To Herd or Not to Herd: Do Mimicking Traders Ignore Their Private Information?

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Abstract

The theory of informational cascades culminating in Grenadier (1999) shows that rational investors who receive private signals and observe each other's trades, trade in sequence: those with stronger signals trade first. Investors who follow (i.e., mimic) earlier trades do not 'herd', unless acting contrary to their own signals. We built a set of observations of fund managers' daily trades, unique proxies for trades' informational content based on inferences from 'stealth trading,' and whether or not private information is acted upon. This enabled us to conduct the first test of herding models. To qualify as the initial and highly informed trade the trade must be disguised by the use of two or more brokers. We find that these are exceptionally profitable (relative to the market) for all horizons of up to one year. To qualify as a mimicking trade the trade must be in the same stock and in the same direction and within five days of the completion of the initial trade package. Now suppose that mimicking fund mangers up until number *n*-1 generate profitable trades for all horizons of up to one year. For the *n*th or greater mimicking fund manager to qualify as trading against their own private information, the addition of such trades must be associated with losses (relative to the market) for all horizons up to one year. That is, a follower who turns out to have made a bad choice is assumed to have traded against their private information. We find that fund managers do trade in sequence, in support of an earlier conjecture. They also identify the most valuable leader trades to mimic. There is little evidence of herding other than for a horizon of a year with four or more followers.

Key words: Herding; Informational cascades; Trade sequences; Leader and follower trades.

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1. Introduction

For several millennia the human species has been transfixed by the way that either disaster or effective learning occurs as a result of imitation. Is it the biblical parable, 'If the blind lead the blind, both shall fall into the ditch' (*The Bible, Matthew* 15:14)? The sentiment is itself possibly mimicked from texts dating from as early as 800 BC[1]. Alternatively, is imitation of the knowledgeable in society the basis for most progress? The Italian philosopher, Niccolo Machiavelli (1514), wrote, 'Men nearly always follow in the tracks made by others and proceed in their affairs by imitation'. The issue of whether imitation is a curse or to be applauded remains unsettled, especially with respect to the present subject matter—mimicking investment managers. Keynes (1936) argued that investors in asset markets are unable to process information efficiently as in the biblical example, likening them to judges in a beauty contest who act contrary to their own opinions. As a consequence of this, he believed that markets display 'animal spirits'.

The issues raised by Keynes have never been satisfactorily addressed. One of the reasons for this state of affairs is the lack of any formal testing of the manner in which information is incorporated into asset prices by mimickers, despite a plethora of theoretical models. We set out to provide such a test based on observed sequences of imitating daily trades made by fund managers. Since we are required to discover if these mimicking managers either act in favor of, or contrary to, their private informational signals that are not directly revealed to any-one, we have set ourselves a difficult task in proposing to provide formal tests of models of 'informational cascades' for the first time.

Theoretical models predict 'rational herding' and informational cascades in which traders acting sequentially rationally imitate an earlier trade, even though they receive a private signal that would motivate them to do the opposite (for example, see Banerjee, 1992, Bikhchandani, Hirshleifer and Welch, 1992, 1998, Welch, 1992, Froot, Scharfstein, and Stein, 1992, and Avery and Zemsky,

[1] From the Upanishads, the sacred Hindu treatises, *Katha Upanishad,* we have*:* 'fools go aimlessly hither and thither, like blind led by the blind' (http://www.phrases.org.uk/meanings/67150.html)

1998).[2] By way of illustration, a group of traders may each receive a private signal that the price of a stock is significantly different from its current value, but do not know if the signal they have received is correct. If they see another trader buy the stock, they infer that this trader received a signal that the stock was undervalued, and may therefore purchase the stock even though their own private signal was to the contrary.

These earlier contributions model informational cascades when the order of decisions by imperfectly informed decision-makers is exogenous. For example, when prospective diners arrive in a pre-ordered sequence at two restaurants, one busier than the other, the busier is chosen on the grounds that earlier diners have discerned the best restaurant. This would be true even if the later arrivals are acknowledged experts on the restaurant scene. One of the pioneering contributions, Bikhchandani, Hirshleifer and Welch (1992), conjectures that if agents receive signals with different degrees of precision then there is an incentive to delay so as to free-ride on the agents acting earlier. The agent who receives the most precise signal gains the least from waiting and thus acts first. Chamley and Gale (1994) analyze the timing of mimicking decisions when all agents receive signals of the same precision. Zhang (1997) shows that the most informed agent will act first when there is a cost of delay and agents receive private binary signals (good or bad) of varying precision. The private nature of information signals means that there is uncertainty about who possesses the most informative signal. The first-mover receiving the most precise signal precipitates an immediate informational cascade because nothing more can be learned by waiting longer. Zhang (1997) conjectures that cascading can be postponed until more than one agent has mimicked when signals are no longer binary. Grenadier (1999) shows that a minimum of two mimickers is required

[2] In the context of investment management, Scharfstein and Stein (1990) use a reputational agency model to show that investment manager 'share-the-blame' by mimicking each other and avoid individual blame for poor performance when the market goes sour. Once again, investors only herd when they ignore their own private information. Lee (1998) extends models of informational cascades to trading in the context of stock market bubbles and crashes. Devenow and and Welch (1996) provide a survey of rational herding, while Hirshleifer and Teoh (2003) provide a more general survey of the area.

before an informational cascade occurs. The remaining agents have observed evidence provided by the more informed agents that have traded first. These latecomers will simultaneously mimic the observed trades regardless of their own private signals. This then satisfies the definition of herding.

There is a parallel and hence largely non-intersecting literature on the choice of an optimal trade size by informed investors wishing to camouflage their desired orders by spreading them over time (see, for example, Kyle, 1985). Barclay and Warner (1993) show that informed investors split large packages of orders up into medium-sized trades. These information-rich trades are largely initiated by institutional investors (Chakravarty, 2001). In Grenadier's (1999) approach based on the earlier conjecture, the agent receiving the strongest positive signal about an underpriced stock must logically purchase first as the lesser-informed agents prefer to wait so as to observe the purchase decision. The agent receiving the strongest signal will also wish to make the largest stock acquisition. However, it is not in the interests of the agent acting first to publicly reveal their action as it is a credible signal as to both the direction and magnitude of their private signal. The theoretical herding literature is predicated on the actions of informed agents being observable, even though such revelation is not necessarily in their interests. Any empirical test must not only be cognizant of this incentive to disguise, but should also try to exploit it to the full. Our approach is based on this important twist to the existing literature.

On observing the most informed agent's choice, mimicking agents immediately raise the cost to the agent of acquiring stock by purchasing in competition with him. Therefore, the trade initiating agent adopts camouflaging activities, such as splitting a large purchase order into multiple 'medium-sized' trades, as indicated by Barclay and Warner (1993). A related form of disguise includes splitting the order over multiple days so that on any given day there is less indication of unusual buying activity. Additional disguise can be obtained by splitting up the order over multiple brokers so that no one broker knows the size of the order. Moreover, this stratagem makes it harder for participants to know which agent is placing the orders and therefore to infer either the strength

or direction of the signal. We subsequently establish that conditional on order size, the more days and the more brokers the order is split over, the greater is the long-term profitability of the order.

On the basis of this empirical finding we then hypothesize that the stronger the unobservable signal received by the agent (and hence the greater the long-run profitability) the greater will be the element of camouflage adopted in executing a given order. This hypothesis immediately identifies for us the agent who trades 'first' in the sense of Grenadier (1999), that is, the one who disguises an order by splitting it up over multiple days and multiple brokers. The agent making one of these highly disguised trades is hypothesized to have received the strongest informational signal relative to other agents and is rewarded by obtaining the highest long-run return. We then investigate the responses of would-be followers to these highly disguised trades.[3]

The empirical literature on the mimicking patterns of trading behavior has typically not addressed the central issue of whether or not investors act contrary to their own private signals. In fact, indicative of a mismatch between the theoretical and extant empirical studies, the term 'herding' has come to encapsulate all correlated trading situations, in which one investor copies the trades of another by trading in the same stock and in the same direction (see, for example, Lakonishok, Shleifer and Vishny, 1992, hereafter LSV, Wermers, 1999, and Nofsinger and Sias, 1999). This empirically-motivated definition says little about whether this behavior is true herding in the sense that mimickers act contrary to their own private signals.

