Two Essays on Herding in Financial Markets

Vivek Sharma

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Finance

Approved by:

John C. Easterwood, Co-Chair
Raman Kumar, Co-Chair
Don M. Chance
Huseyin Gulen
Douglas M. Patterson

April 14th, 2004
Blacksburg, Virginia

Keywords: Herding, Behavioral Finance, Institutional Investors, Market Efficiency, Intra-Day Trading

Two Essays on Herding in Financial Markets

Vivek Sharma

John C. Easterwood, Co-Chair

Raman Kumar, Co-Chair

ABSTRACT

The dissertation consists of two essays. In the first essay, we measure herding by institutional investors in the new economy (internet) stocks during 1998-2001 by examining the changes in the quarterly institutional holdings of internet stocks relative to an average stock. More than 95% of the stocks that are examined are listed on NASDAQ. The second essay attempts to detect intra-day herding using two new measures in an average NYSE stock during 1998-2001. In the second essay, rather than asking whether institutional investors herd in a specific segment of the market, we endeavor to ask if herding occurs in an average stock across all categories of investors.

The first essay analyzes herding in one of the largest bull runs in the history of U.S. equity markets. Instead of providing a corrective stabilizing force, banks, insurance firms, investment companies, investment advisors, university endowments, hedge funds, and internally managed pension funds participated in herds in the rise and to a lesser extent in the fall of new economy stocks. In contrast to previous research, we find strong evidence of herding by all categories of institutional investors across stocks of all sizes of companies, including the stocks of large companies, which are their preferred holdings. We present evidence that institutional investors herded into all performance categories of new economy stocks, and thus the documented herding cannot be explained by simple momentum-based trading. Institutional investors' buying exerted upward price pressure, and the reversal of excess returns in the subsequent quarter provides evidence that the herding was destabilizing and not based on information.

The second essay attempts to detect herding in financial markets using a set of two methodologies based on runs test and dependence between interarrival trade times. Our first and the most important finding is that markets function efficiently and show no evidence of any meaningful herding in general. Second, herding seems to be confined to very small subset of small stocks. Third, dispersion of opinion among investors does not have much of impact on herding. Fourth, analysts' recommendations do not contribute to herding. Last, the limited amount of herding on price increase days seems to be destabilizing but on the price decrease days, the herding helps impound fundamental information into security prices thus making markets more efficient. Our results are consistent with Avery and Zemsky (1998) prediction that flexible financial asset prices prevent herding from arising.

The seemingly contradictory results of the two essays can be reconciled based on the different sample of stocks, and the different methodologies of the two essays which are designed to detect different types of herding. In the first essay, herding is measured for NASDAQ-listed (primarily) internet stocks relative to an average stock, while the second essay documents herding for an average stock. In the first essay, we document herding in more volatile internet stocks, but we do not find any evidence of herding in more established NYSE stocks. The first essay examines herding by institutional investors, while the second essay examines herding, irrespective of the investor type. Consequently, in the first essay, we find that a subset of investors herd but in the second essay market as a whole does not exhibit any herding. Moreover, the first essay measures herding by examining the quarterly institutional holdings of internet stocks, while the second essay measures herding by examining the intra-day trading patterns for stocks. This suggests that it takes a while for investors to find out what others are doing leading to herding at quarterly interval but no herding is observed at intra-day level. The evidence presented in the two essays suggests that while institutional investors herded in the internet stocks during 1998-2001, there was very little herding by all investors in an average stock during this period.

DEDICATION

I DEDICATE THIS WORK

TO MY PARENTS

BIMLA AND CHANRANJIT

WHO HAVE GIVEN ME SO MUCH WITHOUT EXPECTING ANYTHING IN RETURN

ACKNOWLEDGEMENTS

I would like to take this opportunity to thank all those people who have helped me in this work. My heartfelt thanks and appreciation go out to my committee Co-Chair, John Easterwood and Raman Kumar without whose invaluable guidance and mentoring, this work would not exist. I will always be grateful for the opportunities both have given me and for their assistance in preparing me for the job market. I look forward to continue to work with them in future. A special note of thanks also goes to Douglas Patterson who guided me and played an important role in the second essay in my dissertation.

