Value of all sell trades ($A millions)	8,716	224	431	54
Number of buy trades	65,656	1,684	1,768	959
Number of sell trades	47,424	1,216	1,487	664
Number of securities traded		153	97	123
Number of securities traded per week		12	9	11
Average buy size ($ thousands)		250	627	63
Average sell size ($ thousands)		236	540	75
Turnover ($ thousands)		681	963	231
Percentage of trades that are buys		60.18	9.31	57.83

This table provides descriptive statistics on the Portfolio Analytics Database for the period 2 January 1994 to 31 December 2001. Panel A contains statistics for the monthly holdings, with end of year figures. The 'other' category contains assets such as warrants, convertible notes, and floating rate notes. We exclude these securities due to the small size of these securities in the portfolios; their omission would not significantly affect our findings. Panel B contains statistics for the daily trades.

Table 2
Comparison of LSV Herding Measure at Monthly and Quarterly Intervals

		Total			Buy Herding			Sell Herding			Total			Buy Herding			Sell Herding	
	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat
Panel A: Total					**Monthly Intervals**									**Quarterly Intervals**				
Total	1.39	4,649	8.25	0.95	2,400	4.41	1.85	2,249	7.13	2.70	2,425	10.98	2.26	1,254	7.34	3.17	1,171	8.18
Panel B: Size																		
S1 (small, stocks 200+)	5.91	210	5.39	3.01	123	2.49	10.02	87	5.15	8.36	178	5.39	3.01	162	2.49	10.02	157	5.15
S2 (stocks 121-200)	2.75	274	3.35	0.46	154	0.46	5.70	120	4.23	2.75	212	3.35	2.23	108	1.80	4.70	104	3.12
S3 (stocks 71-120)	0.95	732	2.20	0.54	376	0.93	1.38	356	2.14	0.95	445	2.20	1.94	231	2.46	2.02	214	2.34
S4 (stocks 31-70)	0.57	1,535	2.03	0.67	736	1.72	0.48	799	1.19	1.95	754	4.81	1.70	380	3.15	2.21	374	3.64
S5 (large, stocks 1-30)	1.38	1,636	5.36	0.99	875	3.13	1.83	761	4.28	1.99	650	4.89	2.56	350	5.02	1.33	300	2.03
Panel C: Book-to-market																		
BM1 (low/growth)	3.07	382	4.53	2.21	215	2.74	4.17	167	3.64	3.42	213	3.88	3.35	114	2.98	3.51	99	2.51
BM2	1.39	687	3.07	1.04	332	1.61	1.71	355	2.71	2.77	377	4.42	2.23	184	2.73	3.29	193	3.48
BM3	1.58	2,019	6.44	1.26	1,075	4.11	1.94	944	4.97	3.05	1,014	8.02	2.61	546	5.78	3.57	468	5.62
BM4	0.70	992	1.37	0.07	489	0.10	1.32	503	1.79	1.98	532	2.76	1.16	268	1.25	2.81	264	2.60
BM5 (high/value)	0.76	569	0.84	0.28	289	0.24	1.24	280	0.92	2.16	289	1.65	2.14	142	1.12	2.18	147	1.22
Panel D: Earnings Yield																		
EY1 (low/growth)	3.01	407	4.87	2.30	217	2.99	3.83	190	3.87	5.11	227	5.34	4.29	118	3.66	6.00	109	3.90
EY2	2.01	1,045	5.59	1.56	564	3.42	2.54	481	4.45	3.08	529	5.71	3.55	270	5.24	2.59	259	3.06
EY3	0.63	1,259	2.07	0.38	628	0.93	0.88	631	1.94	2.14	641	4.84	1.71	328	3.11	2.59	313	3.71
EY4	0.31	1,335	1.01	-0.08	669	-0.21	0.70	666	1.50	1.28	662	2.98	0.63	345	1.17	1.99	317	2.94
EY5 (high/value)	3.16	603	4.22	2.25	322	2.47	4.20	281	3.41	4.20	366	4.47	3.04	193	2.62	5.49	173	3.63
Panel E: Momentum																		
M1 (low prior return)	1.71	615	3.58	0.44	289	0.71	2.83	326	4.01	4.15	364	6.06	1.99	151	2.04	5.68	213	6.09
M2	0.71	933	1.93	0.31	478	0.63	1.13	455	2.07	1.96	463	3.70	1.01	220	1.38	2.83	243	3.72
M3	1.96	1,165	5.42	1.46	605	3.19	2.50	560	4.42	4.19	626	7.62	3.44	334	5.22	5.05	292	5.57
M4	1.04	1,020	2.95	1.03	545	2.30	1.06	475	1.88	1.69	511	3.31	2.31	273	3.69	0.99	238	1.19
M5 (high prior return)	1.50	916	3.61	1.17	483	2.25	1.87	433	2.83	1.39	461	2.32	1.92	276	2.82	0.59	185	0.53

We calculate the LSV herding measure, $H_{i,t} = |p_{i,t} - E[p_{i,t}]| - E[|p_{i,t} - E[p_{i,t}]|]$ using quarterly intervals followed by monthly intervals to infer trades, during periods when five or more managers are trading. $p_{i,t}$ is the proportion of managers who traded during period t who had a net purchase of stock i. Averages of H_{it} values are shown across periods and stocks, (which fulfil the various criteria, i.e., belong in size group 1). Buy and Sell-side herding is calculated when $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$ respectively. The figures in the left (right) half of the table are calculated for monthly (quarterly) intervals. Panels B, C, D and E show the average herding measure value with stocks partitioned according to size, book-to-market, earnings yield and momentum. All figures in the mean column are in percentage terms. The count column contains the number of stock periods used to calculate the level of herding.

