# Leading the Herd to Greener Pastures: When Trade Imitation is the Most ‘Profitable’ Form of Flattery

Kingsley Fong, David R. Gallagher, Peter Gardner, and Peter L. Swan*

School of Banking and Finance, The University of New South Wales

## Abstract

In what we believe to be a world first, we analyze fund managers’ daily trades and the identity of all brokers for each trade. In an ex-ante fashion we identify “leaders” – the funds’ most “disguised” trade packages which utilize multiple brokers over multiple days. We find that leader trades are highly profitable and typically followed by rival managers – “followers”. Leaders’ profitability is diminishing in the number of followers over a one-year horizon. Better disguise is successful in raising profitability and preventing following. This finding, together with high profitability of early following, suggests that following is deliberate. We also show that followers aid the price discovery process.



* Fong, k.fong@unsw.edu.au, (+612) 93854932, Gallagher, david.gallagher@unsw.edu.au, (+612) 92369106, Gardner, peterg@sirca.org.au, (+612) 92369153, Swan, peter.swan@unsw.edu.au, (+612) 93855871, School of Banking and Finance, The University of New South Wales, Sydney, N.S.W. 2052 Australia. The authors thank an anonymous referee, the Editor (Hendrik Bessembinder), as well as David Feldman, Marty Gruber, Richard Sias, and Terry Walter, for helpful comments. The authors also express their thanks to Portfolio Analytics and the Securities Industry Research Centre of Asia-Pacific (SIRCA) for the provision of data. The authors also gratefully acknowledge research funding from the Australian Research Council (DP0346064). An earlier draft of this paper was entitled ‘A Closer Examination of Investment Manager Herding Behavior’.

# Leading the Herd to Greener Pastures: When Trade Imitation is the Most 'Profitable' Form of Flattery


## Abstract

In what we believe to be a world first, we analyze fund managers' daily trades and the identity of all brokers for each trade. In an ex-ante fashion we identify "leaders" – the funds' most "disguised" trade packages which utilize multiple brokers over multiple days. We find that leader trades are highly profitable and typically followed by rival managers – "followers". Leaders' profitability is diminishing in the number of followers over a one-year horizon. Better disguise is successful in raising profitability and preventing following. This finding, together with high profitability of early following, suggests that following is deliberate. We also show that followers aid the price discovery process.


## I. Introduction

The literature identifies motivations for fund managers to follow the trades of other managers, i.e., engage in "herding" behavior, and provides evidence of herding in the U.S., U.K. and Japanese markets. The fundamental contribution of our study is to provide an *ex ante* mechanism to identify information-rich "leader" trade packages independently of whether or not the trade is followed and, indeed, how intensively it is followed. Our measure is based on "stealth", the degree to which a fund manager's trade package is "disguised" by splitting it up both over days and across multiple brokers. Basically, the greater is the stealth, the greater the profitability. Information-rich trades are like the prey in the African felt; their very survival depends on being able to blend in with the scenery. Consequently, we are able to model a sequence of mimicking trades by institutional investors, that is, the number of "followers". This enables us to determine their profitability, an array of explanatory factors giving rise to following, and the impact of these follower trades on stock price movements both in the short- and long-term.

This focus on the mechanism to identify leaders and followers enables us to highlight many important questions and empirical results about herding behavior. For example, is it rational for institutional investors to engage in herding activity? Are leaders harmed by the presence of more followers or do they benefit? To what extent do early followers benefit from mimicking behavior? In what sense can herding be considered intentional by followers? If a fund manager's "leader" trades are responsible for a large number of followers, does this indicate his success as a leader or the failure of his strategy to successfully disguise informed trades? If herding is both intentional and beneficial for one or more of these market participants, does it benefit the market as a whole? These new perspectives provide a far more policy-relevant framework than has been possible until now. Indeed, these questions can only be empirically tested with the availability of unique, highly detailed data that we obtain for the first time. This is the first study to exploit such an opportunity in a leader-follower framework, with actual signed fund manager daily trades in every stock, the ability to accurately construct actual trade packages and, most importantly, detailed broker identity information on every trade.

The financial community and media have paid increasing attention to herding behavior, particularly since the high-tech bubble of 2000.[1] Commentators have argued that fund managers are subject to a "moral hazard" problem in that they seek to protect their reputation through herding, such that herders will only report poor results as part of the crowd. Herding is of public and regulatory concern because this trend-following behavior may dilute the information quality of stock prices, exacerbate volatility, and destabilize markets (Scharfstein and Stein (1990)).

A number of studies have focused on the existence of institutional herding activity, and its impact on stock prices (for example, see Lakonishok, Shleifer and Vishny (1992), Grinblatt, Titman and Wermers (1995), Wermers (1999), Sias (2004), Wylie (2005) and Kim and Nofsinger (2005)). Wermers (1999) outlines four general hypotheses concerning institutional herding behavior[2]:

1) As indicated above, institutions are subject to reputation risk when they act differently to 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)). Informational cascades are like fashions and fads and occur when it is optimal for a manager to follow an earlier trade and to ignore his own private information.
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)).

Of these four explanations, our findings are most consistent with a modified version of 2), namely, informational cascades, with the proviso that the private information of followers also plays an important role with followers exercising good judgment.

The leader and follower framework that we adopt is related to Hong, Kubik and Stein (2005), who analyze the word-of-mouth effect in relation to the trades and holdings of mutual fund managers. They 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. Fund managers may also observe the trades of others due to an information leakage by brokers or the investment managers themselves (particularly after that manager's trade package is completed (Froot *et al.* (1992)).

In this study we group fund manager transactions (for a sample of equity funds) into trade packages, and use broker execution information to infer fund manager effort in disguising the full trade package size. We find managers complete 74 (72), 10 (11), 6 (7), and 10 (10) percent of buy (sell) trade volume, using one, two, three and four or more brokers, respectively. Intuitively, the larger the size of the overall trade package and the greater the disguising effort (i.e., the use of multiple brokers), the more likely the trade is 'information-based'. Unless the information is relatively short-lived, we would also expect large packages to be completed over multiple days to further disguise the nature of the trade. We find confirming evidence that these multiple broker trade packages are informed. These trade packages generate higher returns over the subsequent year and impact the stock price more over their duration, than do trade packages executed by a single broker.[3] We also find that this disguise is more profitable the more days over which the package is spread, indicating that short-lived information is not a concern. We term these information-rich highly disguised packages "leader trades". Moreover, greater disguise is effective in reducing the numbers of rival fund managers that mimic leader trades, what we have termed "followers", and mimicking behavior by early followers is highly profitable, providing evidence suggestive that following is intentional.

Our evidence, that multiple broker trades are more informed, provides further support to Chiyachantana *et al.* (2004), who show fund managers commonly use multiple brokers to execute their trades. Fund managers may do this in order to 'work' a trade, attempting to minimize the market impact of trading, or more generally, to disguise the nature of trades that contain information. These results are particularly relevant for Australia with its high concentration of trades amongst the largest five brokers.[4] Bartholomeusz (2003) suggests that brokers divulge broker identifiers (ID) information to their institutional clients, which may lead to mimicking behavior.[5] Only fellow brokers are supposed to be able to observe the broker ID on a trade.

We investigate to what extent managers mimic these informed trade packages and the profitability of leaders (i.e., informed trade packages) and followers. We find that other fund managers follow over fifty percent of all informed trade packages within five days after package completion.

Informed trade packages with one or more followers out-perform informed trade packages without followers by more than three percent in the next year. While this result appears to suggest there are incentives for fund managers to reveal trade information after the completion of their trade packages, this conclusion is premature. The presence of both a large number of followers and high leader returns is due to the informational superiority of the trade. More in-depth analysis suggests that after controlling for leader reputation, follower reputation, and trade disguise characteristics, the number of followers is actually negatively correlated with stock return. This suggests that it is in the interests of leaders to disguise their trade.

Followers do gain from herding, through from the first to the sixth follower. The first follower, on average, earns one percent more over the next year than the fourth follower, who in turn earns one percent more than the seventh follower. Therefore, it is important for followers to mimic leader trades early to maximize returns. These findings suggest that herding is certainly rational as well as intentional on the part of early followers. Also, following is not blind. It is focused on the most desirable leader trades, and typically, on leaders with better reputations, reinforcing both its benefits and its deliberate, rather than accidental, nature.

Followers' gains from herding, as well as the long-lived return from leader trades, suggest that active fund managers do not completely exploit their superior information. We find evidence that explains such behavior, where security returns subsequent to leader trades are higher when the lead manager is facing portfolio risk constraints (relative to market index weights).