In order to be able to analyze the agent's underlying order prior to disguise being adopted we combine the trades of active fund managers into trade packages (hereafter, packages) using the approach of Chan and Lakonishok (1995). This lifts the cloak provided by the stealth-like nature of

[3] Consider some alternative methodology such as identifying trades surrounding conventional information events such as (say) earnings announcements. There would be obvious problems such as establishing which trade was the 'first', which trade was the most informed, and so on. Even if one relied on establishing the trader with the best track-record or reputation, on any given occasion such a manager may not have received the strongest signal and therefore may not have made the 'first' trade in the sense of Grenadier (1999).

strategic trading to convey the underlying orders that reflect the true signal strength received by the agent.

We show that disguised trades utilizing trades utilizing two or more brokers over two or more days leads to (i) statistically and economically significant higher returns over the subsequent year, and (ii) these disguised trades that are mimicked have a higher return over the subsequent year than disguised trades that are not mimicked. This establishes that such mimicking is not true herding since these traders do not ignore their own private information and, importantly, do contribute to the long-term success of the trade sequence. We do find an exception to this non-herding result when there are four or more followers with the one-year horizon. There is no evidence at all of herding with a six-month horizon so that neither the models of Zhang (1997) nor Grenadier (1999) are supported. Nonetheless, we do find strong empirical support for Grenadier's (1999) result and the earlier conjecture by Bikhchandani, Hirshleifer and Welch (1992): the order in which trade sequences occur is reflective of relative signal strengths, with the most informed agent as the trade initiator, and follower trades taking place in sequence with declining signal strength.

The traditional correlated trading approach does not tell us whether mimickers ignore their own private information. However, one in particular of these studies, Wermers (1999), does tell us that such correlated trading is beneficial to market efficiency as it is strongly associated with price discovery. Stocks bought heavily by mutual funds outperform stocks heavily sold over the next six months.

The remainder of this paper is organized as follows. Section 2 describes the data. For comparison with the literature and to show that our data is consistent with the CDA/Spectrum mutual fund portfolio holdings data, Section 3 contains the research design and empirical results, based on the empirical herding measure used in previous studies over monthly and quarterly intervals. For robustness, we also employ the herding measure proposed by Sias (2004).[4] In Section

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

4, we present the trade package approach to address the issue of whether trade mimickers act on or ignore private signals. Our conclusions are presented in the final section.

2. Data

2.1 Description of Databases

The absence of any formal tests of the existence of herding equilibria in which mimickers ignore their own private information is not surprising as the test requires: (i) both observation and identification of the 'first' trade for which the strongest private signal has been received, even in circumstances where there may be no mimicking trades; (ii) the ability to observe and measure the long-term profitability of the first trade to trader 1 (the trade initiator), second trade to trader 2 (the first mimicker), if there is a second trade, third trade to trader 3 if there is a third trade, and so on; and (iii), as described in Sections 4.1 and 4.7 below, the ability to measure the long-run profitability of the first trade to trader 1, both when there is mimicking from agents 2 to *n* and without it. Hence the informational demands are severe. They require at the very least full daily trading information for fund managers, as well as meaningful indicators of unobservable informational signals underlying every fund manager trade and whether or not fund managers act on this information or contrary to it.

Our sample comprises 30 active equity managers, sourced from the *Portfolio Analytics Database*. Individual fund managers provided daily trade summaries and monthly holdings, together with broker identification for each trade, under conditions of strict confidentiality. The sample period of this study is 2nd January 1994 to 31st December 2001. Therefore, our data contains the two prerequisites for testing the herding hypothesis—comprehensive daily trading information at the fund manager level for major fund managers and indicators of the extent to which disguise has been adopted via the inclusion of broker identifiers for every trade and the ability to detect the splitting up of orders over multiple days.

The information in the database we constructed was elicited by invitation from active investment managers operating in Australia, based on total funds under management.[5] We asked the investment managers to provide portfolio information for either their largest or largest and second-largest, active institutional Australian equities fund but only eight of the thirty managers provided more than one.[6] Hence, 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.[7] This database comprises a sample that is representative of the Australian investment management industry, and includes six of the ten largest managers, six from the next ten, and four from those managers ranked 21-30 (measured by funds under management as of 31 December 2001). The remaining fourteen of the thirty managers represent smaller funds including six boutique firms that manage less than AUD$100 million each.

Due to this 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' are included, hence potentially overstating performance. Similarly, selection bias may also be present, in that it is possible that managers who contributed data were more successful than non-contributors.

Studies including Grinblatt, Titman, and Wermers (1995) show that funds that engage in correlated trading tend to earn higher returns. Thus, these biases may also overstate the level of mimicking behavior. However, we have the opportunity to gain insight into these possible effects by comparing the fund returns of managers in our study with the returns for the population of

[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 realized (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 those with the highest marked-to-market valuation as of 31 December 2001. We specified this condition as a means of limiting the significant effort required for compiling the data, as well as for maximizing the chances of cooperation.

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

investment managers (including non-surviving funds) sourced from the 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 the considerably lesser amount of 0.35 percent per annum.[8] Hence, the level of out-performance for our sample is small compared with the mean out performance of the entire industry. Therefore, we can conclude that survivorship and selection bias are unlikely to be significant problems for our study.[9]

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 Security and Exchange Commission's (SEC's) 13(f) filings require, at best, only quarterly stock holdings data to be disclosed without any requirements for derivative securities.[10] Thus the commonly used CDA/Spectrum mutual fund data based on SEC filings contains no information on derivative security holdings.

[8] 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.

[9] In unreported results, we test the sensitivity of our empirical 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.

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

We present descriptive statistics on the *Portfolio Analytics Database* in Table 1. Panel A shows that the number of funds across years varies from ten to thirty-six, although there are thirty eight funds represented in total. Panel B illustrates the high variability in fund sizes, with a large number of small funds, but a concentration of investor assets among the few largest funds. Panel C shows that 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, and 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 these data via a direct feed from the electronic trading systems of the ASX. (These data have been used previously in Aitken, Frino, McCorry, and Swan, 1998, and Jackson, 2005, and even earlier ASX data by Aitken, Garvey, and Swan, 1995).

2.2 The Australian Equity Market

The Australian market is both small and developed, and provides a unique environment for examining mimicking activity and hypotheses relating to herding. This is due primarily to the concentrated nature of both (i) stocks listed on the ASX and (ii) 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 out of AUD$688.9 billion). There is a pronounced level of concentration in Australian equity investments. The ten largest 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 ten largest stocks account for 48 percent of the index, the fifty largest, 82 percent.

This higher level of concentration in the Australian market may lead to a reduced level of positively correlated trading. 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 correlated trading that is possible (see the next section for LSV correlated trading measure). Intuitively, if the funds in our sample were to make up 100 percent of the market, then no correlated trading could be possible, as for each buyer there must also be a seller. Broker activity in Australia is also concentrated among 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.

3. LSV Contemporaneous Herding (Correlated Trading) Measure

A number of empirical studies have focused on the existence of institutional correlated trading activity and its impact on stock prices (for example, LSV, Grinblatt, Titman, and Wermers, 1995, Wermers, 1999, Nofsinger and Sias, 1999, Sias, 2004, Wylie, 2005, and Kim and Nofsinger, 2005). This literature provides evidence of herding in the U.S., U.K., and Japanese markets as associations or commonalities in trading behavior. For example, how many fund managers are likely to be trading in the same stocks and in the same direction over the same time period? LSV and subsequent researchers find that, while there tends to be more correlated trading in smaller stocks, even here the magnitude is not dramatic.

To establish that the change in the monthly and quarterly snapshots of our daily data provide very similar estimates of contemporaneous correlated trading to that using U.S. fund manager data, we now replicate these studies using our dataset.