Table 3
LSV Buy and Sell Herding Measure Segregated according to Manager Size and Style Characteristics

	Total			Buy Herding			Sell Herding		
	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat
Manager Characteristics									
Small Managers	1.16	1,045	3.05	1.05	532	2.05	1.27	513	2.26
Large Managers	1.14	3,243	5.44	0.57	1,695	2.15	1.76	1,548	5.38
Growth Managers	2.30	1,683	7.51	1.55	885	4.12	3.13	798	6.37
Value Managers	2.43	824	3.67	2.00	426	2.42	2.90	398	2.77

We calculate the LSV herding measure, $H_{i,t} = | p_{i,t} - E[p_{i,t}]| - E[| p_{i,t} - E[p_{i,t}]|]$ using monthly intervals to infer trades, during periods when five or more managers (of the same size or style) are trading. $p_{i,t}$ is the proportion of managers who traded during period *t* who had a net purchase of stock *i*. We present averages of H_{it} values across periods and stocks. Buy and Sell-side herding is calculated when $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$, respectively. We calculate these values for managers segregated according to size and style. All figures in the mean column are in percentage terms. The count column contains the number of stock periods used to calculate the level of herding.

Table 4
LSV Buy and Sell Herding Measure Calculated During Specific Periods and Across Industry Sectors

	Total			Buy Herding			Sell Herding		
	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat
Panel A: Earnings Announcements									
Month of Earnings Announcement	1.15	750	2.70	0.27	376	0.51	2.02	374	3.14
Month Before Earnings Announcement	1.04	703	1.17	0.90	350	0.56	1.18	353	0.68
Month After Earnings Announcement	0.90	638	2.13	1.65	325	2.85	0.11	313	0.17
Panel B: Index Changes									
Month of Index Change	17.75	81	9.42	12.04	45	6.28	24.88	36	7.93
Panel C: End of Calendar Year									
Herding during the Month of December	0.73	380	1.32	0.43	195	0.57	1.05	185	1.29
Herding during the Month of January	1.50	328	2.40	0.76	173	0.95	2.33	155	2.39
Panel D: End of Financial Year									
Herding during the Month of June	1.55	437	2.85	1.17	222	1.54	1.94	215	2.49
Herding during the Month of July	1.02	392	1.83	1.08	200	1.51	0.96	192	1.11
Panel E: Herding at an Industry Level									
Total	6.16	2,183	24.28	6.56	1,071	17.58	5.77	1,112	16.76

We calculate the LSV herding measure, $H_{i,t} = | p_{i,t} - E[p_{i,t}]| - E[| p_{i,t} - E[p_{i,t}]|]$ using monthly intervals to infer trades, during periods when five or more managers are trading. $p_{i,t}$ is the proportion of managers who traded during period *t* who had a net purchase of stock *i*. We average $H_{i,t}$ values across periods and stocks. Buy and Sell-side herding is calculated when $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$, respectively. Panels A, B, C, and D show the average herding measure value during periods of earnings announcements, index changes, and at the end of the both the year and the financial year. Panel E displays the LSV herding measure when stocks are aggregated in industries and the $p_{i,t}$ is the proportion of managers during period *t* who had a positive change in weight of industry *i* All figures in the mean column are in percentage terms. The count column contains the number of stock periods used to calculate the level of herding.

Table 5
Herding Due to Brokers

	Total			Buy Herding			Sell Herding		
	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat
Herding for the 6 most popular brokers									
Broker 1	17.03	180	14.04	16.55	88	9.66	17.49	92	10.36
Broker 2	15.54	332	17.35	15.19	163	11.55	15.88	169	13.06
Broker 3	16.11	349	18.58	17.87	162	16.02	14.58	187	11.29
Broker 4	15.64	299	13.47	14.53	153	9.59	16.79	146	9.38
Broker 5	20.61	214	11.08	20.32	101	8.35	20.87	113	7.53
Broker 6	16.20	328	16.37	16.39	159	11.61	16.04	169	11.45

We calculate the LSV herding measure, $H_{i,t} = | p_{i,t} - E[p_{i,t}]| - E[| p_{i,t} - E[p_{i,t}]|]$, using monthly intervals to infer trades, during periods when five or more managers are trading. $p_{i,t}$ is the proportion of managers who traded during period *t* who had a net purchase of stock *i*. We average $H_{i,t}$ values across periods and stocks. Buy and Sell-side herding is calculated when $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$ respectively. This table calculates the level of herding for trades completed with six specific brokers. These brokers chosen are the most active (or frequently used) brokers engaged by the managers in our sample. All figures in the mean column are in percentage terms. The count column contains the number of stock periods used to calculate the level of herding.