These findings in relation to fund managers' trade behavior are remarkable enough. However, more remarkable still is the finding that the market as a whole benefits from much greater price discovery. In the microstructure literature, price discovery is commonly assumed if there is no price reversal after as little as a few seconds, minutes, or one or more subsequent trades. We find that the positions taken by herding institutional managers continue to be highly profitable for up to twelve months. Our analysis also shows that while it is common for leaders to later reverse their positions in the next year, they do not appear to profit from this behavior; hence, it is unlikely that fund managers are manipulating their position as leaders. From a public policy perspective, herding appears to be information-based. It should not be discouraged, and perhaps should even be encouraged, as it leads to a more effective price discovery process that benefits the market as a whole.

The remainder of this paper is organized as follows. Section II describes the data. For comparison with the literature, Section III contains the research design and empirical results, based on the herding measure used in previous studies over monthly and quarterly interval(s). For robustness, we also employ the herding measure proposed by Sias (2004).[6] In Section IV, we present the trade package approach to study leader and follower relationships. In conclusion, we outline suggestions for future research.

## II. Data

### A. Description of Databases

Data relating to investment manager trades have been scarce, due to their highly sensitive and confidential nature. Prior studies employ U.S. fund managers' mandatory filings of portfolio holdings in each quarter or half-yearly period as a basis to infer aggregate trades. This is the first study, to our knowledge, that utilizes actual daily trading data of active investment managers to study herding. Moreover, we believe it is also the first to be able to identify every broker for every trade. Our sample comprises 30 active equity managers, sourced from the *Portfolio Analytics Database*. Individual managers provide daily trade summaries and monthly holdings, together with broker identification, under conditions of strict confidentiality. The sample period of this study is 2nd January 1994 to 31st December 2001.

Construction of the database occurred on an invitation basis to active investment managers operating in Australia, based on total funds under management.[7] We asked the investment managers to provide portfolio information for their largest two active institutional Australian equities funds.[8] For this study, thirty-eight funds comprise the total sample, with the portfolios benchmarked against either the S&P/ASX 200 or S&P/ASX 300 accumulation indices.[9] This database comprises a sample that is representative of the Australian investment management industry, and includes six of the largest ten managers, six from the next ten, and four from those managers ranked 21-30 (measured by funds under management as at 31 December 2001). The sample also includes six boutique firms that manage less than AUD$100 million 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 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. 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 S&P/ASX 300 by 1.78 percent per annum, with a standard deviation of 1.39 percent. The mean manager in our sample group outperformed the industry average by 0.35 percent per annum.[10] 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. In unreported results, we test the sensitivity of our herding results based on fund managers having constraints of between one and seven years of performance data. As the length of returns history increases, our herding measure first decreases then increases, providing some evidence that those funds with a longer history engage in more herding.

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 fund manager for particular stocks. It is also important to note that our adjustment for option securities overcomes one of the limitations of previous U.S. studies, given that the SEC's 13F filings only require stock holdings data to be disclosed.[11]

We present descriptive statistics on the *Portfolio Analytics Database* in Table 1. Panel A shows the number of funds across years varies from ten to thirty-six. Panel B illustrates high variability in fund sizes, with a large number of small funds, but a concentration of investor assets amongst the few largest funds. Panel C shows the average number of stocks held by each fund is approximately sixty. Panel D reveals that the active equity managers hold over 95 percent of portfolio assets in equities.

(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, stock-specific data such as market capitalization, 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. We collect this data via a direct feed from the electronic trading systems of the ASX. (This data has been used previously in Aitken *et al.* (1998) and Jackson (2005).)

## B. The Australian Equity 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 ASX, as well as (b) investment manager funds under management. According to ASSIRT (2002), the largest ten investment managers hold 58 percent of total assets under management (AUD$399.9 billion of AUD$688.9 billion). There is a very pronounced level of concentration in Australian equity investments. The largest ten investment managers control 69 percent of the total Australian equity assets. There is also a high level of concentration amongst stocks in the S&P/ASX 300. The largest ten (fifty) stocks account for 48 (82) percent of the index.

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 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 (see the next section for LSV herding measure). Intuitively, if the funds in our sample were to make up 100 percent 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 may be revealed (whether intentionally or not) by the brokers employed.

## III. LSV Contemporaneous Herding Measure

### A. The LSV Herding Measure

Lakonishok, Shleifer and Vishny (1992) (hereafter LSV) define the Herding Measure, $\mathrm{H}_{i,t}$, for stock *i* and period *t* as follows:

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

where $p_{i,t}$ is the proportion of managers who had a net purchase in stock $i$ during period $t$. We only calculate $H_{i,t}$ for periods when five or more managers are trading in the same stock. For robustness, we calculate $H_{i,t}$ using alternative minimum numbers of managers, yielding similar results. 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. Subtracting E[$p_{i,t}$] from $p_{i,t}$ controls for market-wide net fund flows driving purchase decisions. The second 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 herding behavior.

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

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

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

In order to measure the effect of various stock characteristics, the securities are partitioned into quintiles for size (market capitalization), book-to-market ratio, earnings yield (earnings per share divided by stock price), 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 capitalization on ASX due to the concentration of trades executed in the largest stocks. Limiting quintiles ranking to the largest 300 stocks prevents smaller and less liquid stocks from causing bias to the composition of the quintiles. The size groups also balance the trading activities engaged by the managers, where the largest 30 stocks comprise the first group; stocks 31-70, the second group; 71-120, the third; 121-200, the fourth; and lastly, stocks greater than 200 represented in group five.[12]

B. Empirical Results

In Table 2 we present the levels of herding using the LSV measure. The overall level of herding calculated using monthly (quarterly) holdings in Panel A is 1.39 (2.70) percent. This estimate indicates that if one hundred funds are trading in a particular stock, then approximately one (three) more fund(s) would be trading on the same side of the market than would be expected if all managers traded in a random and independent manner. This result is comparable with previous U.S. (Wermers (1999)), U.K. (Wylie (2005)) and Japanese studies (Kim and Nofsinger (2005)), indicating a similarity between Australian and foreign markets. The increased herding level from monthly to quarterly intervals could be an artifact of lengthening the measurement horizon. Firstly, aggregating trades over longer periods lowers the risk of classifying follower trades into separate periods, and hence it increases this contemporaneous herding measure. Secondly, a longer measurement horizon also increases the risk we aggregate independent trades as if they are herding trades.[13] This measurement horizon issue illustrates an important weakness in contemporaneous herding measures.

We find 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 find greater levels of herding on the buy-side. This suggests that active managers are more likely to sell than buy in herds. Consistent with Wermers (1999), in Panels B-D of Table 2 we also find herding is greatest in small growth stocks, as the precision of information concerning these stocks is likely to be lower. Panel E shows that momentum trading appears unrelated to herding in the Australian market.

(INSERT TABLE 2)

## IV. Informed Trade Packages Approach to Herding

This study uses a leader-follower trade packages framework to study herding. We first define trade packages and identify trade packages that are likely to be informed. Second, we assess the extent to which other fund managers follow these informed trade packages. Third, we examine the profitability of leader and follower trade packages. Then we study leader risk constraints and post-package returns. Finally we attempt to identify the characteristics of lead managers.

## A. Defining Trade Packages

We adopt the trade package definition of Chan and Lakonishok (1995), who show that managers trade stocks over multiple days to minimize trading costs and market impact. They use a five-day gap definition of a trade package, implying a new trade package begins if there is a five-day gap between manager trades (in the same direction), or if the manager executes a trade in the opposite direction. Table 1 reports the frequency distribution of trade packages for both package length and stock size quintiles.[14] Panels E and F contain the statistics for buys and sells, respectively. These results show the benefit of using a trade package methodology, as institutions complete only 25.3 (27.7) percent of buy (sell) volume in one day. Note also that the largest thirty stocks account for 52.1 to 53.1 percent of the number of all trade packages. We find that the mean institutional trade package is 84 percent of the average daily trading volume and is thus very large. Even for large firms, trade packages average 64 percent of the average daily trading volume. From these statistics, we see the need for managers to break up trades over multiple days in order to minimize the price impact of trading and possibly to make the package less visible to would-be followers.

## B. Identifying Informed Trade Packages

In the second step, we identify those manager trade packages that are likely to contain information. Chiyachantana *et al.* (2004) suggest managers who wish to lower market impact costs will complete trades over multiple days using multiple brokers, but the same tactic can also discourage copycat followers. Manager trades are signals to the broker executing the trade, and more generally to the market, of managers' views concerning the prospects of that stock (following Kyle (1985)). As trade size increases, the likelihood of that trade being informed also increases. Therefore, managers reveal less information to brokers and fellow investment managers by splitting their orders across multiple brokers. However, we do not claim that using this multiple-broker criterion identifies all informed trade packages, which is not necessary or possible in our study.