3.1 The LSV Herding (Correlated Trading) Measure

LSV defines the Herding Measure, $H_{i,t}$, for stock *i* and period *t* as follows:

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

where $p_{i,t}$ is the proportion of managers who had a net purchase in stock *i* during period *t*. We calculate $H_{i,t}$ only 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:

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

and

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

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 stocks greater than 200 the fifth.[11]

3.2 Empirical Results

In Table 2 we present the levels of herding using the LSV measure. The overall level of herding calculated using monthly holdings in Panel A is 1.39, or 2.70 percent based on quarterly holdings. This monthly estimate indicates that if one hundred funds are trading in a particular stock, then approximately one more fund 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 respective figure for quarterly holdings is three funds. 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. First, aggregating trades over longer periods lowers the risk of classifying follower packages into separate periods, and hence it increases this contemporaneous herding measure. Second, a longer measurement horizon also increases the risk that we may aggregate independent trades as if they are herding trades.[12] This measurement horizon issue illustrates an important weakness in contemporaneous trading measures.

We find managers display greater levels of correlated trading when selling. This is consistent with the findings of Wermers (1999), but is in contrast to the findings of Grinblatt, Titman, and Wermers (1995) who find greater levels of correlated trading on the buy-side. This suggests that correlated trading among active managers is more likely to be applicable to the sell than buy side.

[11] We note that the typical quintile definition involves five groups of equal number of members. We measure quintiles in this way later, but for this analysis, using this methodology would result in an unbalanced partitioning of manager trading activities.

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

Consistent with Wermers (1999), in Panels B-D of Table 2 we also find that correlated trading 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 correlated trading in the Australian market.

(INSERT TABLE 2)

4. Disguised Packages Approach to Herding and Informational Cascades

4.1 Theory

The trigger mechanism adopted by Grenadier (1999) provides valuable intuition in terms of motivating our approach. Let $X(\theta)$, where $\theta = \mu + s_1 + s_2$, represent the payoff from a stock purchase decision. μ is the expected value of θ and is common knowledge and s_1 and s_2 are independent, mean zero, random signals received by agents 1 and 2, respectively. A leader purchase by agent 1 (assumed to receive the most precise estimate) is observed by a fellow fund manager (agent 2). It is interpreted by that second agent as a positive signal of value, $s_1 = +\varepsilon_1$ (similarly, $-\varepsilon_1$ for no response and agent 2 now becomes a prospective leader as agent 1 has failed to trade). Where our approach builds on Grenadier's (1999) is in recognizing that information disclosed to agent 2 by observing the initial trade will almost certainly be costly to agent 1. Agent 1 will wish to disguise the trade but, in keeping with the spirit of the model, it is nonetheless detected.

A potential follower (agent 2) by assumption receives a less precise signal, s_2, as $\varepsilon_2 < \varepsilon_1$. If he is able to see through the disguise provided by agent 1, he will mimic if the trigger condition, $X(t) \geq X^*(+\varepsilon_1 + \varepsilon_2 + \mu)$, is met, where $X^*(+\varepsilon_1 + \varepsilon_2 + \mu)$ indicates the trigger point, and $t = \theta = \mu + \varepsilon_1 + s_2$ is the information available to the second agent. Too low a private signal received by agent 2, $s_2 < \varepsilon_2$, may mean the absence of followers even when it is worthwhile for the leader-

manager to act based on his strong favorable signal, $s_1 = +\varepsilon_1$, without waiting to observe the actions of other funds managers. Hence, the absence of a follower (or more generally multiple followers) is taken to mean that private signals received by the competing active fund managers are too weak to result in mimicking trades. In this case, $X\left(t = +\varepsilon_1 + s_2 + \mu\right) < X^*\left(+\varepsilon_1 + \varepsilon_2 + \mu\right)$ and the trigger point is not met. Latecomers observing both the initiating trade and the mimicking trades infer correctly that this sequence of trades credibly reveals information from agents that have received stronger positive signals than their own. The trade sequence must be in order of signal strength. This is why they are latecomers in terms of taking action. This is also why they may rationally ignore their (by inference) weaker negative signals and join the herd. If the latecomers all decide to ignore their own signals in this way then by assumption the leader and mimicker's signals must be faulty and the (long-term) payoff from the sequence of herding trades must be less profitable than an initiating trade that is not copied because potential mimickers heeded the negative signals about the trade that they themselves observed, and hence failed to copy.

Of concern to us is how fund managers observe these informative trades, given the disguise adopted for leader packages. Complete disguise would rule out mimicking behavior. One possible mechanism is inference from the identities of brokers. Over the period of our study, broker identities were transparent, but only to other fellow brokers, on every limit order prior to the trade, as well as to market orders. Under the rules at least, this information could not be passed on to clients, although there were many allegations that these rules were breached (see Bartholomeusz, 2003). If, as seems likely, there was inference from broker identities, the tactic of using multiple brokers in an attempt to further disguise the most informed trades would seem highly plausible. Using this tactic, multiple brokers rather than a single broker would need to pass on information, assisting the initiating funds manager in delaying disclosure of his identity. Feng and Seasholes (2004) investigate geographically isolated groups of traders that display correlated trading patterns that have traditionally been termed herding. They downplay word of mouth transferal in favor of heterogeneously informed investors, with those geographically more closely located to a company's

headquarters being more informed about that company's stock. By contrast, word of mouth transmittal is the focus of Hong, Kubik, and Stein (2005).

4.2 Defining Packages

To implement this approach we begin by recognizing that the leader (agent 1) must have a strong desire to disguise their actions. This disguise takes the form of splitting up orders that we denote as trade packages into a series of trades conducted over one or multiple days. We first define trade packages and identify packages that are likely to be based on the strongest private signal. Second, we assess the extent to which other fund managers follow these 'leader' packages that are conjectured to contain the most information. Third, we examine the profitability of leader and follower packages. In particular, we examine how profitability varies according to the extent of mimicking behavior. Then we attempt to identify the characteristics of lead managers. Finally we study leader risk constraints and post-package returns.

We adopt the 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 package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction.

Table 1 reports the frequency distribution of packages for both package length and stock size quintiles.[13] Panels E and F contain the statistics for buys and sells, respectively. These results show the benefit of using a package methodology, as institutions complete only 25.3 percent of buy volume and 27.7 percent of sell volume in one day. Note also that the thirty largest stocks account for 52.1 and 53.1 percent, respectively, of buy and sell packages. We find that the mean institutional package is 84 percent of the average daily trading volume and is thus very large. Even for large

[13] We form quintiles using the largest 300 stocks traded on the ASX. We did this since there are many illiquid stocks that, if included, would result in the majority of liquid stocks' being classified in the top two quintiles.

firms, 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. A crucial part of this process of minimizing impact is to make the package less visible to would-be followers. The distribution of packages is broadly consistent with Chan and Lakonishok (1995) who report that 20.1 percent of total buy package volume and 22.1 of sell volume is completed in one day with a mean package size of 66 percent relative to normal trading volume.

4.3 Identifying Packages Based on the Strongest Informational Signal

We identify those manager packages that are not only likely to contain information but are also likely to the recipient of the strongest signal. Chiyachantana, Jain, Jiang, and Wood (2004) suggest that managers who wish to lower market impact costs will complete packages over multiple days using multiple brokers. Consistent with this aim, the same tactic will lessen the chance of being followed. Fund manager trades are signals to the broker executing the trade, and more generally to the market, of fund managers' views concerning the prospects of that stock (following Kyle, 1985). As package size increases, the likelihood that that trade is informed also increases. Therefore, fund managers attempt to 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 packages, which is neither necessary nor possible in our study.

Our data suggest that 26 percent of buy package volume and 28 percent of sell volume are completed using multiple brokers. Not surprisingly, managers complete these packages that tend to be larger over longer periods. We also find that these informed packages are associated with significantly fewer packages in the preceding five days than an average package. This provides further support for our hypothesis that these packages tend to lead the actions of fellow managers. They thus meet the expectation that the manager has received the strongest signal of the group of competing fund managers.

In analyzing the returns from packages with different characteristics we examine periods of up to a year (250 trading days) as the measure of the long-run. This design enables us to exclude any possibly temporary price pressure effect due to the leader and subsequent follower's trades (see Nofsinger and Sias, 1999). If non- or less-mimicked purchases are more profitable in the long-term than mimicked purchases, then mimicking purchases simply represent herding. These trades do not contain valuable information. This implies that mimickers are ignoring their adverse private signal to either sell (or do nothing) and are jumping on to the herding bandwagon.