Table 6
Manager Correlations for the Largest 50 Stocks

Manager	1	2	3	4	5	6	7	8	9	10	11	12	13
Panel A: Quarterly													
No Lag (herding)	13.0	10.5	28.9	11.6	17.0	7.7	8.7	12.7	9.1	13.5	6.5	13.5	18.2
One Lag follower	1.2	8.9	21.2	11.1	7.3	-0.6	9.2	8.7	6.3	9.0	6.6	6.6	8.9
One Lag leader	11.7	9.7	18.8	7.5	7.4	4.2	3.2	9.7	3.8	8.8	-4.4	10.6	5.3
Panel B: Monthly													
No Lag (herding)	8.4	8.2	24.2	8.5	9.6	2.4	4.2	8.5	8.9	8.6	4.5	7.2	8.3
One Lag follower	5.7	4.8	14.9	8.1	7.6	3.4	3.6	7.7	3.8	11.2	4.5	3.3	8.0
One Lag leader	5.3	6.9	18.7	3.5	7.6	0.6	2.4	7.7	2.1	7.0	2.3	7.5	6.7
Panel C: Fortnightly													
No Lag (herding)	8.2	4.1	17.1	7.6	6.0	2.8	3.2	7.7	8.9	9.2	4.1	5.9	6.9
One Lag follower	5.5	0.8	12.2	4.7	4.7	1.5	4.3	6.2	2.7	3.8	-2.4	2.5	1.5
One Lag leader	4.5	2.4	11.2	2.0	5.7	2.6	0.3	6.5	5.1	3.9	3.1	2.4	4.0
Two Lags follower	5.3	2.4	14.0	6.1	6.2	2.8	3.3	6.3	3.4	5.8	0.7	3.1	1.5
Two Lags leader	6.2	3.3	14.7	3.4	6.5	1.5	0.7	7.5	3.8	5.3	1.1	4.0	5.1
Panel D: Weekly													
No Lag (herding)	5.4	2.7	13.8	6.2	6.2	2.0	3.1	5.9	8.3	6.7	3.9	4.8	5.4
One Lag follower	3.0	0.9	6.7	3.7	3.5	2.1	2.8	4.6	4.1	4.6	-1.4	3.2	2.3
One Lag leader	2.6	0.2	10.6	-0.1	2.8	4.4	1.0	3.5	3.6	3.3	3.5	3.6	3.9
Two Lags follower	3.0	1.7	10.0	5.2	2.8	1.4	3.2	5.3	3.9	3.2	-2.3	2.8	2.3
Two Lags leader	3.9	1.4	10.6	1.1	4.5	2.9	0.9	4.4	3.4	2.7	2.4	3.2	4.6
Three Lags follower	3.2	2.0	11.5	4.9	3.3	1.2	3.6	5.4	3.4	3.2	-0.9	3.2	1.0
Three Lags leader	5.5	2.1	10.1	2.0	4.3	2.8	1.2	4.7	3.2	3.5	1.6	2.6	5.8
Four lags follower	2.9	2.7	12.0	4.9	4.9	1.8	3.1	5.6	3.4	3.7	0.2	3.4	0.8
Four lags leader	5.3	2.4	10.7	3.0	3.9	2.7	1.1	5.8	2.6	4.4	0.4	3.4	5.3

In each period *t*, we determine a rank in deciles for each stock *i* based upon each managers $\text{Proportional Trade}_{i,t} = (\sum(\text{aggregated trades}_{i,t}))/(\text{holding}_{i,t\text{-}1})$. The correlation of this rank for each of the largest 50 stocks with the average rank of the other 37 managers is determined in order to find the level of herding present. The correlation of these ranks against lagged and future average ranks is then determined. We measure two lags based upon the rank determined based on trades in the next two periods after the initial period of trade. In Panels A, B, C and D, the manager's proportional trade is calculated by accumulating the manager's aggregated trades over quarterly, monthly, fortnightly and weekly intervals. The Spearman Rank Correlation Test is then used, which, due to the large numbers of stocks and periods in our sample, finds that all our results are significant at the 1% level. Thus, we do not report these. All numbers quoted are percentages.

Table 6 - Continued

Manager	14	15	16	17	18	19	20	21	22	23	24	25	26
Panel A: Quarterly													
No Lag (herding)	8.7	19.2	12.8	13.4	11.6	13.9	18.8	4.9	6.5	20.5	16.8	14.4	10.0
One Lag follower	12.6	14.0	13.7	18.0	4.5	21.0	-6.0	1.6	0.9	6.6	23.6	7.6	1.1
One Lag leader	5.1	14.7	21.2	14.5	6.9	-6.7	19.1	3.2	-5.7	6.2	16.4	6.1	-1.6
Panel B: Monthly													
No Lag (herding)	9.0	15.8	11.7	8.9	5.1	3.2	10.0	4.6	4.7	18.6	6.3	7.9	12.5
One Lag follower	0.6	12.9	9.9	9.2	2.5	14.4	5.5	-0.6	2.5	11.6	12.8	1.7	5.9
One Lag leader	6.8	13.1	10.7	-0.9	5.8	-2.5	4.9	4.3	-1.6	12.3	5.2	6.9	4.5
Panel C: Fortnightly													
No Lag (herding)	7.8	11.0	8.4	7.7	3.2	1.6	6.4	4.4	3.7	21.0	9.1	7.3	14.9
One Lag follower	4.1	10.3	3.8	1.4	0.5	7.3	0.8	3.3	0.9	11.0	3.7	1.1	6.4
One Lag leader	2.9	6.4	8.3	3.4	3.2	-4.8	-0.1	3.5	1.0	10.2	1.7	5.2	6.0
Two Lags follower	5.4	10.3	5.9	3.3	1.5	8.2	4.7	0.8	2.0	12.4	7.5	1.9	6.8
Two Lags leader	3.3	9.4	10.0	4.1	3.9	-2.6	1.6	0.8	-2.0	11.1	4.3	4.8	4.4
Panel D: Weekly													
No Lag (herding)	7.9	7.5	5.8	7.8	3.6	0.2	2.8	7.9	2.8	20.1	5.1	7.0	15.5
One Lag follower	3.3	6.6	3.8	2.8	0.7	6.5	0.4	1.7	4.4	10.8	7.3	3.2	8.7
One Lag leader	2.5	6.6	5.8	3.6	1.2	-0.7	2.6	0.9	1.4	11.3	2.0	4.2	8.8
Two Lags follower	3.5	7.2	4.3	2.7	1.5	3.1	2.4	2.2	2.0	11.8	5.3	1.7	7.5
Two Lags leader	2.7	7.0	7.3	4.3	2.2	-1.1	1.4	2.8	-0.2	9.7	0.7	4.9	7.3
Three Lags follower	3.6	7.7	5.0	3.3	1.4	4.0	2.7	2.2	1.4	11.6	4.9	2.1	6.9
Three Lags leader	2.9	7.6	8.3	2.2	2.3	0.3	1.2	4.9	-2.7	8.7	1.7	4.7	5.8
Four lags follower	4.7	7.8	5.7	3.0	1.8	3.0	3.4	1.1	0.8	11.6	5.6	2.4	6.8
Four lags leader	3.2	9.1	9.2	3.1	2.5	-1.4	-1.3	3.8	-2.9	9.1	1.3	3.8	5.1