Our data suggest 26 (28) percent of buy (sell) trade package volume is completed using multiple brokers. Not surprisingly, managers complete these larger trades over longer periods. We also find that these informed trade packages are associated with significantly fewer trade packages in the preceding five days than an average trade package, providing further support for our hypothesis that these trade packages tend to lead the actions of fellow managers.

Table 3 provides evidence that multiple broker trades are informed. Buy trade packages involving multiple brokers have a greater return over the execution period of the package, as well as a greater 250-day return from the start of the trade package, than do similar sized purchases completed using one broker over one day (see Start to Vwap Rtn in column three).

When we match similar-sized buy trade packages, completed over the same number of days for trades using either one broker or two or more brokers, we find that the execution period return is significantly higher for purchases using two or more brokers (see column six). This suggests using one broker has a lower stock price impact. Alternatively, when managers hold valuable information, they employ multiple brokers to execute their purchases. Supporting this second proposition is the statistically significant positive excess return difference between the one year return earned by multiple broker and single broker trade packages (see the bottom two rows in Table 3, Start to 1 Year After).

(INSERT TABLE 3)

For robustness, we examine three variations on the analysis to date. First, we use two alternative definitions of informed trade packages: where managers complete large trade packages over a short time period; and where managers increase (decrease) their portfolio weight from zero (above index) weight to above index (zero) weight for buys (sells). Second, we calculate excess return using the method developed by Daniel, Grinblatt, Titman and Wermers (1997) (hereafter DGTW return), modified by Gallagher and Looi (2006) for the Australian context. Third, we match trades by a variety of methods: by trade size, by number of package days, by trades of the same manager in the same stock, either of the same size or in the same year. All these additional tests yield consistent findings.

Unreported pre-trade return data suggest managers employ multiple brokers after periods of high return in order to minimize market impact, and possibly also the number of followers, by attempting to disguise the identity of the investment manager placing the trades. This suggests our result might be due to the momentum effect, where managers commonly purchase stocks with a highest past six month return, which outperform over the next year (documented in Australia by Demir *et al.* (2004)). To further examine this possibility, we firstly calculate the DGTW return which accounts for the momentum factor, and we find similar results. These findings reveal that the stocks purchased by fund managers outperform other similar momentum stocks, and suggest managers have stock-specific information in addition to exploiting momentum strategies. Secondly, we divide our trades into quintiles based on the prior six month return. We then compare the fund manager's return to S&P/ASX 300 stocks in the same momentum quintile. Manager trades outperformed over the next ninety days in four of the five quintiles, underperforming only in quintile 4. This further supports our hypothesis that multiple broker trades contain valuable information, rather than being wholly based on momentum strategies.

Our excess return may also be driven by the release of analyst earnings forecasts and recommendations that precede manager trade packages. Womack (1996) and Jegadeesh, Kim, Krische and Lee (2004), among others, show that reputable analyst recommendation changes are associated with statistically significant securities returns. However, there are multiple analysts for each stock and some analysts even provide weekly revisions. Identifying the lead or reputable analyst is crucial for studying the interaction of institutional trading and analyst earnings forecasts and recommendation revisions. Fong, Gallagher and Ng (2005) identify lead I/B/E/S stock analysts in Australia by ranking analysts according to their past forecast accuracy, forecast timeliness and price response. Their logistic regression model shows that lead analysts' earnings forecast releases have an insignificant impact on the probability of institutional trading subsequent to forecast releases.

In another unreported test, we find the results for sell trade packages are consistent. Both purchase and sale results lead us to conclude that trades using two or more brokers contain more information than similar trades using one broker. However, as our database includes long-only funds, managers can generate excess returns from purchases, but are constrained by a zero weight position for sales. Hence, throughout the remainder of our analysis we concentrate only on buy trade packages.

The observation that the trades executed using multiple brokers more heavily impact the price during the package execution than those trades using single brokers, indicates managers are not only using multiple brokers to minimize market impact (which indeed raises the question of why managers wouldn't use this tactic for all their trades), but are also using multiple brokers to execute their most profitable trades. These trades, which are motivated by valuable information, would presumably have an even greater impact on price, had they been executed using a single broker. Other brokers/managers might witness multiple large trades using the same broker and assume an informed trader is in the market, or the broker him/herself might reveal non-specific information regarding the trades of the manager to other clients trying to generate higher brokerage. Moreover, it is intuitive for brokers, who provide valuable information to investment managers, to be rewarded by the recipient manager trading exclusively with the information-providing broker. Hence multiple brokers' trades suggest that the investment manager may have acquired information independently of brokers that is exclusive to that investment manager.

### C. Leader-Follower Behavior

In Figure 1 we present manager trading behavior and market impact around informed trade packages. In order to highlight the leader-follower trading that these informed trade packages induce, we call them leader trade packages. For the purpose of aggregation, we standardize the duration of trade packages executed to five days, so that trade packages completed over more (less) than five days are compressed (expanded) into five days. This enables us to show on the graph how leader trades are distributed over our standardized five-day period. Furthermore, it enables us to display the distribution of follower trade packages both during and following the completion of the leader trades. These are expressed as a percentage of the leader's trade package volume. We find that purchases by the first (all) follower(s) account for approximately 45 (160) percent of the leader's total trade package volume, suggesting that followers complete a large proportion of trades both during and subsequent to the leader's trade package. This displays the importance of follower behavior to the leader. Finally we calculate the market impact around the trade package, finding that the majority of price run-up occurs towards the start of the leader package, staying steady during the following five days.

(INSERT FIGURE 1)

We find 32.0 (36.9) percent of informed buys (sells) have zero followers, while 18.3 (20.3), 13.4 (14.3), 10.0 (9.6), 6.8 (6.2) and 19.5 (12.7) percent have one, two, three, four and five or more followers, respectively. This shows that managers are more likely to follow buys than sells, suggesting buys have additional information content (Pinnuck (2003)). This asymmetry might also be due to the ease in mimicking a buy trade. Long-only managers can buy any stock, but they can only sell a stock if it is owned in the portfolio. This finding further supports our decision to concentrate our analysis on purchases.

Managers initiate 63 (61) percent of buy (sell) follower trade packages (unreported) before the completion of the leader trade package. There are two possible explanations. Firstly, attempts by managers to disguise information are not completely successful. This is particularly relevant in Australia, as broker identification accompanies each trade over our sample period. Consequently, brokers may infer information from market data, passing on this information to their valuable institutional clients. Alternatively, managers may release information regarding their trade before the end of the package. Secondly, managers may have correlated private information, thus, these leader-follower relationships might be due to the relative speed of information acquisition and analysis. It is not surprising that competing managers obtain this common information before the completion of the initial informed trade package. However, this hypothesis does not explain why it is that the trade packages of leaders with the best reputation are more likely to be followed than those of the less reputable managers (see section E). Additionally, we later show that, as manager disguise increases, the number of followers decrease, emphasizing the implication we draw that both following behavior and leader disguise are intentional.

### D. Trade Package Profitability

In this section our objective is to determine if informed trade packages with followers are more profitable than those trade packages with no followers, and thus to understand whether herding is associated with higher returns earned by the leader. Further, we can determine whether herding also accompanies higher returns and what degree of judgment or discretion is exercised by followers. We can also ascertain if the trades of followers are price destabilizing, or if they speed the price discovery process.

In Table 4 we partition trade packages based on manager reputation and whether followers exist. We consider top (bottom) quartile performing fund managers in the past six months who have good (poor) reputations.[15] Table 4 shows that purchases from good reputation managers generally outperform those from managers with a poor reputation. Leader purchases with followers also outperform those without followers, suggesting that followers can either identify the leader trade packages that are most likely to be successful (i.e., which contain valuable information) regardless of reputation, or that followers drive stock prices higher.

(INSERT TABLE 4)

Could the apparent herding that is observed be simply an accidental consequence of differences in fund manager response times? Suppose that all fund mangers receive the same information that is public at the same time. More responsive managers trade first and this trade initiation is followed by the trades of slower managers but without a causal link other than response times**.** This is similar to the model of Hirshleifer *et al.* (1994). Under this scenario, following is not intentional. However, it does not explain why managers are more likely to follow their better performing colleagues. Nor does it explain the relative absence of followers for the less successful trades initiated by the leader. Further, we find that leader trades with greater disguise are followed less, affirming our conjecture that following is intentional. Hence, the balance of evidence supports intentional and beneficial following, with the trade initiator attempting to discourage following in the initial stage, at least until an appropriate position in a stock has been obtained. Table 5 shows followers are still profitable up to the sixth follower over the following year (see the last two rows). Being one of the first three followers is more than one percent more profitable over the next year, than acting as the fifth or sixth follower. The fifth follower is also around half a percent more profitable than the seventh follower. This demonstrates that herding is profitable for the first six followers. Over shorter intervals than one year, following appears profitable for all followers. This result is consistent with the finding of Wermers (1999) that herding speeds the price discovery process.