Table 3 provides evidence that multiple broker packages are informed. Buy 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 package (i.e., one year), than do similar sized purchases completed using one broker over one day (see Start to VWAP (volume-weighted average price) in column three). When we match similar-sized buy 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 either the counterintuitive result that not adopting disguise by using one broker has a lower stock price impact or, more reasonably, that greater validating information is revealed shortly after the commencement of multi-broker packages than for single-broker packages.

(INSERT TABLE 3)

4.4 Robustness Checks

For robustness, we examine three variations on the analysis. First, we use two alternative definitions of informed packages: (i) where managers complete large packages over a short time period; and (ii) 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, and 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 due to mimickers or other reasons by attempting to disguise the identity of the investment manager placing the trades. This suggests that our result might be due to the momentum effect, where managers commonly purchase stocks with the highest prior-six-months return, which outperform over the next year (documented in Australia by Demir, Muthuswamy and Walter, 2004). To examine this possibility further, we first calculate the DGTW return, which accounts for the momentum factor, yielding similar results. These findings reveal that the stocks purchased by fund managers earn higher returns than other stocks having similar momentum, and suggest that managers have stock-specific information in addition to exploiting momentum strategies. Second, we divide our trades into quintiles based on the prior-six-months return. We then compare the fund manager's return to S&P/ASX 300 stocks in the same momentum quintile. Manager trades outperformed the index 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.[14]

[14] Our excess return may also be driven by the release of analyst earnings forecasts and recommendations that precede manager 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 logistical 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 test (unreported), we find that the results for sell packages are consistent. Both purchase and sale results lead us to conclude that packages using two or more brokers contain more information than similar packages 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 packages.

4.5 Discussion

What could explain the findings in Table 3 suggesting that the most heavily disguised packages have the largest market impact? Consider the following: First, at the intuitive level, the manager's decision to disguise a trade is not made at random. Being costly, it is obvious that the more others can learn from one's actions and thus cause harm, the more effort will be put into disguising the actions. A murderer subject to the death penalty if convicted might eliminate witnesses but it is not worthwhile for a parking violator.

Second, the price impact is measured conditional on only the broadest facts—single or multiple brokers and the reputation of the trade initiator—whereas the degree of disguise is clearly endogenous and subsequently we estimate this via a model taking into account this endogeneity and controlling for a whole host of other influences. The efforts made to disguise trades based on information are shown to be worthwhile.

Third, the strength and direction of informative signals is likely to be far from random, that is, when the first manager receives a strong positive signal that motivates him to disguise his trade, other managers are likely to have also received signals, perhaps almost as strong, and are waiting for telltale signs of a trade that might validate the signal that they have already received. That is, it is not the disguise that has produced the high market impact. Rather, it is the correlated set of strong signals received by the initiating (first) agent and his competitors. When these agents detect indications of (say) a purchase that validate their own strong signals, the informed mimicking trades of these agents impact greatly on price. Hence, the public release of information at the

commencement of disguised packages causing high market impact is likely to be due to mimicking by other agents also in receipt of lesser but still strong signals.

The high market impact with multiple brokers indicates that managers are not only using multiple brokers to minimize market impact (which indeed raises the question of why managers would not use this tactic for all their trades), but are also using multiple brokers to execute packages for which they have received the strongest signal. Clearly, there is something different about these highly disguised trades that mere disguise does not fully capture. Our hypothesis is that not only does our leader manager adopting disguise receive the strongest signal of all the competing managers but that these other managers also receive, on balance, very strong signals. Supporting the proposition in favor of a rich information content shared by a number of competing managers is the statistically significant positive excess return difference between the one-year return earned by multiple broker and single broker packages (see the bottom two rows in Table 3, Start to End + 1year). These findings confirm that price discovery is not only associated with the salience of the trader, as in Massa and Simonov (2003), but also on the salience of the particular trade itself—the degree of disguise adopted.

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 the use of multiple-broker packages suggests that the investment manager may have acquired information independently of brokers that is either exclusive to that investment manager or is revealed in part to other fund managers as well.

4.6 Leader-Follower Behavior

In this section we assess the extent to which competing fund managers mimic leader packages by counting the number of fund managers who subsequently trade on the same side in the same security, commencing either on the same day or immediately after the commencement of the

disguised package. This procedure identifies what we call the number of followers[15]; recognizing that some of these packages might be coincidental or might represent a delayed response by other managers to the same information received by the leader.

In fact, as Grenadier (1999) hypothesizes, any such delay need be neither coincidental nor indicating an inability to act quickly based on fresh information. Rather, it could be a rational response to the perceived relative weakness of the signal, requiring a confirming signal from the manager who acts first and thus identifies himself in a credible fashion as having the strongest signal of all. The leader not only maximally disguises his trade but undertakes it not knowing if his signal is in agreement with the signals received by competing fund managers

In Figure 1 we present manager trading behavior and market impact around informed packages. In order to highlight the leader-follower trading that these informed packages appear to induce, we call them *leader packages*. For the purpose of aggregation, we standardize the duration of packages executed to five days, so that packages completed over more (or fewer) than five days are compressed (or expanded) into five days. This enables the production of a graph showing how leader packages are distributed over our standardized five-day period. Furthermore, it enables us to display the distribution of follower packages both during and after the completion of the leader package. These are expressed as a percentage of the leader's package volume.

We find that purchases by the first follower accounts for approximately 45 percent of the leader's total package volume while all followers account for 160 percent of the leader's total package volume, suggesting that followers in aggregate amplify the magnitude of the leader's package and can adversely affect the ability of the leader to acquire his package on the most favorable terms. This indicates the importance of follower behavior to the leader and helps explain his desire to disguise his trading pattern. Finally we calculate the market impact around the package, finding that the majority of price run-ups occur towards the start of the leader package, staying steady during the following five days. This suggests that the impact of followers on the

[15] Note that we include within the follower category packages disguised by the use of multiple

market response is quite rapid in terms of its effect even given the elements of disguise adopted by the leader.

(INSERT FIGURE 1)

We find the 32.0 percent of informed buys and 36.9 percent of informed sells, respectively, have zero followers, while 18.3 and 20.3 respectively, 13.4 and 14.3, respectively, 10.0 and 9.6, 6.8 and 6.2 respectively and 19.5 and 12.7 percent, respectively, have one, two, three, four, and five or more followers, respectively. This shows that managers are more likely to follow buys than sells, suggesting that buys have additional information content (Pinnuck, 2003). This asymmetry might also be due to the ease of 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 as these fund managers are not permitted to short-sell. This finding further supports our decision to concentrate our analysis on purchases.

Fund managers initiate 63 and 61 percent of buy and sell follower packages (unreported), respectively, before the completion of the leader package. There are two possible explanations. First, 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.

Second, managers may have correlated private information; thus, these leader-follower relationships might be due to the relative speed of information acquisition and analysis. Alternatively, while followers may have correlated private information obtained at the same time as the leader they may be, in principle, just as quick to act. Nonetheless, they rationally wait until they observe the leader trade prior to trading in the same direction. The leader trade, if disguise is not

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brokers.

100 percent successful, provides a credible signal that a competing funds manager has received the strongest private signal. It is sufficiently strong to act on, without waiting for evidence that other fund managers have also received signals indicating the same action is required.

It is not surprising that competing managers obtain some information in common, either before the start of the initial informed package or before completion. However, it is questionable that they would have acted on it without observing the leader trade, unless convinced that their signal is the strongest. If they would have acted anyway without observing any sign of a leader trade, this does not explain why, as manager disguise increases, the number of followers decrease, emphasizing the inference we draw that both following behavior and leader disguise are intentional (see section 4.8 below) and that, despite the attempt at disguise, the follower does become aware of the leader trade.