Table 6 - Continued

Manager	27	28	29	30	31	32	33	34	35	36	37	38
Panel A: Quarterly												
No Lag (herding)	25.7	12.2	24.2	6.0	6.0	19.6	14.1	15.0	22.6	12.5	4.5	8.6
One Lag follower	15.9	10.7	17.1	-1.6	2.4	15.6	-2.5	-3.7	14.2	7.2	7.9	-1.3
One Lag leader	12.2	9.5	11.5	2.3	4.3	15.1	8.6	11.1	8.6	15.3	6.0	3.9
Panel B: Monthly												
No Lag (herding)	15.3	11.6	18.3	5.0	6.5	12.7	15.8	14.6	15.1	11.7	8.0	2.8
One Lag follower	4.5	9.0	13.4	0.0	4.3	6.3	3.3	4.0	9.5	5.5	1.8	-0.1
One Lag leader	5.3	9.6	8.1	2.7	3.2	10.3	9.0	9.2	7.3	5.0	2.4	5.7
Panel C: Fortnightly												
No Lag (herding)	10.1	9.2	10.9	2.0	5.1	7.6	14.5	14.5	9.4	14.7	13.2	4.1
One Lag follower	7.4	6.4	8.0	-0.2	2.7	5.0	7.4	6.2	6.0	4.9	4.0	-0.9
One Lag leader	1.1	8.6	5.5	0.8	3.2	7.3	5.0	5.5	5.8	3.6	3.5	2.5
Two Lags follower	7.7	7.2	11.2	0.6	2.9	7.6	4.9	4.3	6.0	4.6	3.1	0.7
Two Lags leader	2.1	9.3	4.8	2.1	3.5	8.0	6.4	6.9	5.8	4.7	2.2	5.0
Panel D: Weekly												
No Lag (herding)	6.8	5.7	7.1	2.4	2.6	5.5	16.6	16.0	6.2	16.8	16.0	2.3
One Lag follower	9.0	4.7	6.2	-0.1	0.1	3.8	6.1	6.0	3.6	2.4	1.4	0.5
One Lag leader	2.9	7.3	3.3	-0.8	1.9	4.6	7.0	7.3	3.8	6.0	2.6	1.1
Two Lags follower	7.8	4.8	7.0	-1.5	0.9	4.2	6.0	5.6	4.5	3.2	3.3	1.2
Two Lags leader	3.8	7.4	2.7	0.1	1.9	5.4	7.3	7.1	4.6	4.8	3.3	0.9
Three Lags follower	7.6	5.5	7.8	0.3	1.4	4.9	5.2	4.8	4.4	2.1	3.1	1.4
Three Lags leader	4.2	8.1	3.2	0.8	1.7	5.2	6.1	6.0	5.5	5.6	2.8	2.4
Four lags follower	8.1	6.1	9.0	1.4	2.1	6.4	4.0	3.7	5.0	1.8	2.7	1.3
Four lags leader	3.4	8.0	3.1	0.9	1.8	6.0	7.4	7.5	4.5	5.9	2.7	3.5

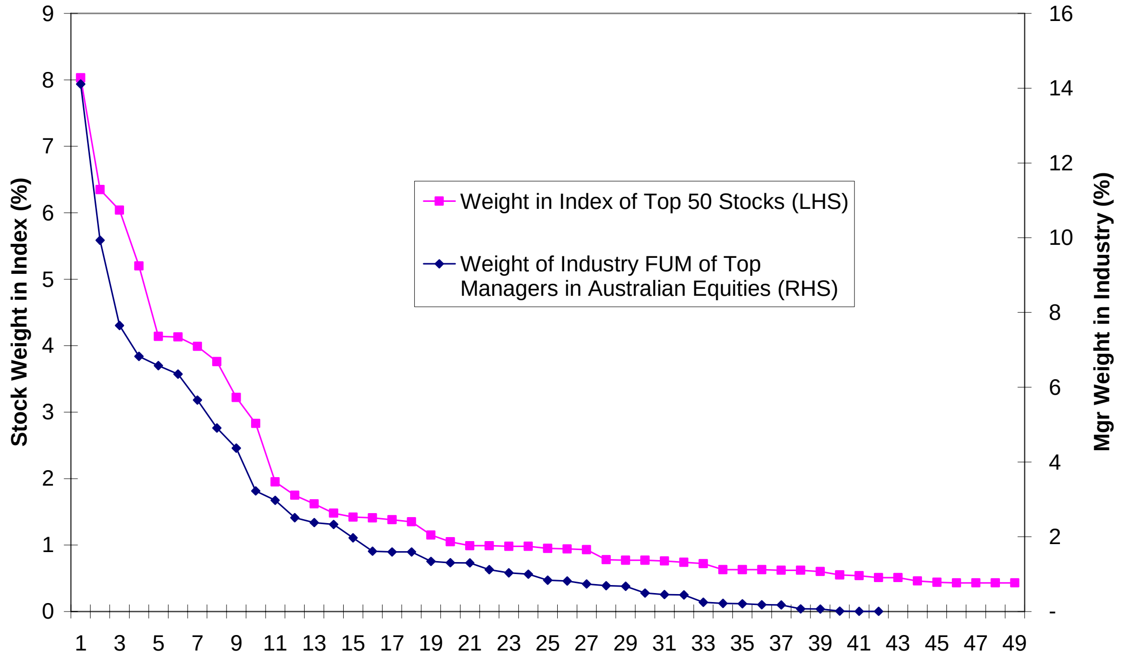
Table 7
Regression of Manager Correlations Against Prior 3 Month Returns for the Largest 50 Stocks