(INSERT TABLE 5)

## E. Trade Characteristics

In this section, we attempt to determine whether the mere presence of followers leads to excess returns, or whether followers have discretion, mimicking the most desirable leader trades, resulting in excess returns. Secondly, we wish to understand whether following is intentional or spurious, i.e., do our followers witness the leader's trade package and consciously decide to follow that package, or are these nearby trades coincidental: due to correlated information, stock preferences or liquidity needs?

In order to investigate these hypotheses, we regress stock excess return against the number of followers, as well as against a number of manager, stock and trade characteristics. However, as the number of followers and the excess return are not independent, we employ a two-stage least squares regression, using our predicted values for our number of followers variable (in our first stage) to forecast our excess return.[16] Additional variables in our first stage include: stock size quintile, book-to-market rank, leader prior reputation rank, whether our leader already held the stock in his/her portfolio before the purchase (Already Held), whether the average follower already held the stock (if there are no followers, then we take the average value for all managers, FollowerAlreadyHeld), the number of days over which the package was completed, and the log of trade size. Due to the significant difference of our leader trade packages in terms of information content and trade execution, we also introduce a leader trade dummy variable, which is equal to one if the package is classified as a leader trade package. We then interact that dummy variable against our previous variables to determine whether these trades are indeed different.

In our second stage, we regress the excess return over the next year against the predicted number of followers as well as against various other manager and trade characteristics. Our additional variables for this second stage include leader prior reputation rank, average follower prior reputation rank (if there are no followers, we include the average follower reputation for the trades with followers), the number of days over which the package was completed, the number of brokers employed in the trade package, and the log of trade size.

Table 6 displays the results from our two-stage least squares regression. In our first stage regression of the number of followers, we find that when studying all trades, there are more likely to be more followers in large and growth stocks. Managers with a higher reputation tend to attract more followers, particularly in stocks they already hold. Followers are also more likely to follow a trade when they already hold the stock, suggesting managers are more aware of trading activity in stocks they hold. Larger trades completed over a longer period also attract more followers. This is unsurprising, since, if trading were random, more traders would follow as the package length increases. However, when we analyze our interacted variables (which allow us to separate our leader packages) we find similar results for all trade packages, except for our number of package days variable, which becomes negative. For our leader trades, we find that the longer the package length, the fewer the number of followers. This suggests that we are picking up intentional following for our leader trade packages, since the probability of intentional followers identifying these packages as containing information, decreases when managers disguise their trades more by splitting their trade up over a longer period. A counter argument suggests that fund managers may trade over fewer days, as their informational advantage is short-lived. However, this does not explain why the excess return is greater over the next year for trades completed over a longer period (see below).

Our second stage least squares regression suggests trades that involve leaders with a high reputation achieve a higher return, once again confirming the informational nature of our trades.[17] Follower reputation appears to be weakly associated with greater returns, significant at the ten percent level. Those packages employing a greater number of brokers and spread over a longer period also yield a higher return. This shows that trade disguise is intentional and that more valuable trades are spread over more days. Importantly, the predicted number of followers coefficient is significantly negative, suggesting that leaders do not wish to encourage followers to achieve a greater return. These findings also suggest that following is not blind. Instead it focuses on the most desirable leader trade packages, and typically, on leaders with better reputations, reinforcing both its benefits and its deliberate, rather than accidental, nature. This emphasizes that it is the superiority of the leader trade, and the recognition of this by followers, that drives the strong association between the presence of follower packages and the superior performance of leader packages, rather than simply the mere presence of followers.

(INSERT TABLE 6)

### F. Portfolio Risk Constraints and Post-Execution Returns

We evaluate whether fund managers fail to completely exploit their superior information as a result of risk constraints. Risk constraints arise from tracking error considerations, which limit the degree to which a manager's positions deviate from the index. Risk constraints are different for various stock sizes; that is, a manager's maximum weight in a large stock may be twice index weight, whereas, for small stocks, this overweight position may be ten times the index weight. Consequently, after partitioning our 'informed' trade packages into eight stock size groups, we partition these trades into quintiles based on the manager relative weight after the completion of the trade package. We compute the manager relative weight by dividing the manager portfolio weight in a stock by the S&P/ASX 300 index weight.[18] We then compute the average return during the execution of the trade package, as well as the return in the subsequent 5, 10, 30, 60, 90 days. We interpret the average return post-execution as manager failure to fully exploit his/her superior information. Fund managers are most likely to face portfolio risk constraints in those stocks in which they are most overweight relative to benchmark. Hence, we study the difference between top and bottom quintiles of managers' relative weight positions in stocks, and subsequent post-execution stock returns. If portfolio risk constraints are an important motivation for managers not to fully exploit their superior information, then we would expect a higher post-execution return in the top quintile of manager weight for stocks than in the lowest stock quintile.

Table 7 shows that stocks for which the manager faces the greatest likelihood of risk constraints have a higher post-execution return. Considering the one-year post execution return (last two rows), returns across all eight stock size groups are positive, and four of them are statistically significant at the 5% level. Similarly, the return during the trade package is greater in all eight groups for low relative weight quintile stocks, suggesting managers are trading more in those trades with lower risk constraints, and for longer. We present the cumulative return for the highest and lowest relative weight positions in stock size group 8 (the largest five stocks) in Figure 2. Underweight positions initially outperform the overweight positions, due to greater price pressure from our managers trading more aggressively, but then underperform them after 90 days (approximately). This suggests that risk constraints, which limit the degree to which managers can overweight stocks in the portfolio, are responsible for managers not exploiting their superior information in its entirety.

(INSERT TABLE 7 & FIGURE 2)

Following on from our analysis of risk constraints, we next ask the question whether fund managers inflate stock prices, only to sell out of their positions to subsequent followers. We find that managers often reverse their positions, with 15.4 (37.9), 36.2 (64.0) and 59.2 (78.7) percent of trade packages subsequently being completely (partially) reversed over the next 30 days, 90 days and 12 months, respectively. However, this reversal does not systematically occur at the peak, and indeed, managers lose 0.57 percent per trade of excess performance over the index during the next year after reversing their initial position in a stock. Managers do not appear to sell to subsequent followers, with only 6.8 percent of sales within a day of followers entering the market. Overall, there is little evidence to suggest that fund managers are creating stock price bubbles so as to profit from followers. It is more likely that managers are reducing their initial position to decrease risk (Hirshleifer *et al.* (1994))

## V. Conclusion and Suggestions for Future Research

This study supports previous research showing evidence of active manager herding activity. We find stronger evidence for herding amongst small and growth stocks, where information transparency is relatively low and institutional share ownership is more concentrated. These findings suggest that our quarterly portfolio positions data are quite similar to those available from the SEC for U.S. fund managers.

Utilizing a database of daily trades, we find active fund managers disguise valuable information by executing trades through multiple brokers. This disguise is effective in reducing the numbers of followers, providing evidence that following is intentional. Despite the initial positive correlation between trade initiator profits and the presence of followers, this association is more likely to arise due to both the informational superiority of the initiating trade, and its recognition by followers, rather than to the mere presence of followers. Indeed, more in-depth analysis shows that after controlling for leader reputation, follower reputation, and trade disguise characteristics, greater numbers of followers actually lead to lower post-trade return. Moreover, followers do not follow blindly, but apply their judgment as to which trades are value-enhancing. The trade-initiating leader therefore orients his/her discerning herd to greener pastures, whereby the entire market benefits from more rapid and greater price discovery.

We find that following prior institutional trades is profitable up to the seventh follower, suggesting, again, that following by the first six managers speeds the price discovery process, with the judgment of followers contributing to this process. This shows that following is rational, in addition to being intentional. Thus, regulators should perhaps be less concerned about intentional and mutually beneficial information-based herding, as it improves the price discovery process.

Managers fail to completely exploit their superior information as a result of risk constraints, limiting their relative weight in stocks with respect to the index.

Our research leads to a number of interesting research questions that can be further explored with our unique daily trading database. In particular, the use of multiple brokers by fund managers represents a significant and prospective opportunity, whereby we may better understand institutional traders' order routing preferences. In addition, our work aims to cast light on how information flow occurs between brokers and active fund managers, as well as the extent to which the information provided by brokers is relied upon and rewarded by institutions.

## REFERENCES

Aitken, M.J., G. Garvey, and P.L. Swan. "How Brokers Facilitate Trade for Long-Term Clients in Competitive Securities Markets." *Journal of Business*, 68 (1995), 1-33.

Aitken, M.J., A. Frino, M. McCorry, and P. Swan. "Short Sales are almost Instantaneously Bad News: Evidence from the Australian Stock Exchange." *Journal of Finance*, 53 (1998), 2205-2223.