4.7 Inference on Private Signal from Package Profitability

How do we obtain the direction of the private signal received by the mimicking agent? We rank agents by signal strength from highest to lowest, representing the observable trade order. Suppose by way of example that agent 1 receives a strong positive signal to purchase a stock and all other agents, 2 and above, negative signals. In sequence 1, agents 2 and above observe the purchase by agent 1 but choose not to mimic due to their unfavorable signals. In sequence 2, agents 2 and above choose to ignore their bad signals and mimic the trade of agent 1. This constitutes herding. Under these circumstances an initial trade by agent 1 that is not mimicked at all (sequence 1) should outperform the mimicked trade (sequence 2) as the latter has involved disregarding all the unfavorable signals. In the case of the non-mimicked trade by agent 1, agents 2 and following have not received sufficiently positive signals to make it worthwhile for them to mimic. Their potentially negative information is valuable and has not been disregarded. By observing the change in subsequent performance as mimickers are added to an initial trade of high signal strength, the identities of mimickers who herd are revealed.

In the above example the first mimicker (agent 2) and subsequent mimickers could also be herders. In fact, in Zhang's (1997) model, they must all be herders if signals are binary. More generally, agents numbered *n* and above are potentially herders. We now compare the profitability of two sequences: sequence 1, agent 1 purchase followed by *n*-2 mimicking trades with agent *n*-1 as the marginal agent and two, agent 1 purchase followed by *n*-1 or more mimicking trades, so that agents numbered *n* or greater are marginal mimickers. If the first (shorter) sequence is more successful than the second, agents numbered *n* and above are herding. These agents have disregarded their private signal that the purchase will be unsuccessful by mimicking the sequence of purchases they have observed. Subsequently, purchases meeting this criterion have underperformed.

We first implement the methodology described above conditional on manager reputation. Table 4 shows the consequences when we partition packages based on manager reputation and whether followers exist. We consider top (or bottom) quartile performing fund managers over the past six months who have good (or poor) reputations.[16] Table 4 shows that purchases from managers of good reputation generally outperform those from managers with a poor reputation. Leader purchases with followers also outperform those without followers. This suggests that followers can either identify the leader packages that are most likely to be successful regardless of reputation, or drive stock prices higher in the short-term as a consequence of the price pressure hypothesis. If the former, they infer that the trade contains valuable information that is in agreement with their own private signal. It is validated by observing the disguised leader trade. Hence, the trigger threshold has been met. If the latter and out-performance is due to price pressure, this can explain the short-run price impact but not the superior long-run performance over the following year. The short-term out-performance demonstrated by the large price impact during the sequence of trades is not only permanent but is amplified over the subsequent year.

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

(INSERT TABLE 4)

Strikingly, as Table 4 shows, these leader packages attracting mimickers continue to be profitable for all intervals over the subsequent twelve months. By contrast, in the market microstructure literature (for example, Keim and Madhavan, 1996) it is common for price reversal to be measured after as little as a few seconds, minutes, or only one or more subsequent trades. In other words, for our leaders there is no evidence of price reversal and in fact there appears to be an initial 'underreaction', not only by the leader-manager to his private signal, but also by the subsequent followers in the vicinity of the leader package. Subsequently, in section 4.9 below, we show that the degree of under-reaction by the leader is increasing in the extent to which he is initially overweight in the stock. This long period of underreaction of up to a year as new information is gradually incorporated into asset prices is consistent with a unified model of under- and over-reaction and momentum trading (Hong and Stein, 1999).

In Table 5 we carry out a formal test of the herding hypothesis using precisely the method of comparing the profitability of trade sequences described above. We again partition our sample dependent on the number of followers, where the number of followers is less than, or alternatively greater than, a particular number of followers ranging from one to five or more. In this way, we can determine whether, after a particular number of followers, these new followers are actually trading against their own private information as the performance becomes worse with the addition of more followers.

We find that trade sequences with one or more followers are significantly more profitable than with no followers, trade sequences with two or more followers are significantly more profitable than trade sequences with just one follower, and the same is true for three or more followers compared with just two followers. These findings show that followers from one to three are still bringing valuable information to the table, as the trades they mimic are more profitable than those they disregard. However, trade sequences with four or more followers are less profitable over the

next twelve months than those sequences with three followers, suggesting that, consistent with Grenadier's (1999) arguments, there appears to be some limited evidence that managers are herding when the tail of mimickers is very long. We find no evidence of herding for horizons of six months or less for any number of followers. Arguably, all horizons up to six months are quite adequate to demonstrate a permanent price impact. In which case, we should disregard the relatively weak evidence for herding with a horizon of one year and a long tail of mimickers.

(INSERT TABLE 5)

Moreover, the long-term profitability of the trade sequences, at least for three or fewer followers, indicates that mimicking speeds the price discovery process commencing with the manager who first acts on his strong signal by adopting maximal trade disguise. Although there is some evidence of a decline in profitability with four or more followers and a very long-term horizon, the overall performance of all sequences with followers is still exceptional.

Followers take account of their own private signals that are insufficiently powerful for them to act as leader. However, only when these signals are sufficiently validated and augmented by observing the trades of the leader and earlier followers, do they act by mimicking these earlier trades (with the possible exception of four or more followers). We conclude that we are not observing lemming-like mimicking that ignores private information. Hence, followers are not members of a herd or part of an informational cascade, other than weak indications of herding when there are four mimickers or more that are alluded too above.

Could the apparent mimicking that is observed be simply an accidental consequence of differences in fund manager response times? Suppose that all fund managers receive the same identical signals at the same time so that there is no relationship between signal strength and the trade sequence ordering. Managers with faster responses 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, Subrahmanyam and Titman (1994). Under this scenario, neither leading nor following is intentional and the trading sequence is exogenous. The accidental leader may still wish to reduce market impact by adopting disguise. However, it does not explain why leader packages with greater disguise (spread over more days and more brokers) are followed less (as shown in section 4.8 and Table 7 below), affirming our conjecture that following is intentional. If it is simply a case of a sequence of correlated informational trades then disguise will have no impact. Hence, the balance of evidence supports intentional and beneficial following. Those who wait and see gain the benefit of observing credible signals of those fund mangers who acted first on the strength of strong private signals. The trade initiator attempts to discourage following in the initial stage, at least until an appropriate position in a stock has been obtained.

Table 6 shows followers still make a profit 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 being the fifth or sixth follower. The fifth follower also earns around half a percent more profit than the seventh follower. This demonstrates that herding is profitable for the first six followers. Over intervals shorter than one year, following appears profitable for all followers. What we observe is not true herding or informational cascades. Rather, it is the efficient combination of the information, provided by the leader to competitors observing his trade, and the strength of private signals received by these actual and prospective mimickers.

(INSERT TABLE 6)

4.8 Package 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 packages, resulting in excess returns. Second, we wish to understand whether following is intentional or spurious, i.e., do our followers witness the leader's package and consciously decide to follow that

package, or are these nearby trades coincidental—due to correlated information, stock preferences or liquidity needs unrelated to surmising the existence of the leader's package that validates the manager's own signal?

In order to investigate these questions we regress stock excess return against the number of followers, as well as against a number of manager, stock, and trade characteristics. However, the number of followers and the excess return are not independent, since leaders adopt more disguise as both signal strength and expected excess return increase, in order to reduce market impact cost by discouraging followers. These are also likely to have received signals almost as strong. Consequently, we employ a 2SLS regression, using the predicted values from our number-of-followers variable (estimated in our first stage) to forecast the excess return.[17] The dependent variable in the first stage is the actual number of followers for every single trade package, regardless of whether a single or multiple brokers have been utilized.

The independent variable of most interest in the first stage is the LeaderPackageDummy that takes the value 1 if multiple brokers have been used and 0 otherwise. This dummy is interacted with the LeaderReputationRank and other characteristics of the leader and follower that are of interest. Significant values for the interacted dummy would indicate that indeed the packages undertaken using multiple brokers have very different informational characteristics. In fact, we confirm this. 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. 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

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

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 package, and the log of package size. Our structural equations are appropriately identified.

Table 7 displays the results from our 2SLS 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. This suggests that managers are more aware of trading activity in stocks they hold.