My sincere appreciation also goes out to my other committee members: Dr. Don Chance, and Dr. Huseyin Gulen for not only gave valuable input and constructive suggestions throughout this work, but also guided me when I was their student during my years of the PhD program. What I learnt in their classes and from their professionalism has not only made me more knowledgeable but, I hope, a better person too.

I would like to acknowledge the support of my dear family at this juncture, my wife Mala and my daughter Vatsala who have stood by me throughout my PhD program. Their sacrifice and love are at par with that of my parents. I also would like to acknowledge selfless love of my sisters, Winsome, Deepali and Nikita. I wish them and their families all happiness and prosperity. I would also like to thank my parents-in-law; Somasundram and Kathayee, who have always considered me no different from their own sons.

Finally, I would like to thank my other friends in Blacksburg for making life so enjoyable: Amit, Jungshik, Prahalad, Pramod, Promod and Saiyid. I wish them the best in their respective careers.

TABLE OF CONTENTS

LIST OF TABLES

Tables for Chapter 1

Tables for Chapter 2

LIST OF FIGURES

Figures for Chapter 1

Figures for Chapter 2

Chapter 1

Did Institutional Investors Herd into New Economy Stocks?

1. Introduction

Financial commentators and investors often say that herding in the financial markets is rampant[1]. In the extreme form, it manifests itself when investors act as a herd and flock to the same stock by buying (selling) at the same time even if there is no information supporting their actions. If we were to agree with this viewpoint, then investors' actions are destabilizing and induce excess volatility in the financial markets. In more benign cases, their actions could be justified as ex post rational if price trends continue or are not reversed. In this case, investors by acting in a herd help impound news into each security's price. However, in the absence of access to their private information, it is difficult to say whether observed herding is a result of investors acting independently on the same piece of information or the result of imitative behavior as suggested by many herding theories.

There is a rich theoretical literature suggesting both rational and irrational explanations for herding by investors. Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992) and Welch (1992) argue that investors infer information by observing the trades of others, and end up in informational cascades. Froot, Scharfstein and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994), attribute herding to investors following the same sources of information. Scharfstein and Stein (1990) advance reputation costs arising out of acting differently from others as a cause of herding. Investors may also exhibit herding

[1]"Institutions are herding animals. We watch the same indicators and listen to the same prognostications. Like lemmings, we tend to move in the same direction at the same time. And that naturally, exacerbates price movements."- A Pension Fund Manager (Wall Street Journal (October 17, 1989))

"There is nothing new about picking stocks based on guesses about what others might pick, but these days, the practice is apparently being taken to new extremes."-Lee Jones on 2003 Tech. Rebound & Money Managers (Wall Street Journal (August 4th, 2003)) because by coincidence they are attracted to securities with similar attributes, e.g. past returns, size, and liquidity etc. (Falkenstein (1996); Del Guercio (1996); Gompers and Metrick (2001)). Lastly, investors could exhibit herding as a consequence of fads (Friedman (1984); Dreman (1979); Barberis and Shleifer (2003)). Despite the perceptions of market watchers and herding theories, empirical evidence on herding is mixed. Lakonishok, Shleifer, and Vishny (1992) find no evidence of herding by pension funds in stocks. Similarly, Grinblatt, Titman, and Wermers (1995) document economically insignificant level of herding by mutual funds. Wermers (1999) finds only weak evidence of herding by mutual funds. More recently, Sias (2003) and Pirinsky (2002) using different methodologies find significant level of herding in an average stock by institutional investors.

Individual investors may plausibly herd more than institutional investors. However, it would be more interesting to examine institutional herding for a number of reasons. First, Gompers and Metrick (2001) document that by 1996 institutional investors held 51.6% of the entire market value of all publicly traded stocks[2]. Moreover, in 1989, trading by institutions and member firms of NYSE contributed to more than 70% of trading volume on NYSE (Schwartz and Shapiro (1992)). Second, given the large order sizes, institutions normally execute, it is more likely that they have much greater impact on the prices. Finally, it would be much more surprising to find institutional investors herding because they are usually regarded as more sophisticated and better informed than individuals. Consequently, a number of studies have attempted to investigate whether institutional investors herd in the financial markets.