Avery, C., and P. Zemsky. "Multidimensional Uncertainty and Herd Behavior in Financial Markets." *American Economic Review*, 88 (1998), 724-748.

Banerjee, A. "A Simple Model of Herd Behavior." *Quarterly Journal of Economics*, 107 (1992), 797-818.

Bartholomeusz, S. "Why the ASX Wants a Fairer Go for All on Broker IDs." *The Sydney Morning Herald*, November 20 (2003).

Bikhchandani, S., D. Hirshleifer, and I. Welch. "A Theory of Fads, Fashion, Custom and Cultural Change as Informational Cascades." *Journal of Political Economy*, 100 (1992), 992-1026.

Chan, L., and J. Lakonishok. "The Behavior of Stock Prices around Institutional Trades." *Journal of Finance*, 50 (1995), 1147-1174.

Chiyachantana, C., P. Jain, C. Jiang, and R. Wood. "International Evidence on Institutional Trading Behavior and Price Impact." *Journal of Finance*, 59 (2004), 869-898.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks." *Journal of Finance*, 52 (1997), 1035-1058.

Demir, I., J. Muthuswamy, and T. Walter. "Momentum Returns in Australian Equities: The Influences of Size, Risk, Liquidity and Return Computation." *Pacific-Basin Finance Journal*, 12 (2004), 143-158.

Falkenstein, E. "Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings." *Journal of Finance*, 51 (1996), 111-135.

Fong, K., D.R. Gallagher, and J. Ng. "The Value of Analyst Forecast Revisions to Institutional Investment Managers." UNSW *Working Paper*, (2005).

Froot, K., D. Scharfstein, and J. Stein. "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation." *Journal of Finance*, 47 (1992), 1461-1484.

Gallagher, D.R., and A. Looi. "Trading Behaviour and the Performance of Daily Institutional Trades." *Accounting and Finance*, 46 (2006), 125-147.

Grinblatt, M., S. Titman, and R. Wermers. "Momentum Investment Strategies, Portfolio Performance and Herding: A Study of Mutual Fund Behavior." *American Economic Review*, 85 (1995), 1088-1105.

Hirshleifer, D., A. Subrahmanyam, and S. Titman. "Security Analysis and Trading Patterns when Some Investors Receive Information Before Others." *Journal of Finance*, 49 (1994), 1665-1698.

Hong, H., J. Kubik, and J. Stein. "Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers." *Journal of Finance,* Forthcoming (2005).

Jackson, A.R. "Trade Generation, Reputation and Sell-Side Analysts." *Journal of Finance*, 60 (2005), 673-717.

Jegadeesh, N., J. Kim, S.D. Krische, and C.M.C. Lee. "Analyzing the Analysts: When do Recommendations Add Value?" *Journal of Finance*, 59 (2004), 1083-1124.

Jegadeesh, N., and S. Titman. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *Journal of Finance*, 56 (2001), 699-720.

Kim, K., and J. Nofsinger. "Institutional Herding, Business Groups, and Economic Regimes: Evidence from Japan." *Journal of Business*, 78 (2005), 213-242.

Kyle, A. "Continuous Auctions and Insider Trading." *Econometrica*, 53 (1985), 1315-1335.

Lakonishok, J., A. Shleifer, R. Thaler, and R. Vishny. "Window Dressing by Pension Fund Managers." *American Economic Review*, 81 (1991), 227-231.

Pinnuck, M. "An Examination of the Performance of the Trades and Stockholdings of Fund Managers: New Evidence." *Journal of Financial and Quantitative Analysis*, 38 (2003), 811-828.

Sampson, A. "Shrinking Returns Put Spotlight on Fund Managers." *The Sydney Morning Herald*, July 20 (2002).

Scharfstein, D., and J. Stein. "Herd Behavior and Investment." *American Economic Review*, 80 (1990), 465-479.

Sias, R. "Institutional Herding." *Review of Financial Studies*, 17 (2004), 165-206.

Wermers, R. "Mutual Fund Herding and the Impact on Stock Prices." *Journal of Finance*, 54 (1999), 581-622.

Womack, K. "Do Brokerage Analysts' Recommendations Have Investment Value?" *Journal of Finance*, 51 (1996), 127-167.

Wylie, S. "Fund Manager Herding: A Test of the Accuracy of Empirical Results Using U.K. Data." *Journal of Business*, 78 (2005), 381-403.

TABLE 1

**Descriptive Statistics on the Portfolio Analytics Database**

| | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|---|---|---|---|
| Panel A: No. of Managers | | | | | | | | |
| As at End of Year | 10 | 12 | 15 | 19 | 26 | 29 | 36 | 36 |
| Panel B: 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 C: No. Stocks Held per Manager | | | | | | | | |
| 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 D: 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 |

| | | 1 Day | 2-3 Days | 4-6 Days | 7-10 Days | 11+ Days |
|---|---|---|---|---|---|---|
| Panel E: Buys (41,781 Packages, $46.1 Billion Principal) | | | | | | |
| All Buys | | 61.9 (25.3) | 13.5 (14.4) | 13.2 (18.0) | 6.0 (14.6) | 5.4 (27.8) |
| 1 (small) | 7.0% of packages, 1.9% of principal | 69.1 (43.9) | 10.7 (12.8) | 10.7 (14.9) | 5.1 (11.7) | 4.4 (16.8) |
| 2 | 5.5% of packages, 2.0% of principal | 65.9 (37.9) | 12.5 (15.6) | 11.4 (12.7) | 4.8 (14.1) | 5.4 (19.6) |
| 3 | 12.5% of packages, 9.1% of principal | 61.5 (26.4) | 13.7 (12.2) | 12.9 (17.1) | 6.2 (13.0) | 5.7 (31.3) |
| 4 | 21.9% of packages, 17.3% of principal | 60.5 (24.5) | 13.9 (13.8) | 13.8 (19.4) | 6.1 (16.2) | 5.7 (26.1) |
| 5 (large) | 53.1% of packages, 69.7% of principal | 61.0 (24.4) | 13.7 (14.8) | 13.6 (17.9) | 6.2 (14.5) | 5.5 (28.4) |
| Panel F: Sells (32,609 Packages, $35.4 Billion Principal) | | | | | | |
| All Sells | | 61.9 (27.7) | 15.2 (16.5) | 12.3 (18.6) | 5.9 (14.6) | 4.7 (22.6) |
| 1 (small) | 7.7% of packages, 2.1% of principal | 66.5 (44.1) | 12.2 (12.5) | 11.4 (14.7) | 5.4 (12.7) | 4.5 (16.0) |
| 2 | 5.6% of packages, 2.0% of principal | 62.5 (31.0) | 14.7 (13.4) | 11.9 (20.0) | 6.2 (13.5) | 4.7 (22.1) |
| 3 | 12.1% of packages, 8.2% of principal | 59.5 (32.9) | 15.4 (14.0) | 13.5 (20.2) | 6.3 (12.9) | 5.3 (20.0) |
| 4 | 22.5% of packages, 18.3% of principal | 59.4 (23.0) | 15.5 (16.6) | 12.3 (18.3) | 7.1 (16.5) | 5.7 (25.6) |
| 5 (large) | 52.1% of packages, 69.4% of principal | 62.2 (27.5) | 15.6 (17.0) | 12.4 (18.6) | 5.5 (14.5) | 4.3 (22.4) |

This table provides descriptive statistics on the Portfolio Analytics Database for the period 2 January 1994 to 31 December 2001. Panels A to D contain 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. Each number in Panels E and F provides the percentage of manager trades completed over the specified number of trading days for all buys/sells and those buys/sells contained within stock size quintiles. The numbers within parentheses represent the percent of the dollar value principal.

TABLE 2

**Comparison of LSV Herding Measure at Monthly and Quarterly Intervals**

| | Monthly Intervals | | | | | | | | | 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 | | | | | | | | | | | | | | | | | | |
| 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 | 5.7** | 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 | 2.3** | 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 | 4.2** | 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 | 2.5** | 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 fulfill 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.