Larger packages 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 increased. However, when we analyze our interacted variables (which allow us to separate our leader packages) we find similar results for all packages, except for our number-of-package-days variable, which becomes negative. For our leader packages, we find that the longer the package length, the fewer the number of followers. This suggests that we are picking up intentional following of our leader packages. This is because the probability of intentional followers identifying these packages as containing information decreases when managers further disguise their packages by splitting them 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 packages completed over a longer period (see below). Thus the leader managers appear to be trading based on very long-lived information.

The second stage of our 2SLS regression suggests that packages that involve leaders with a high reputation achieve a higher return, once again confirming the informational nature of our packages

and the strength of the signals received by these managers.[18] 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 wish to minimize market impact by discouraging followers, and that disguise is effective up to a point.

The findings (as set out in Table 4) also suggest that following is based, at least in part on the reputation of the leader. Followers display a preference for the informed packages of reputable leaders, once they learn of them. This could also be consistent with more reputable leaders' identifying good information earlier and acting on it systematically before other fund managers. However, if this is the case then other fund managers, knowing that they are receiving weaker signals, would deliberately wish to wait to observe the actions of the most informed and reputable manager. They will mimic if the surmised direction reinforces their weaker private signal once the trigger condition has been met.

(INSERT TABLE 7)

4.9 Portfolio Risk Constraints and Post-Execution Returns

We evaluate whether fund managers fail to exploit their superior information completely 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. While for small stocks this overweight position may be ten times the index weight.

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

Consequently, after partitioning our informed packages into eight stock size groups, we partition these trades into quintiles based on the manager relative weight after the completion of the package. We compute the manager relative weight by dividing the manager portfolio weight in a stock by the S&P/ASX 300 index weight.[19] We then compute the average return during the execution of the package, as well as the return in the subsequent 5, 10, 30, 60, and 90 days. We interpret the average return post-execution as manager failure to fully exploit his 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 and thus 'leave money on the table', then we would expect a post-execution return that is higher in the top quintile of manager weight for stocks than in the lowest quintile. This is because recognizing the higher risks involved, an overweight manager rationally sets a higher trigger value on the signal necessary to precipitate a disguised leader trade than when he is underweight.

Table 8 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 package is greater in all eight groups for low-relative-weight quintile stocks, suggesting that managers are trading more in those stocks 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'

[19] 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.

trading more aggressively, but then underperform after (approximately) 90 days. 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 8 & FIGURE 2)

Following on our analysis of risk constraints, we next ask the question whether fund managers artificially inflate stock prices, only to sell out of their positions to subsequent followers in a form of market manipulation. For example, a leader fund manager could provide false signals that particular packages are informed. We find that managers often reverse their positions, with 15.4 percent of packages being completely reversed and 37.9 percent partially reversed over the next 30 days, 36.2 and 64.0, respectively over the next 90 days, and 59.2 and 78.7 percent of packages, respectively, over 12 months. 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 when followers enter the market. We also find that while it is common for leaders to reverse their positions in the next year, they do not appear to be deliberately manipulating followers. An exploitative strategy might involve promoting (or ramping) a stock by falsely announcing an informed trade to a would-be mimicker and then selling out to the follower at the artificially created bubble peak. Presumably, such behavior is not observed because in fact mimicking only occurs when the sum of the signal received by the potential mimicker plus the credible signal of the leader undertaking a package in a disguised manner exceeds the trigger threshold. In fact, leaders could have done better still by further delaying trade reversal, suggesting a risk reduction motivation (see Hirshleifer, Subrahmanyam, and Titman, 1994).

5. Conclusions

We find strong evidence of the sorts of mimicking trading sequences that commence with highly informed trades, as envisioned by Bikhchandani; Hirshleifer and Welch (1992) and Grenadier (1999). Our crucial test of herding (informational cascades) is conducted by comparing the profitability of the packages undertaken using multiple brokers trading over multiple days as a disguise both with and without mimicking trades by competing fund managers. We find utilizing an exceedingly long horizon of a year that profitability is higher when the trade is mimicked, compared to situations in which it is not, when there are from one to three mimickers. For shorter and arguably more realistic horizons more mimicking is always associated with higher profitability. This simple computation of profitability according to the number of mimickers reflects the fact that potential mimickers are not stampeded into mimicking simply because the packages of the trade initiator who is likely to be better informed have been detected. Hence potential mimickers do not ignore their own signal when deciding whether or not to follow. The sequence of mimicked trades contains valuable information that is supplied by most, if not all, the participants.

Overall, we observe that this highly informed mimicking behavior is beneficial to the market as a whole, as is the valuable opportunity identified by the prospective leader or trade initiator. From a public policy perspective, fund manager mimicking appears to be information-based and non-manipulative, motivationally speaking.

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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 January 2, 1994 to December 31, 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 their small size in the portfolios; their omission would not significantly affect our findings. Each number in Panels E and F represents the percentage of manager packages completed over the specified number of trading days for all buys/sells and those buys/sells contained within stock size quintiles (classified according to the largest 300 stocks). Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. 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. $p_{i,t}$ (p_t) is the proportion of managers who traded during period *t* and had a net purchase of stock *i* (all stocks). $E[| p_{i,t} - E[p_{i,t}] |]$ is calculated using a binomial distribution under the assumption of independent trading decisions by investment managers. 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), are expressed as: (2) $BH_{i,t} = H_{i,t} \mid p_{i,t} > E[p_{i,t}]$, and (3) $SH_{i,t} = H_{i,t} \mid p_{i,t} < E[p_{i,t}]$. Averages of H_{it} values are shown across periods and stocks, (which fulfill the various criteria, i.e., belong in size group 1). 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. The sample comprises all stock positions of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.
*, ** 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	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	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 End + 5days	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 End + 10days	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 End + 30days	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 End + 60days	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 End + 90days	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 End + 6months	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 End + 1year	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 this table, we present the equally-weighted average return (over the specified period) for purchase packages completed by multiple brokers over multiple days. We match these packages against similar packages using three methods. In the three left columns, we match these multiple-broker multiple-day packages against purchase packages of a similar size (within ten percent of the dollar value, where packages within one percent were preferred) completed over *one day*, by *one* broker. In the middle three columns, we match these packages against purchase packages of a similar size (within ten percent of the dollar value, where packages within one percent were preferred) completed over *the same number of days*, by one broker. In the three right columns, we match these packages against purchase packages of the same manager in the same stock, completed by a single broker. Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. All figures not in parentheses are excess returns, calculated by taking the difference between manager returns and S&P/ASX 300 index returns, and are in percentage terms. Returns are calculated from the closing price on the day before the package starts, to the closing price of the respective day following the last day of the package (End). The VWAP (volume-weighted average price) return refers to the volume weighted average price that the manager obtained when executing their package. The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.
*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

TABLE 4

Profitiability Comparison of Informed Trade Packages

	Leader Good Reputation			Leader Poor Reputation		
	With Followers	Without Followers	Difference	With Followers	Without Followers	Difference
Buy Packages						
Start to VWAP	-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	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 End + 5days	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 End + 10days	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 End + 30days	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 End + 60days	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 End + 90days	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 End + 6months	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 End + 1year	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 present the equally-weighted average return of fund manager packages completed using multiple brokers over multiple days (leader packages). We partition first by reputation, and second by whether these packages are followed by other managers. Followers are defined as managers who trade in the same stock in the same direction during the period from one day after the beginning of the leader package to five days after the completion of the package. Good- (or poor-) reputation leaders are defined as those with a top (or bottom) quartile performance over the prior 6 months. Excess returns are calculated by taking the difference between manager returns and S&P/ASX 300 index returns. Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. All figures not in parentheses are in percentage terms. Returns are calculated from the closing price on the day before the package starts (Start), to the closing price of the respective day following the last day of the package (End). The VWAP return refers to the volume-weighted average price that the manager obtained when executing their package. The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.