	Coefficient	*t*-statistic	R^2 (%)
Panel A: Quarterly			
No Lag (herding)	-0.37	-0.65	7.8
One Lag follower	1.10	1.74*	8.8
One Lag leader	-0.98	-1.51	7.2
Panel B: Monthly			
No Lag (herding)	0.12	0.26	5.7
One Lag follower	0.48	1.12	4.4
One Lag leader	-0.01	-0.02	3.6
Panel C: Fortnightly			
No Lag (herding)	0.04	0.13	5.6
One Lag follower	0.15	0.49	3.2
One Lag leader	0.65	2.14**	2.1
Two Lags follower	0.16	0.42	3.3
Two Lags leader	0.52	1.93*	2.8
Panel D: Weekly			
No Lag (herding)	0.01	0.03	6.2
One Lag follower	0.11	0.49	2.5
One Lag leader	0.33	1.46	2.8
Two Lags follower	-0.03	-0.15	2.7
Two Lags leader	0.36	1.50	2.1
Three Lags follower	0.43	1.93*	2.5
Three Lags leader	0.53	2.27**	1.9
Four lags follower	0.37	1.59	2.5
Four lags leader	0.42	1.76*	2.2

The correlations of manager rank against the average rank of all other managers (where the manager rank, or the average manager rank is sometimes lagged) is regressed against the prior three monthly return of the manager in order to determine the following statistics. We base the rank of each stock upon this following measure:
$\text{Proportional Trade}_{\text{i,t}} = (\sum(\text{aggregated trades}_{\text{i,t}}))/(\text{holding}_{\text{i,t-1}})$. In Panels A, B, C and D, the manager's proportional trade is calculated by accumulating the manager's aggregated trades over quarterly, monthly, fortnightly and weekly intervals.

Figure 1

Concentration of Top Stocks and Investment Managers in the Australian Market



Sources: Australian Stock Exchange and Assirt (March 2002)

This figure displays the weight in the ASX 300 of the largest 50 stocks (square line) and the weight of funds under management in Australian equities of the largest 50 investment managers (diamond line).

Appendix A
Descriptive Statistics for the Australian Market

Investment Managers	Retail Aust. Equity ($Billion)	Wholesale Aust. Equity ($Billion)	Total Aust. Equity ($Billion)	Market Share (%)	Total Assets ($Billion)	Market Share (%)
Colonial First State	9.73	17.07	26.80	14.11	72.29	10.49
AMP	10.61	8.25	18.86	9.93	70.84	10.28
National/MLC	12.18	2.35	14.54	7.65	50.64	7.35
Perpetual Investments	2.12	10.84	12.96	6.82	18.98	2.75
Maple Brown Abbott	0.00	12.49	12.49	6.58	15.19	2.20
Commonwealth Bank	9.01	3.06	12.06	6.35	31.01	4.50
Deutsche	0.00	10.74	10.74	5.65	32.26	4.68
ING	4.16	5.16	9.32	4.91	30.12	4.37
Merrill Lynch	4.92	3.38	8.30	4.37	15.84	2.30
Barclays	0.00	6.13	6.13	3.23	17.97	2.61
Westpac	5.00	0.65	5.65	2.98	23.25	3.37
AXA	3.68	1.09	4.77	2.51	32.32	4.69
Platinum	2.25	2.27	4.52	2.38	5.32	0.77
Macquarie Bank	0.35	4.07	4.42	2.33	38.21	5.55
Rothschild	1.24	2.50	3.74	1.97	10.55	1.53
Vanguard	0.08	2.99	3.06	1.61	14.75	2.14
Portfolio Partners	1.20	1.83	3.03	1.59	8.83	1.28
ANZ	2.42	0.61	3.02	1.59	16.92	2.46
UBS Asset Management	0.00	2.55	2.55	1.34	13.82	2.01
Invesco	0.06	2.42	2.48	1.31	11.90	1.73
Top 20 Total	69.00	100.46	169.46	89.22	531.01	77.08
Other Investment Managers	11.24	9.24	20.48	10.78	157.92	22.92
Grand Total	80.24	109.70	189.94	100.00	688.93	100.00

Source: ASSIRT (March 2002)

This table provides descriptive statistics on the Australian investment management industry for 31 March 2002, detailing the largest 20 managers in total Australian equity funds under management.

Appendix B
LSV Buy and Sell Herding Measure Segregated according to Manager Size and Stock Characteristics