*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

TABLE 3

**Profitability Comparison of Buy Trade Packages completed by Multiple Brokers over Multiple Days**

| | (based on size of trade) | | | (based on size of trade and no. of package days) | | | (based on same mgr and stock) | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2+ brokers | 1 broker | Difference | 2+ brokers | 1 broker | Difference | 2+ brokers | 1 broker | Difference |
| Buy Packages | | | | | | | | | |
| Start to Vwap Rtn | 0.42** | -0.30** | 0.72** | 0.48** | -0.10 | 0.58** | 0.41** | 0.04 | 0.37** |
| *(t-statistic)* | *(5.22)* | *(-3.83)* | *(5.98)* | *(4.52)* | *(-0.69)* | *(3.00)* | *(5.56)* | *(0.58)* | *(4.14)* |
| Start to End Rtn | 0.70** | 0.06 | 0.64** | 0.68** | 0.07 | 0.61** | 0.65** | 0.20** | 0.46** |
| *(t-statistic)* | *(9.49)* | *(1.46)* | *(6.07)* | *(6.40)* | *(0.58)* | *(3.27)* | *(8.88)* | *(4.64)* | *(5.42)* |
| Start to 5 Days After | 0.79** | 0.24** | 0.55** | 0.65** | 0.30 | 0.35 | 0.85** | 0.20** | 0.66** |
| *(t-statistic)* | *(8.67)* | *(2.74)* | *(3.69)* | *(4.73)* | *(1.88)* | *(1.44)* | *(9.14)* | *(2.79)* | *(5.59)* |
| Start to 10 Days After | 0.96** | 0.39** | 0.57** | 0.68** | 0.48* | 0.20 | 0.98** | 0.21* | 0.77** |
| *(t-statistic)* | *(9.00)* | *(3.57)* | *(3.19)* | *(4.14)* | *(2.50)* | *(0.69)* | *(9.12)* | *(2.38)* | *(5.59)* |
| Start to 30 Days After | 1.34** | 0.39* | 0.95** | 1.19** | 1.1** | 0.09 | 1.43** | 0.32* | 1.11** |
| *(t-statistic)* | *(9.04)* | *(2.32)* | *(3.69)* | *(5.03)* | *(3.76)* | *(0.21)* | *(9.51)* | *(2.29)* | *(5.66)* |
| Start to 60 Days After | 1.49** | 0.18 | 1.31** | 1.14** | 1.25** | -0.11 | 1.51** | 0.56** | 0.95** |
| *(t-statistic)* | *(8.02)* | *(0.78)* | *(4.00)* | *(3.71)* | *(3.22)* | *(-0.20)* | *(7.97)* | *(3.02)* | *(3.88)* |
| Start to 90 Days After | 1.60** | 0.00 | 1.60** | 0.95** | 0.80 | 0.15 | 1.78** | 0.37 | 1.41** |
| *(t-statistic)* | *(7.00)* | *(0.00)* | *(4.18)* | *(2.59)* | *(1.77)* | *(0.24)* | *(7.91)* | *(1.68)* | *(5.10)* |
| Start to 6 Months After | 1.58** | -0.23 | 1.81** | 0.84* | 0.67 | 0.17 | 1.72** | 0.57* | 1.15** |
| *(t-statistic)* | *(6.67)* | *(-0.74)* | *(4.36)* | *(2.20)* | *(1.31)* | *(0.25)* | *(6.52)* | *(2.21)* | *(3.88)* |
| Start to 1 Year After | 1.18** | -0.04 | 1.22* | 0.99 | -0.87 | 1.86* | 1.62** | 0.54 | 1.08** |
| *(t-statistic)* | *(3.55)* | *(-0.09)* | *(2.39)* | *(1.92)* | *(-1.25)* | *(2.23)* | *(4.48)* | *(1.58)* | *(3.28)* |

In the three left columns, we average the matched purchase packages completed by multiple brokers over multiple days against purchase packages of a similar size (within ten percent, where trades within one percent were preferred) completed over one day, by one broker. In the middle three columns, we average the matched purchase packages completed by multiple brokers over multiple days against purchase packages of a similar size (within ten percent, where trades within one percent were preferred) completed over the same number of days, by one broker. In the three right columns, we average the matched purchase packages completed by multiple brokers over multiple days against purchase packages of the same manager in the same stock, completed by a single broker. All figures not in parentheses are excess returns, calculated by taking the difference between manager returns and index returns, and are in percentage terms.

*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

TABLE 4

**Profitiability Comparison of Informed Trade Packages**

| Number of Followers | Leader Good Reputation | | | Leader Poor Reputation | | |
|---|---|---|---|---|---|---|
| | With Followers | Without Followers | Difference | With Followers | Without Followers | Difference |
| Buy Packages | | | | | | |
| Start to Vwap Rtn | -0.02 | 0.20 | -0.22 | -0.07 | -0.02 | -0.05 |
| *(t-statistic)* | *(-0.12)* | *(0.80)* | *(-0.71)* | *(-0.35)* | *(-0.06)* | *(-0.19)* |
| Start to End Rtn | 0.79** | 0.93** | -0.14 | 0.72** | 0.32 | 0.40 |
| *(t-statistic)* | *(4.36)* | *(3.82)* | *(-0.46)* | *(3.84)* | *(1.15)* | *(1.61)* |
| Start to 5 Days After | 0.97** | 0.69* | 0.27 | 0.95** | 0.56 | 0.40 |
| *(t-statistic)* | *(4.43)* | *(2.05)* | *(0.97)* | *(4.11)* | *(1.80)* | *(0.45)* |
| Start to 10 Days After | 1.54** | 0.53 | 1.01** | 1.16** | 0.45 | 0.70 |
| *(t-statistic)* | *(6.10)* | *(1.29)* | *(2.63)* | *(4.20)* | *(1.19)* | *(0.69)* |
| Start to 30 Days After | 2.26** | 1.11 | 1.15 | 1.17** | 0.46 | 0.71 |
| *(t-statistic)* | *(6.79)* | *(1.86)* | *(1.71)* | *(3.17)* | *(0.81)* | *(0.63)* |
| Start to 60 Days After | 2.15** | 1.81* | 0.34 | 1.68** | 0.30 | 1.37 |
| *(t-statistic)* | *(5.06)* | *(2.27)* | *(0.39)* | *(3.55)* | *(0.39)* | *(1.01)* |
| Start to 90 Days After | 2.36** | 2.47* | -0.11 | 2.24** | 0.59 | 1.65** |
| *(t-statistic)* | *(4.73)* | *(2.67)* | *(-0.10)* | *(4.15)* | *(0.66)* | *(4.28)* |
| Start to 6 Months After | 3.11** | 2.18* | 0.93 | 2.24** | 0.13 | 2.10** |
| *(t-statistic)* | *(5.46)* | *(2.04)* | *(0.83)* | *(3.53)* | *(0.13)* | *(4.47)* |
| Start to 1 year After | 5.35** | 3.48** | 1.87 | 4.09** | 1.64 | 2.45** |
| *(t-statistic)* | *(7.06)* | *(2.83)* | *(1.36)* | *(5.04)* | *(1.33)* | *(3.60)* |

In this table, we average the returns of informed trade packages for trades partitioned by reputation, and whether there are followers. Good (poor) reputation leaders are defined as those with a top (bottom) quartile performance over the prior 6 months. Excess returns are calculated by taking the difference between manager returns and index returns. All figures not in parentheses are in percentage terms.

*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

TABLE 5

**Profitability Comparison of Follower Trades**

| Order of Follower | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Buy Packages | | | | | | | | |
| Start to Vwap Rtn | 0.18 | 0.24 | 0.04 | -0.26 | -0.06 | 0.09 | 0.08 | 0.05 |
| *(t-statistic)* | *(1.45)* | *(1.53)* | *(0.22)* | *(-1.47)* | *(-0.28)* | *(0.30)* | *(0.24)* | *(0.12)* |
| Start to End Rtn | 0.12* | 0.11 | 0.13 | 0.19* | 0.31** | 0.33** | 0.35** | 0.30* |
| *(t-statistic)* | *(2.31)* | *(1.73)* | *(1.88)* | *(2.48)* | *(3.35)* | *(3.05)* | *(3.06)* | *(2.20)* |
| Start to 5 Days After | 0.65** | 0.53** | 0.62** | 0.64** | 0.59** | 0.62** | 0.64** | 0.59* |
| *(t-statistic)* | *(7.30)* | *(5.26)* | *(5.52)* | *(5.30)* | *(4.35)* | *(3.65)* | *(3.05)* | *(2.34)* |
| Start to 10 Days After | 0.80** | 0.74** | 0.93** | 0.96** | 0.91** | 0.79** | 0.77** | 0.59 |
| *(t-statistic)* | *(7.25)* | *(5.98)* | *(6.72)* | *(6.28)* | *(5.20)* | *(3.86)* | *(3.12)* | *(1.95)* |
| Start to 30 Days After | 1.13** | 1.05** | 1.36** | 1.31** | 1.19** | 1.17** | 1.26** | 0.98* |
| *(t-statistic)* | *(6.83)* | *(5.78)* | *(6.81)* | *(5.94)* | *(4.80)* | *(4.00)* | *(3.68)* | *(2.47)* |
| Start to 60 Days After | 1.23** | 1.34** | 1.65** | 1.39** | 1.22** | 1.38** | 1.63** | 1.01 |
| *(t-statistic)* | *(5.35)* | *(5.26)* | *(5.86)* | *(4.45)* | *(3.63)* | *(3.57)* | *(3.71)* | *(1.93)* |
| Start to 90 Days After | 1.24** | 1.62** | 1.97** | 1.67** | 1.26** | 1.26** | 1.31* | 0.21 |
| *(t-statistic)* | *(4.44)* | *(5.35)* | *(5.90)* | *(4.50)* | *(3.16)* | *(2.73)* | *(2.45)* | *(0.33)* |
| Start to 6 Months After | 1.22** | 1.60** | 2.02** | 1.92** | 1.49** | 1.53** | 1.85** | 0.60 |
| *(t-statistic)* | *(3.57)* | *(4.36)* | *(5.09)* | *(4.43)* | *(3.13)* | *(2.78)* | *(2.97)* | *(0.85)* |
| Start to 1 year After | 2.05** | 1.83** | 1.56** | 1.07 | 0.24 | 0.18 | -0.21 | -1.74 |
| *(t-statistic)* | *(4.20)* | *(3.56)* | *(2.79)* | *(1.70)* | *(0.35)* | *(0.22)* | *(-0.24)* | *(-1.71)* |