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

Table 5

Profitiability comparison of informed trade packages, dependent on the number of followers

	Excess Returns														
Number of Followers	<=0	1+	Difference	<=1	2+	Difference	<=2	3+	Difference	<=3	4+	Difference	<=4	5+	Difference
Buy Packages															
Start to Vwap Rtn	-0.28	0.26	-0.54	-0.10	0.30	-0.40	-0.10	0.46	-0.56	-0.03	0.50	-0.54	0.04	0.42	-0.38
(T-statistic)	*(-1.61)*	*(2.84)*	*(-2.77)*	*(-0.83)*	*(2.68)*	*(-2.44)*	*(-1.05)*	*(3.17)*	*(-3.21)*	*(-0.38)*	*(2.80)*	*(-2.67)*	*(0.47)*	*(2.05)*	*(-1.70)*
Start to End Rtn	0.72	0.73	-0.01	0.75	0.71	0.04	0.74	0.71	0.03	0.76	0.65	0.11	0.77	0.57	0.20
(T-statistic)	*(5.57)*	*(8.30)*	*(-0.07)*	*(7.16)*	*(6.96)*	*(0.25)*	*(8.14)*	*(5.82)*	*(0.20)*	*(8.96)*	*(4.52)*	*(0.64)*	*(9.54)*	*(3.36)*	*(1.06)*
Start to 5 Days After	0.73	1.03	-0.30	0.86	1.03	-0.17	0.83	1.14	-0.31	0.87	1.15	-0.28	0.91	1.10	-0.19
(T-statistic)	*(4.61)*	*(9.46)*	*(-1.55)*	*(6.63)*	*(8.17)*	*(-0.95)*	*(7.35)*	*(7.56)*	*(-1.67)*	*(8.26)*	*(6.56)*	*(-1.37)*	*(9.09)*	*(5.30)*	*(-0.83)*
Start to 10 Days After	0.77	1.23	-0.46	0.95	1.24	-0.29	0.90	1.42	-0.52	0.96	1.47	-0.51	1.03	1.39	-0.36
(T-statistic)	*(3.92)*	*(9.94)*	*(-2.00)*	*(6.20)*	*(8.63)*	*(-1.39)*	*(6.81)*	*(8.28)*	*(-2.42)*	*(7.83)*	*(7.32)*	*(-2.15)*	*(8.83)*	*(5.90)*	*(-1.37)*
Start to 30 Days After	0.95	1.75	-0.80	1.27	1.76	-0.48	1.25	1.96	-0.71	1.38	1.93	-0.55	1.49	1.72	-0.23
(T-statistic)	*(3.31)*	*(10.49)*	*(-2.42)*	*(5.84)*	*(9.15)*	*(-1.67)*	*(6.67)*	*(8.71)*	*(-2.42)*	*(7.94)*	*(7.48)*	*(-1.77)*	*(9.03)*	*(5.81)*	*(-0.69)*
Start to 60 Days After	0.70	2.11	-1.41	1.18	2.21	-1.03	1.35	2.32	-0.97	1.60	2.08	-0.48	1.72	1.83	-0.11
(T-statistic)	*(1.87)*	*(9.58)*	*(-3.24)*	*(4.05)*	*(8.78)*	*(-2.69)*	*(5.33)*	*(8.10)*	*(-2.54)*	*(6.88)*	*(6.41)*	*(-1.19)*	*(7.71)*	*(5.24)*	*(-0.27)*
Start to 90 Days After	1.06	2.36	-1.30	1.34	2.58	-1.25	1.58	2.67	-1.09	1.87	2.38	-0.50	2.04	1.95	0.10
(T-statistic)	*(2.35)*	*(9.22)*	*(-2.51)*	*(3.85)*	*(8.93)*	*(-2.76)*	*(5.24)*	*(8.15)*	*(-2.46)*	*(6.79)*	*(6.46)*	*(-1.10)*	*(7.77)*	*(4.90)*	*(0.20)*
Start to 6 Months After	0.98	2.68	-1.69	1.39	2.92	-1.53	1.77	2.92	-1.15	2.02	2.76	-0.74	2.24	2.24	0.00
(T-statistic)	*(1.88)*	*(8.99)*	*(-2.81)*	*(3.43)*	*(8.75)*	*(-2.91)*	*(5.01)*	*(7.79)*	*(-2.23)*	*(6.24)*	*(6.63)*	*(-1.41)*	*(7.30)*	*(4.91)*	*(-0.00)*
Start to 1 year After	1.32	4.15	-2.83	2.89	3.85	-0.96	3.64	3.08	0.56	3.86	2.35	1.51	3.93	1.59	2.34
(T-statistic)	*(1.87)*	*(10.06)*	*(-3.46)*	*(5.19)*	*(8.32)*	*(-1.33)*	*(7.50)*	*(5.96)*	*(0.79)*	*(8.77)*	*(3.93)*	*(2.04)*	*(9.43)*	*(2.38)*	*(2.97)*

In this table, we present the equally-weighted average return of fund manager packages completed using multiple brokers over multiple days (leader packages). We partition leader trades by the number of followers and in the difference column we calculate the difference between the previous two columns. Followers are defined as managers who trade in the same stock in the same direction during the period from one day after the beginning of the leader package to five days after the completion of the package. Excess returns are calculated by taking the difference between manager returns and S&P/ASX 300 index returns. Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. All figures not in parentheses are in percentage terms. Returns are calculated from the closing price on the day before the package starts (Start), to the closing price of the respective day following the last day of the package (End). The VWAP return refers to the volume-weighted average price that the manager obtained when executing their package. The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.

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

Table 6

Profitability comparison of follower trade packages

Order of Follower	1	2	3	4	5	6	7	8
Buy Packages								
Start to Vwap	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	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 End + 5days	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 End + 10days	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 End + 30days	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 End + 60days	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 End + 90days	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 End + 6months	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 End + 1year	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 present the equally-weighted average return of the followers of informed packages (i.e., packages completed using multiple brokers over multiple days). Follower returns are averaged according to the order of the followers. Follower packages may be executed using one or many brokers and may be executed over one or multiple days. Follower packages must originate after the beginning of the leader package, and before five days following the completion of the leader package. Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. All figures not in parentheses are excess returns, calculated by taking the difference between manager returns and S&P/ASX 300 index returns, and are in percentage terms. Returns are calculated from the closing price on the day before the package starts (Start), to the closing price of the respective day following the last day of the package (End). The VWAP return refers to the volume-weighted average price that the manager obtained when executing their package. The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.

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

Table 7
Two stage least squares regression

	Number of followers per trade package		1 Year Excess Return
Intercept	-1.578**	Intercept	-0.063**
	(-18.47)		*(-6.46)*
LeaderReputationRank	0.021**	LeaderReputationRank	0.002**
	(15.28)		*(10.14)*
Stock Size	0.215**	FollowerReputationRank	0.013
	(20.60)		*(1.72)*
BookToMarketRank	-1.403**	Number of Brokers	0.001**
	(-24.24)		*(3.02)*
AlreadyHeld	0.164**	Number of Trade Package Days	0.002**
	(5.63)		*(4.02)*
FollowerAlreadyHeld	0.203**	Log(Trade Package Size)	0.004**
	(6.86)		*(5.43)*
Number of Trade Package Days	0.198**	Predicted Number of Followers	-0.005**
	(60.44)		*(-8.01)*
Log(Trade Package Size)	0.093**		
	(14.87)		
LeaderPackageDummy	-1.718**		
	(-7.05)		
(LeaderPackageDummy)*LeaderReputationRank	0.007*		
	(2.11)		
(LeaderPackageDummy)*Stock Size	0.363**		
	(12.05)		
(LeaderPackageDummy)*BookToMarketRank	-0.670**		
	(-4.52)		
(LeaderPackageDummy)*AlreadyHeld	0.501**		
	(7.12)		
(LeaderPackageDummy)*FollowerAlreadyHeld	0.564**		
	(7.51)		
(LeaderPackageDummy)*Number of Package Days	-0.038**		
	(-6.38)		
(LeaderPackageDummy)*Log(Package 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 least squares (2SLS) regression. In the first stage (LHS), we regress the number of followers for all packages, not just packages with multiple brokers, against a number of variables (described below). In the second stage (RHS), we use the predicted values for the number of followers variable (from the first stage), as well as other trade and manager variables, to predict the one-year excess return (over the S&P/ASX 300 Index) for each package. We conduct this regression for all manager purchases, where our leader/informed packages (i.e., packages completed using multiple brokers over multiple days) are given a leader package dummy value of one. We then interact the leader package dummy variable against our other variables. 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. 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 package, and the log of package size. Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. The sample comprises all packages of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.
*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