	Total			Buy Herding			Sell Herding			Total			Buy Herding			Sell Herding		
	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat
Panel A: Total					**Small Managers**									**Large Managers**				
Total	1.16	1,045	3.05	1.05	532	2.05	1.27	513	2.26	1.14	3,243	5.44	0.57	1,695	2.15	1.76	1,548	5.38
Panel B: Size																		
S1 (small, stocks 200+)	-1.80	9	-0.60	-6.17	4	-4.27	1.69	5	0.34	2.11	21	0.83	9.55	4	0.40	0.86	7	0.36
S2 (stocks 121-200)	6.45	27	2.29	9.31	18	2.47	0.74	9	0.22	2.08	101	1.61	1.30	18	0.16	3.66	51	1.90
S3 (stocks 71-120)	0.85	60	0.50	2.22	25	0.87	-0.13	35	-0.06	0.66	397	1.06	0.85	25	0.05	1.08	222	1.26
S4 (stocks 31-70)	1.26	255	1.58	1.20	144	1.14	1.33	111	1.10	0.55	1,048	1.49	-2.53	144	-0.75	1.78	529	3.25
S5 (large, stocks 1-30)	0.63	606	1.35	0.65	290	1.02	0.62	316	0.90	0.99	1,440	3.36	3.09	290	1.82	0.83	630	1.73
Panel C: Book-to-market																		
BM1 (low/growth)	-0.87	60	-0.57	-1.45	38	-0.82	0.13	22	0.05	1.85	225	2.09	3.29	38	0.51	2.95	99	1.98
BM2	2.15	191	2.20	1.67	85	1.17	2.53	106	1.89	0.47	457	0.84	-0.82	85	-0.23	1.28	222	1.57
BM3	0.51	442	0.97	0.40	232	0.56	0.64	210	0.82	1.03	1,151	3.14	1.88	232	1.06	1.40	533	2.68
BM4	3.28	118	1.39	4.70	64	1.43	1.60	54	0.47	0.94	674	1.53	-3.10	64	-0.34	2.31	360	2.71
BM5 (high/value)	-0.42	122	-0.20	-0.31	47	-0.08	-0.49	75	-0.20	0.46	405	0.44	1.87	47	0.14	0.51	192	0.32
Panel D: Earnings Yield																		
EY1 (low/growth)	2.22	113	1.77	1.11	59	0.77	3.43	54	1.64	2.42	276	3.26	6.59	59	1.78	2.24	125	1.82
EY2	1.22	259	1.67	0.57	133	0.57	1.91	126	1.77	0.95	681	2.21	2.45	133	0.90	1.13	285	1.57
EY3	0.00	332	0.00	0.06	169	0.06	-0.06	163	-0.06	0.89	884	2.28	2.58	169	1.10	0.82	425	1.42
EY4	1.46	250	1.61	1.53	123	1.33	1.38	127	1.00	0.22	974	0.56	-5.86	123	-1.56	1.88	496	3.17
EY5 (high/value)	3.08	91	1.13	4.59	48	1.24	1.40	43	0.35	3.17	423	3.37	11.35	48	1.06	3.71	215	2.56
Panel E: Momentum																		
M1 (low prior return)	-0.18	97	-0.14	1.37	43	0.71	-1.41	54	-0.79	0.64	420	1.17	1.74	43	0.20	0.96	203	1.21
M2	0.87	167	0.96	-1.10	76	-0.91	2.52	91	1.94	0.94	676	2.10	3.98	76	0.65	1.09	307	1.53
M3	0.21	210	0.27	-0.69	104	-0.66	1.10	106	0.94	0.34	640	0.77	-0.12	104	-0.04	0.75	305	1.13
M4	0.91	290	1.31	1.05	156	1.11	0.74	134	0.73	0.65	753	1.54	-0.14	156	-0.07	1.41	364	2.09
M5 (high prior return)	1.91	245	2.21	2.60	132	2.30	1.10	113	0.83	1.09	593	1.94	0.07	132	0.03	2.13	298	2.58

We calculate the LSV herding measure, $H_{i,t} = | p_{i,t} - E[p_{i,t}] | - E[| p_{i,t} - E[p_{i,t}] |]$ using monthly intervals to infer trades, during periods when five or more managers are trading. $p_{i,t}$ is the proportion of managers who traded during period t who had a net purchase of stock i. We present averages of H_{it} values across periods and stocks. Buy and Sell-side herding is calculated when $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$, respectively. The various columns show the average herding measure value for all, small and large managers. The figures in the left (right) half of the table are calculated for small (large) managers. Panels B, C, D and E show the averaged herding measure value with stocks partitioned according to size, book-to-market, earnings yield and momentum. All figures in the mean column are in percentage terms. The count column contains the number of stock periods used to calculate the level of herding.

LSV Buy and Sell Herding Measure Segregated according to Manager Style and Stock Characteristics

	Total			Buy Herding			Sell Herding			Total			Buy Herding			Sell Herding		
	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat
Panel A: Total					**Growth Managers**									**Value Managers**				
Total	2.30	1,683	7.51	1.55	885	4.12	3.13	798	6.37	2.43	824	3.67	2.00	426	2.42	2.90	398	2.77
Panel B: Size																		
S1 (small, stocks 200+)	1.09	21	0.46	3.42	14	1.18	-3.56	7	-0.96	10.08	3	1.47	12.57	1	Inf	8.84	2	0.76
S2 (stocks 121-200)	5.71	56	3.53	6.56	41	3.51	3.38	15	1.04	5.83	6	1.53	9.56	3	2.04	2.10	3	0.35
S3 (stocks 71-120)	2.88	139	2.74	0.48	72	0.32	5.46	67	3.84	4.31	76	2.51	2.64	44	1.33	6.62	32	2.17
S4 (stocks 31-70)	2.34	430	3.67	1.39	212	1.71	3.26	218	3.34	2.06	220	2.29	0.65	101	0.56	3.25	119	2.44
S5 (large, stocks 1-30)	1.74	912	4.32	1.03	473	2.16	2.52	439	3.80	2.03	448	3.41	1.97	238	2.64	2.09	210	2.21
Panel C: Book-to-market																		
BM1 (low/growth)	2.48	145	2.34	2.66	95	2.26	2.15	50	1.01	1.74	18	0.66	7.57	8	1.53	-2.92	10	- 1.58
BM2	1.87	319	2.70	1.38	159	1.61	2.36	160	2.17	0.56	59	0.30	1.42	28	0.50	-0.22	31	- 0.09
BM3	2.12	682	4.53	1.62	342	2.67	2.63	340	3.67	2.23	353	3.28	1.77	191	2.19	2.77	162	2.45
BM4	3.86	187	1.89	0.92	88	0.37	6.46	99	2.10	3.65	193	2.57	2.07	86	1.07	4.93	107	2.54
BM5 (high/value)	2.77	159	1.25	1.64	85	0.65	4.08	74	1.06	3.23	125	1.57	1.21	69	0.50	5.71	56	1.64
Panel D: Earnings Yield																		
EY1 (low/growth)	1.09	21	0.46	3.42	14	1.18	-3.56	7	-0.96	10.08	3	1.47	12.57	1	Inf	8.84	2	0.76
EY2	5.71	56	3.53	6.56	41	3.51	3.38	15	1.04	5.83	6	1.53	9.56	3	2.04	2.10	3	0.35
EY3	2.88	139	2.74	0.48	72	0.32	5.46	67	3.84	4.31	76	2.51	2.64	44	1.33	6.62	32	2.17
EY4	2.34	430	3.67	1.39	212	1.71	3.26	218	3.34	2.06	220	2.29	0.65	101	0.56	3.25	119	2.44
EY5 (high/value)	1.74	912	4.32	1.03	473	2.16	2.52	439	3.80	2.03	448	3.41	1.97	238	2.64	2.09	210	2.21
Panel E: Momentum																		
M1 (low prior return)	2.48	145	2.34	2.66	95	2.26	2.15	50	1.01	1.74	18	0.66	7.57	8	1.53	-2.92	10	- 1.58
M2	1.87	319	2.70	1.38	159	1.61	2.36	160	2.17	0.56	59	0.30	1.42	28	0.50	-0.22	31	- 0.09
M3	2.12	682	4.53	1.62	342	2.67	2.63	340	3.67	2.23	353	3.28	1.77	191	2.19	2.77	162	2.45
M4	3.86	187	1.89	0.92	88	0.37	6.46	99	2.10	3.65	193	2.57	2.07	86	1.07	4.93	107	2.54
M5 (high prior return)	2.77	159	1.25	1.64	85	0.65	4.08	74	1.06	3.23	125	1.57	1.21	69	0.50	5.71	56	1.64