We average the returns of the followers of informed trade packages (i.e., trade packages completed using multiple brokers over multiple days), based upon the order of the followers. All figures not in parentheses are excess returns, calculated by taking the difference between manager returns and index returns, and are in percentage terms.
*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

TABLE 6

**Two Stage Least Squares Regression**

| | Number of followers per trade | | 1 Year Excess Return |
|---|---|---|---|
| Intercept | -1.578** | Intercept | -0.063** |
| | *(-18.47)* | | *(-6.31)* |
| LeaderReputationRank | 0.021** | LeaderReputationRank | 0.002** |
| | *(15.28)* | | *(9.86)* |
| Stock Size | 0.215** | FollowerReputationRank | 0.001 |
| | *(20.60)* | | *(1.70)* |
| BookToMarketRank | -1.403** | Number of brokers | 0.005** |
| | *(-24.24)* | | *(3.02)* |
| AlreadyHeld | 0.164** | Number of trade days | 0.002** |
| | *(5.63)* | | *(3.59)* |
| FollowerAlreadyHeld | 2.096** | Log(Trade Size) | 0.004** |
| | *(76.66)* | | *(5.23)* |
| Number of trade days | 0.198** | Predicted Number of Followers | -0.005** |
| | *(60.44)* | | *(-4.33)* |
| Log(Trade Size) | 0.093** | | |
| | *(14.87)* | | |
| LeaderTradeDummy | -1.718** | | |
| | *(-7.05)* | | |
| (LeaderTradeDummy)*LeaderReputationRank | 0.007* | | |
| | *(2.11)* | | |
| (LeaderTradeDummy)*Stock Size | 0.363** | | |
| | *(12.05)* | | |
| (LeaderTradeDummy)*BookToMarketRank | -0.670** | | |
| | *(-4.52)* | | |
| (LeaderTradeDummy)*AlreadyHeld | 0.501** | | |
| | *(7.12)* | | |
| (LeaderTradeDummy)*FollowerAlreadyHeld | 0.564** | | |
| | *(7.51)* | | |
| (LeaderTradeDummy)*Number of trade days | -0.038** | | |
| | *(-6.38)* | | |
| (LeaderTradeDummy)*Log(Trade Size) | -0.003 | | |
| | *(-0.17)* | | |
| No. of Observations | 34080 | No. of Observations | 34080 |
| Adjusted R-squared | 44.7% | Adjusted R-squared | 0.58% |

In this table, we conduct a two stage ordinary least squares regression. In the first stage we regress the number of followers against a number of variables (described in the table). In the second stage, we use the predicted values for the number of followers variable (from the first stage) to predict the one year excess return for our trade. We conduct this regression for all manager purchases, where our leader trades are given a leader trade dummy value of one.

*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

TABLE 7

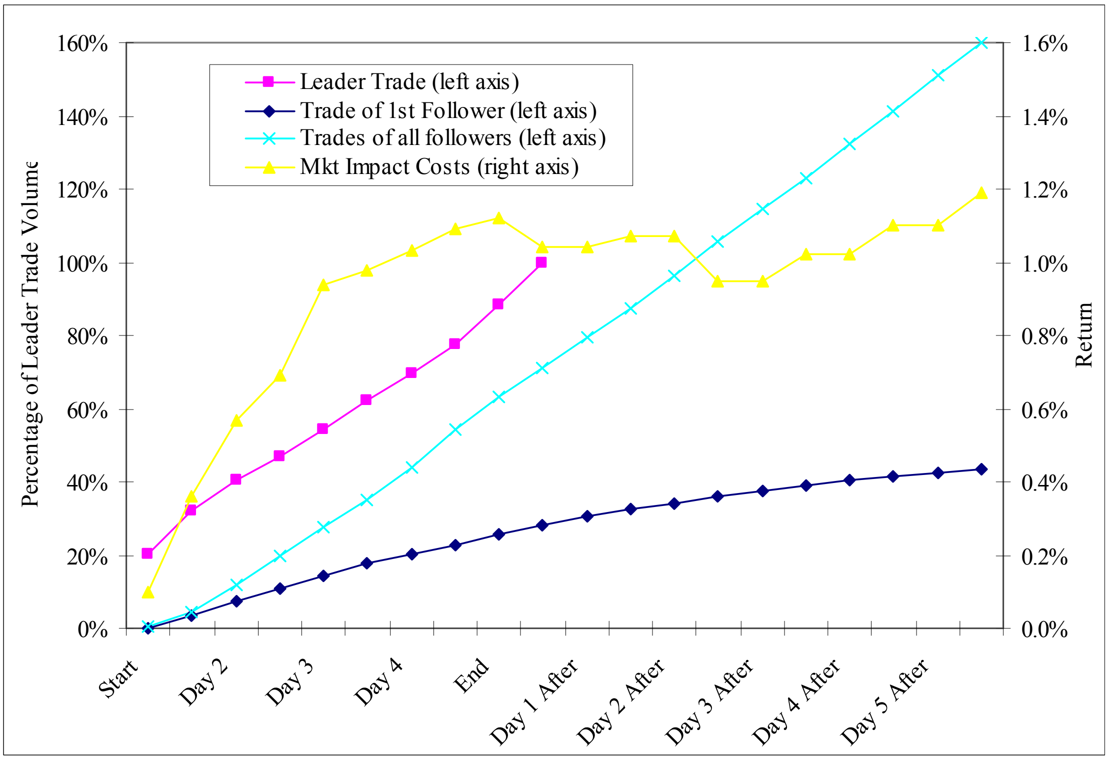
**Risk Constraints and the Profitability of Leader Trades**

| Stock Size Groups | 1 (stocks 200+) | 2 (stocks 151-200) | 3 (stocks 101-150) | 4 (stocks 51-100) | 5 (stocks 21-50) | 6 (stocks 11-20) | 7 (stocks 6-10) | 8 (stocks 1-5) |
|---|---|---|---|---|---|---|---|---|
| Buy Packages | | | | | | | | |
| Start to End Rtn (Q5) - (Q1) | -2.4* | -2.2 | -0.9 | -0.3 | -0.3 | -0.2 | -0.4 | -0.5 |
| *(t-statistic)* | *(-2.41)* | *(-1.60)* | *(-1.18)* | *(-0.47)* | *(-0.51)* | *(-1.53)* | *(-0.97)* | *(-1.93)* |
| Next 5 Day Rtn (Q5) - (Q1) | 0.6 | 0.7 | 0.5 | 0.4 | -0.4 | 0.8 | 1.1 | -0.4 |
| *(t-statistic)* | *(0.85)* | *(0.88)* | *(0.77)* | *(0.84)* | *(-0.74)* | *(1.30)* | *(1.75)* | *(-0.90)* |
| Next 10 Day Rtn (Q5) - (Q1) | 0.7 | 0.6 | 0.3 | 0.4 | -0.5 | 0.7 | 1.3 | -0.6 |
| *(t-statistic)* | *(0.67)* | *(0.45)* | *(0.33)* | *(0.59)* | *(-0.68)* | *(0.85)* | *(1.61)* | *(-1.04)* |
| Next 30 Day Rtn (Q5) - (Q1) | -0.5 | 0.2 | 1.8 | 0.8 | 0.3 | 1.8 | 3.9** | 0.6 |
| *(t-statistic)* | *(-0.23)* | *(0.11)* | *(1.05)* | *(0.81)* | *(0.29)* | *(1.55)* | *(2.99)* | *(0.60)* |
| Next 60 Day Rtn (Q5) - (Q1) | 2.4 | -2.3 | 3.5 | 1.7 | 0.1 | 1.1 | 5.2* | 0.8 |
| *(t-statistic)* | *(0.74)* | *(-0.70)* | *(1.53)* | *(1.24)* | *(0.04)* | *(0.73)* | *(2.49)* | *(0.60)* |
| Next 90 Day Rtn (Q5) - (Q1) | 1.6 | 1.0 | 6.0 | 3.8* | 1.0 | 1.1 | 9.4** | 2.2 |
| *(t-statistic)* | *(0.44)* | *(0.22)* | *(1.88)* | *(2.07)* | *(0.56)* | *(0.54)* | *(4.51)* | *(1.37)* |
| Next 6 Month Rtn (Q5) - (Q1) | 0.9 | 1.6 | 10.4** | 4.9* | 3.0 | 1.8 | 11.3** | 2.8 |
| *(t-statistic)* | *(0.25)* | *(0.32)* | *(2.92)* | *(2.13)* | *(1.48)* | *(0.69)* | *(4.57)* | *(1.53)* |
| Next 1 Year Rtn (Q5) - (Q1) | 3.8 | 6.5 | 12.4* | 10.5** | 5.1 | 0.3 | 17.3** | 5.8** |
| *(t-statistic)* | *(0.74)* | *(0.95)* | *(2.16)* | *(3.12)* | *(1.72)* | *(0.08)* | *(5.33)* | *(2.64)* |