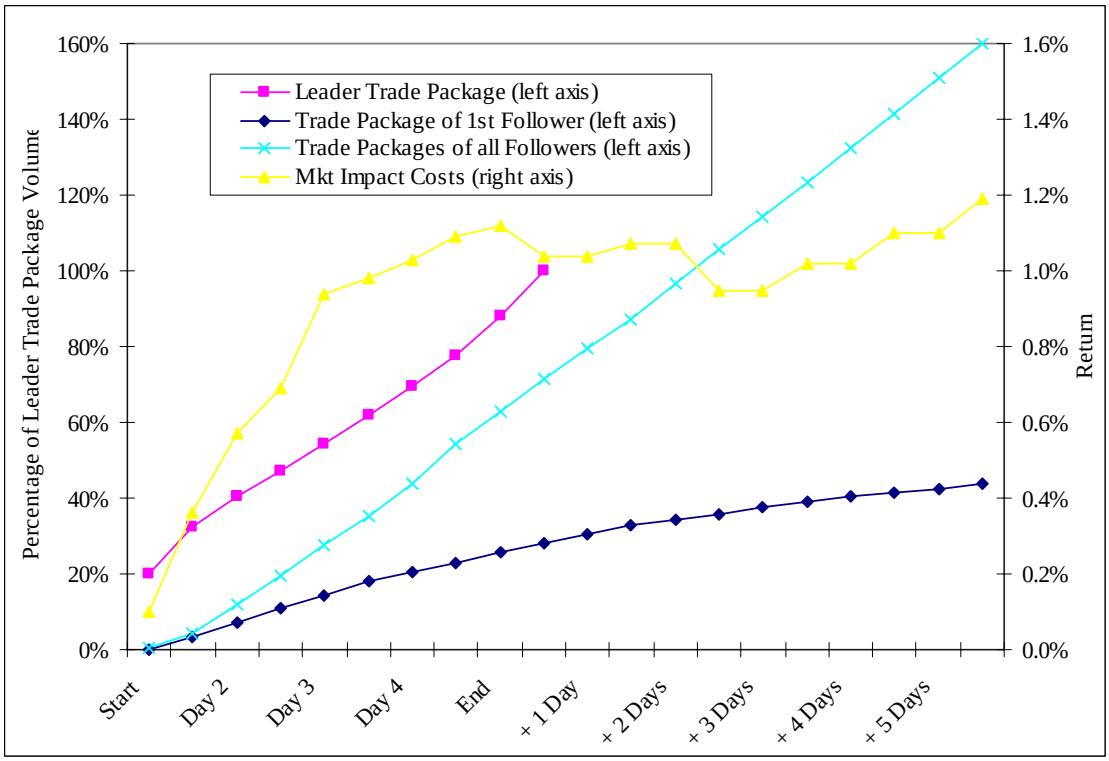
Table 8
Risk constraints and the profitability of leader trades

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 (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)*
End to End + 5days (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)*
End to End + 10days (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)*
End to End + 30days (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)*
End to End + 60days (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)*
End to End + 90days (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)*
End to End + 6months (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)*
End to End + 1year (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 first partition our sample of manager packages into stock size groups, as described in the column headings. Next, we sort our packages into quintiles based on manager relative weight (manager weight divided by index weight in the stock after the package is completed). Packages in the highest (lowest) quintile are most (least) likely to face risk constraints limiting the size of the package. We calculate the difference between the average excess return over various periods, for packages 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 packages where there is the greatest and least likelihood of the manager's facing risk constraints. Excess returns are calculated by taking the difference between manager returns and S&P/ASX 300 index returns. Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. All figures not in parentheses are in percentage terms. Returns are calculated from the closing price on the day before the package starts (Start), to the closing price of the respective day following the last day of the package (End). The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.

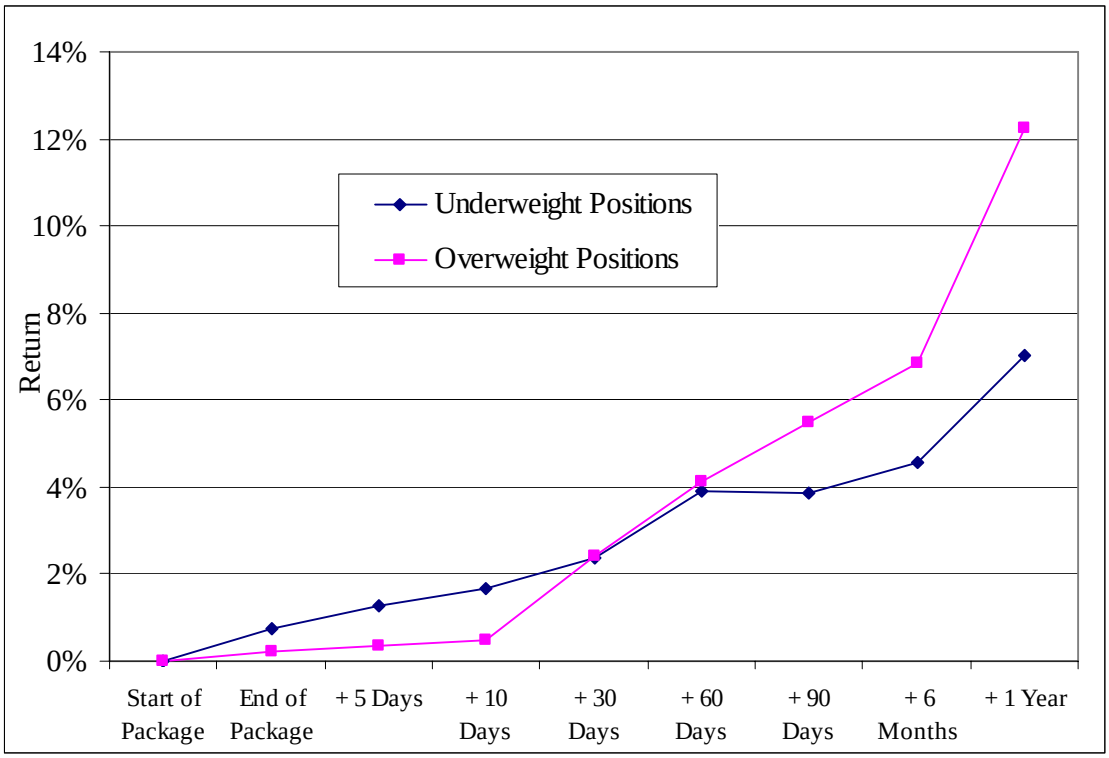
*, ** indicate significance at the 0.05 and 0.01 levels, respectively.

Figure 1
Market impact of manager activity during and after leader packages



This figure shows the trade activity around our leader packages. For the purpose of aggregation, we standardize the duration of packages executed to five days, so that packages completed over more (or fewer) than five days are compressed (or expanded) into five days and measured as a percentage of leader trade volume (summing to 100% at the end of the leader package). We also aggregate the packages of the first (all) follower(s), averaging their trade volume over each day (including the five days following the leader's package) as a percentage of the leader's trade volume (left axis). Secondly, we calculate the average cumulative return (right axis) over the package interval and the following five days. Returns are calculated from the closing price on the day before the package starts (Start), to the closing price of the respective day of the package and after the package finishes (End). Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.

Figure 2
Manager package return for relative weight quintiles



In this figure, we partition our sample of manager packages into stock size groups. For stock size group 8 (in Table 8), containing the largest 5 stocks, we sort our packages into quintiles based on manager relative weight (manager weight divided by index weight in the stock after the package is completed). Packages in the highest (lowest) quintile are most (least) likely to face risk constraints limiting the size of the purchase package. We show the cumulative return over the year following the package completion, for trades in the highest quintile (those with the greatest overweight positions) and the lowest quintile (those with the lowest relative weight). Returns are calculated from the closing price on the day before the package starts (Start), to the closing price of the respective day following the last day of the package (End). Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.