We calculate the LSV herding measure, $H_{i,t} = | p_{i,t} - E[p_{i,t}]| - E[| p_{i,t} - E[p_{i,t}]|]$ using monthly intervals to infer trades, during periods when five or more managers are trading. $p_{i,t}$ is the proportion of managers who traded during period t who had a net purchase of stock i. We present averages of H_{it} values across periods and stocks. Buy and Sell-side herding is calculated when $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$, respectively. The various columns show the average herding measure value for all, small and large managers. The figures in the left (right) half of the table are calculated for growth (value) managers. Panels B, C, D and E show the averaged herding measure value with stocks partitioned according to size, book-to-market, earnings yield and momentum. All figures in the mean column are in percentage terms. The count column contains the number of stock periods used to calculate the level of herding.

Appendix C
Comparison of LSV Herding Measure using Different No.'s of Managers

	Total			Buy Herding			Sell Herding		
	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat
No. of Mgrs					**Monthly Intervals**				
3	1.81	8,194	11.83	0.45	4,383	2.32	3.37	3,811	14.13
4	1.51	6,018	9.50	1.16	3,101	5.79	1.87	2,917	7.56
5	1.39	4,649	1.83	0.95	2,400	2.75	1.85	2,249	0.95
6	1.35	3,684	7.64	1.25	1,869	5.36	1.45	1,815	5.46
7	1.31	3,049	6.97	1.37	1,536	5.49	1.26	1,513	4.45
10	1.60	1,731	6.98	1.38	895	4.53	1.84	836	5.32

We calculate the LSV herding measure, $H_{i,t} = |p_{i,t} - E[p_{i,t}]| - E[|p_{i,t} - E[p_{i,t}]|]$ using quarterly intervals followed by monthly intervals to infer trades, during periods when 3, 4, 5, 6, and 7 or more managers are trading. $p_{i,t}$ is the proportion of managers who traded during period t who had a net purchase of stock i. Averages of H_{it} values are shown across periods and stocks, (which fulfil the various criteria, i.e., belong in size group 1). Buy and Sell-side herding is calculated when $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$ respectively. All figures in the mean column are in percentage terms. The count column contains the number of stock periods used to calculate the level of herding.

Appendix D
LSV Herding Measure after Index Change and Broker Related Herding are excluded

	Total			Buy Herding			Sell Herding		
	Mean	Count	T-stat	Mean	Count	T-stat	Mean	Count	T-stat
Panel A: Total				**Monthly Intervals**					
Total	1.03	3,499	5.35	0.69	1,801	2.74	1.39	1,698	4.74
Panel B: Size									
S1 (small, stocks 200+)	3.86	154	3.42	2.35	93	1.64	6.16	61	3.41
S2 (stocks 121-200)	2.75	193	2.79	0.25	113	0.22	6.29	80	3.75
S3 (stocks 71-120)	0.56	561	1.17	0.17	284	0.27	0.96	277	1.33
S4 (stocks 31-70)	0.46	1,205	1.44	0.56	578	1.27	0.38	627	0.81
S5 (large, stocks 1-30)	1.04	1,195	3.37	0.61	640	1.63	1.53	555	2.89
Panel C: Book-to-market									
BM1 (low/growth)	2.69	264	3.25	2.18	143	2.11	3.30	121	2.47
BM2	1.59	483	2.89	1.27	238	1.64	1.90	245	2.44
BM3	0.99	1,504	3.58	0.87	791	2.46	1.12	713	2.60
BM4	0.46	812	0.87	-0.11	407	-0.16	1.05	405	1.35
BM5 (high/value)	0.56	436	0.55	-0.10	222	-0.08	1.25	214	0.79
Panel D: Earnings Yield									
EY1 (low/growth)	1.32	290	1.93	0.63	154	0.75	2.10	136	1.91
EY2	1.84	749	4.32	1.41	397	2.55	2.33	352	3.54
EY3	0.57	935	1.58	0.43	457	0.87	0.70	478	1.33
EY4	0.11	1,063	0.33	-0.09	553	-0.20	0.32	510	0.62
EY5 (high/value)	2.55	462	2.97	1.78	240	1.61	3.38	222	2.55
Panel E: Momentum									
M1 (low prior return)	1.61	481	2.97	0.20	234	0.30	2.96	247	3.52
M2	0.71	743	1.72	0.48	388	0.86	0.97	355	1.56
M3	1.09	855	2.74	0.71	435	1.34	1.48	420	2.50
M4	0.80	764	1.94	0.86	415	1.68	0.73	349	1.08
M5 (high prior return)	1.12	656	2.26	1.02	329	1.54	1.23	327	1.65