In this table, we firstly partition our sample of manager trade packages into stock size groups, as described in the column headings. Next, we sort our trade packages into quintiles based on manager relative weight (mgr weight divided by index weight in the stock after the trade package is completed). Trades in the highest (lowest) quintile are most (least) likely to face risk constraints limiting the size of the trade. We calculate the difference between the average excess return over various periods, for trades in the highest quintile (those with the greatest overweight positions) and the lowest quintile (those with the lowest relative weight). Hence, this table measures the difference in average excess return of the trades where there is the greatest and least likelihood of the manager facing risk constraints. Excess returns are calculated by taking the difference between manager returns and index returns. All figures not in parentheses are in percentage terms.

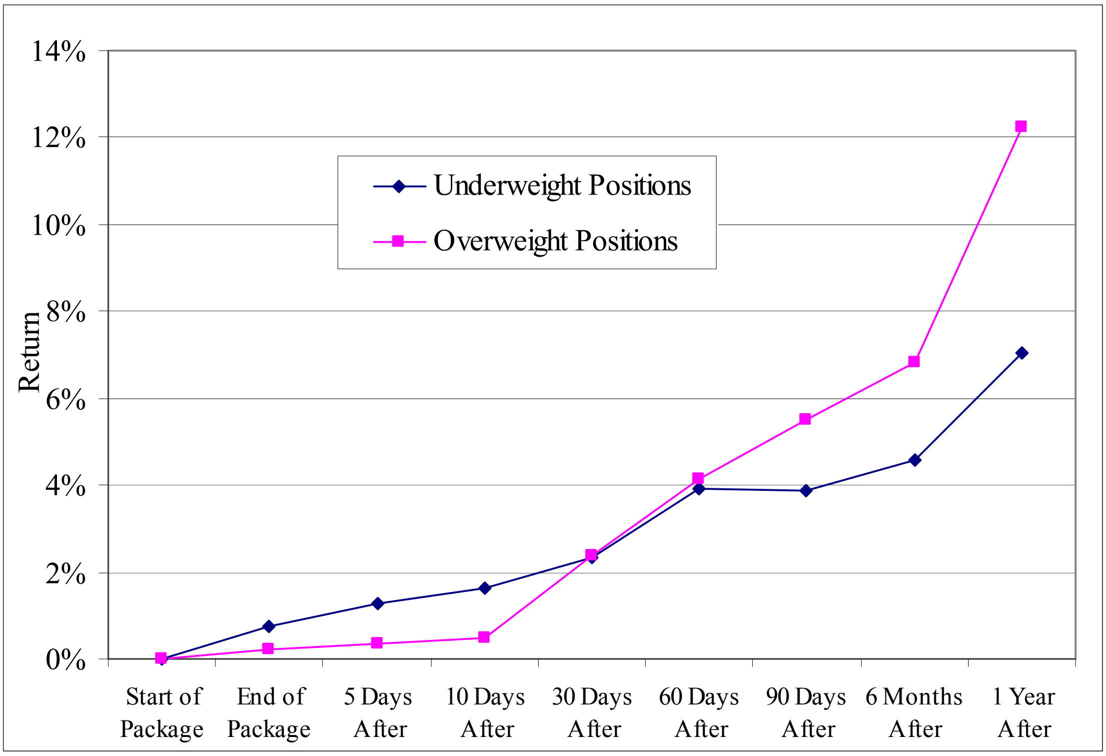
*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

**Figure 1**
**Market Impact of Manager Activity During and After Leader Trade Packages**




This figure shows the trade activity around our leader trade packages. We aggregate all leader trade packages into one representative package over five days to show the distribution over days (summing to 100%). We also aggregate follower packages, averaging their trade volume over each day (including the five days following the leader's trade package) as a percentage of the leader's trade volume (left axis). Secondly, we calculate the average cumulative return (right axis) over the trade package interval and the following five days.

**Figure 2**
**Manager Trade Package Return for Relative Weight Quintiles**




In this figure, we partition our sample of manager trade packages into stock size groups. For stock size group 8, containing the largest 5 stocks, we sort our trade packages into quintiles based on manager relative weight (mgr weight divided by index weight in the stock after the trade package is completed). Trades in the highest (lowest) quintile are most (least) likely to face risk constraints limiting the size of the trade. We show the cumulative return over the year following the trade package, for trades in the highest quintile (those with the greatest overweight positions) and the lowest quintile (those with the lowest relative weight).

[1] 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 destabilizing to markets". See also Sampson (2002).

[2] The first two theories explain herding or *intentional* herding. 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.

[3] We test the relative profitability of 'informed' trade packages, matching against trades of a similar size yet completed by a single broker over a single day. We also match against similar sized trade packages, again completed by a single broker but over the same number of days. We find that those trades executed using multiple brokers are more profitable. We also use the definition that those trades are completed using multiple brokers (but not over multiple days), finding consistent results. Secondly, to account for stock size, we complete this test, matching for trades where trade size is divided by the index weight of that stock, as similar sized trades have a different impact when executed in stocks of a different size. This test also yields consistent results. Thirdly, to remove any manager-specific trade and stock biases, we match trades of the same manager in the same stock. We again perform these tests using the condition that the matched trades are of the same size or completed over the same year. Lastly, we complete all these checks using both the excess return over the S&P/ASX 300 Index, and over the DGTW return, as modified for the Australian context by Gallagher and Looi (2006). These numerous robustness checks all yield consistent results, particularly for buy packages.

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

[5] For a more detailed analysis of broker activity in Australia, see Aitken *et al.* (1995). From 28$^{th}$ November 2005, the pre-trade disclosure of broker IDs to other brokers ceased. It was replaced by a system of post-trade transparency with respect to broker IDs on settlement, three days after the trade.

[6] These findings suggest that managers follow the trades of their competitors, and are available upon request. We thank Richard Sias for his encouragement to pursue this part of the analysis.

[7] 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.

[8] 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.

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

[10] We calculate these statistics for all the managers in our sample over the period 1994-2001. Mercer Investment Consulting supplied investment returns for their entire investment universe.

[11] This improvement, while minor, due to the low number of options holdings in our sample, allows for a more accurate measure of portfolio holdings of investment managers.

[12] We note that the typical quintile definition involves five groups of equal number of members. This is not the case for our size groups.

[13] Using contemporaneous herding measure may lead to another type of error, i.e., classifying mimicking trades into separate periods, thereby incorrectly reducing the level of herding.

[14] We form quintiles using the largest 250 stocks traded on the ASX. We did this, since there are many illiquid stocks, which if included, would result in the majority of liquid stocks being classified in the top two quintiles.

[15] For robustness, we also partition managers based on their performance over the previous three months, yielding similar findings.

[16] Hausman tests confirm that for our leader trades, a two-stage regression achieves significant different results from an ordinary least squares model. This difference, however, is not present for all trades.

[17] When we regress leader trade dummy interaction variables in our second stage regression, we find all these variables to be insignificantly different from zero.

[18] We partition the stock size groups as follows: Q8 includes the largest five stocks; Q7, stocks 6-10; Q6, stocks 11-20; Q5, stocks 21-50; Q4, stocks 51-100; Q3, stocks 101-150; Q2, stocks 151-200; and Q1, stocks 200+. For robustness, we tested other variations, including standard stock quintiles and our previous definition of stock groups, all yielding similar results.