We calculate the LSV herding measure, $H_{i,t} = |\, p_{i,t} - E[p_{i,t}]\,| - E[\,|\, p_{i,t} - E[p_{i,t}]\,|\,]$ using monthly intervals to infer trades, during periods when five or more managers are trading. $p_{i,t}$ is the proportion of managers who traded during period *t* who had a net purchase of stock *i*. Averages of H_{it} values are shown across periods and stocks, (which fulfil the various criteria, i.e., belong in size group 1). Buy and Sell-side herding is calculated when $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$ respectively. We exclude periods in which five or more managers trade in a certain stock using the same broker, and also periods in which index changes occur. Panels B, C, D and E show the average herding measure value with stocks partitioned according to size, book-to-market, earnings yield and momentum. All figures in the mean column are in percentage terms. The count column contains the number of stock periods used to calculate the level of herding.

ENDNOTES

[1] This definition of herding does not include passive managers who mimic the benchmark, rather than competing managers, according to a rules-based approach.

[2] The *Australian Financial Review* (2002) quotes Harvard's Michael Porter as saying that managers are "herd members who live in packs and follow trends." Porter argues that herding is detrimental to the financial markets as it encourages "short-termism in companies and is also destabilising to markets".

[3] Reuters 1999 Survey of Australia and New Zealand found that the top five sell-side houses have won 60% of the overall research vote cast by fund management groups. Consequently, those brokers receive a similarly high concentration of fund manager trades.

[4] Wermers (1999, page 618) admits that a caveat of his findings is the frequency of data used. Quarterly portfolio holdings are not ideal in order to locate certain elements of herding because investment manager buying (selling) cycles last on average 26 (40) days respectively (Gallagher and Looi (2003)). Consequently, by using the measure employed by Wermers (1999), we aggregate two or even three trade packages into the same period, providing an incomplete picture of the trading activity of managers.

[5] We define active funds as those with a target (ex-ante) tracking error of greater than 100 basis points per annum. Admittedly, 'active' funds may have an actual realised (ex-post) tracking error lower than this level after implementing a strategy that closely resembles the index.

[6] We deem the largest funds to be representative of the manager's overall investment strategy. The largest funds are the funds with the highest marked-to-market valuation as at 31 December 2001. We specified this condition as a means of limiting the

significant effort required in compiling the data, as well as maximising the chances of cooperation.

[7] The ASX All Ordinaries Accumulation Index is applicable as the appropriate benchmark prior to 3 April 2000.

[8] We calculate these statistics for all the managers in our sample over the period 1994-2001. Mercer Consulting Reports supplied investment returns for the entire industry.

[9] There are 24 industries classified according to Standard & Poor's ASX Survey; Gold, Other Metals, Diversified Resources, Energy, Infrastructure and Utilities, Developers and Contractors, Building Materials, Alcohol and Tobacco, Food and Household, Chemicals, Engineering, Paper and Packaging, Retail, Transport, Media, Banks and Finance, Insurance, Telecommunications, Investment and Financial Services, Property Trusts, Healthcare and Biotechnology, Miscellaneous Industries, Diversified Industrials, Tourism and Leisure.

[10] We chose six brokers, which account for over 50% of manager trades in the Australian market, as the remaining 100 or more brokers did not have a significant number of periods in which more than five managers traded with these firms.

11 This manager size rank was not significantly correlated with the manager importance rank, hence this regression does not suffer from multicolinearity.

[12] This gives the proportional trade of the manager during the period, so that trades in large stocks do not bias our findings. Thus, we gave a ten percent increase in a small stock holding the same value as a ten percent increase in a large stock holding.

[13] We provide a ranking of ten to stocks bought during period *t* with a prior period holding at *t*-1 of zero, as these stocks had an effective infinite proportional change according to this measure.

[14] We test these correlations for significance using the Spearman Rank Correlation Test. For our measure, with ranks put into deciles, we re-rank all these ranks once more from one to 50, so that we can use the Spearman Rank test. Due to large sample sizes, all the correlations where found to be highly significant. Hence, reporting does not occur in Table IX.

[15] We found consistent findings by employing the research design of Sias (2004). Results suggest that managers follow the trades of their competitors. These results are available upon request. We thank Richard Sias for his encouragement to pursue this part of the analysis.

[16] 'Front running' is where investors purchase stocks ahead of their inclusion to the index. Primarily attribution belongs to risk arbitrageurs. A succinct summary of this behavior is provided by Frino *et al.* (2004) stating that "in the case of risk arbitrageurs, one would expect such agents to accumulate impending stocks immediately following the announcement date, with the expectation of selling at higher prices when the change becomes effective."

[17] Towards the end of the financial year, investors may sell out of low performing stocks in order to gain tax credits. Window dressing is another documented phenomenon that may cause institutions to sell out of low performing stocks, as the perceived risk level of their portfolio may form the basis for evaluation. They also do not have to explain their rationale behind holding those stocks that under-performed.

[18] For further information on broker-client relationships in Australia, see Aitken *et al.* (1995).

[19] In unreported results, we similarly find that managers follow the trades of their competitors, and that these trades yield positive returns.

[20] Since brokers may not differentiate between the values of similar sized clients, hence, we perform robustness checks in which we gave managers with a similar size (less than 20% or 100% difference) the same ranking. These checks resulted in similar unreported results.

[21] The *t*-statistic for the manager activity variable is also significant at traditional levels, however it is not large enough to be significant when we take into account the large sample size.

[22] We support these results with similar (unreported) findings for the largest 20 stocks.

[23] We support this finding with (unreported) results for the largest 20 stocks.