Prior studies have generally focused on large cross-sections of stocks. However, if institutional investors herd, we should examine their trading in a setting where herding is most likely to be present. Christie and Huang (1995) argue that investors are more likely to suppress their private beliefs in favor of consensus during periods of unusual market movement. Thus herding is most likely to emerge during periods of market stress, or

[2]According to the 1999 Security Industry Fact Book, financial institutions held 59% of publicly traded equities in the United States at the end of 1998.

during huge price movements. Furthermore, Bikhchandani and Sharma (2000) argue that investors cannot observe other investors' portfolio changes at the individual stock level soon enough to imitate another investor's behavior. But it is more likely that such changes are observable at industry levels. Additionally, it could be argued that herding should be more pronounced in certain industry groups of stocks, such as high-technology stocks with uncertain cash flows. For instance, we might observe greater herding in a glamorous stock like ebay.com than in Sears. To this end, the price run-up during 1998 to early 2000 in the internet stocks and the subsequent crash in April 2000 gives us a good setting to test whether herding manifested itself in the period and contributed to the mania. The dramatic price run-up was based on two opposing views about the valuation of stocks. This situation for internet firms, wherein information signals were very noisy, is a good setting for cascades to form. Furthermore, these firms were young and had the common feature of highly uncertain earnings. All of these features contributed to noisy signals. The eventual decline was triggered with minor new public information. This is indicative of the fragility of the cascade.

Although internet stocks present a good setting to detect herding, it does not necessarily imply that institutional investors herded in internet firms during this period. First, institutional investors hold a big proportion of the overall market, and, in such a large group it is possible to find both buyers and sellers in equal proportions, even within a particular industry. Second, institutional investors are not a homogenous category. They consist of banks, insurance firms, mutual funds, brokerage houses, pension funds, hedge funds, and university endowments, etc. They are subject to varying regulatory requirements and competition and have different holding periods and investment styles. Even within a type of institution, there is substantial heterogeneity (e.g., Growth versus Income mutual Funds). Thus, it is possible that they follow different portfolio strategies, which offset one another at the aggregate level. All of these factors bias against detecting herding.

If we do not observe herding in the above setting, then the conclusion that institutional investors herd and destabilize prices is questionable. Lack of herding at the aggregate level, however, does not eliminate the possibility that there were cross-sectional differences in the level of herding across different types of institutional investors (e.g., mutual funds versus banks). On the other hand, if we do find herding, then in addition to highlighting the role of institutional investors in one of the largest price run-ups in US stock markets, we would be in a better position to comment on the circumstances in which herding manifests itself. It would also be interesting to determine whether institutional investors herded more on the buy-side or sell-side during the run-up than during the subsequent decline[3]. If institutional investors have better information than individuals then, in aggregate, institutions should have herded more on sell-side when the market was going up (contrarian strategy) and individuals should have been herding more on buy side. We would expect to see exactly the opposite behavior during the price decline. Furthermore, the claim that institutional herding, if present, is stabilizing in nature could be examined. In addition, the observed cross-sectional differences in herding between different types of institutions could help us in better understanding the different roles of institutions, which has not been documented so far.

Our first major finding is that in contrast to prior research, institutional investors, regardless of the type, herded into internet stocks with substantial intensity. Second, institutional investors exerted no correcting force on new economy stocks during the period of 1998 to March 2000. On the contrary, they participated in it by buying in herds. We find no cross-sectional differences in herding by banks, insurance firms, mutual funds, etc. Thus, herding by institutions was much more than what could be explained by inflow of funds to internet funds by retail investors. Third, amongst internet stocks, herding was spread across all size quintiles, and was largely unrelated to past performance. Lastly, institutional investors' buying exerted upward price pressure, and the reversal of excess returns in the subsequent quarter indicates that institutional trading was destabilizing and not based on information. However, the results on institutional selling are consistent with the idea that institutional herding enhances market efficiency by incorporating information into stock prices. Our evidence of herding seems to be most

[3]Shiller (2000) and Ofek and Richardson (2003) imply that stock price increase was largely driven by individual investor.

consistent with the fads explanations of Friedman (1984), Dreman (1979), and Barberis and Shleifer (2003). We also document classification errors related to investor type with Thomson Financial 13-F data and provide a simple correction for it.

Two recent papers have documented some related evidence that suggests that institutions contributed to the internet bubble. Brunnermeier and Nagel (2003) find that the 53 hedge funds for which they had quarterly holdings data overweighted their portfolios in (overpriced) technology stocks during 1998-2000. Griffin, Harris and Topaloglu (2003) examine intra-day and daily trading patterns of institutional versus individual trading in NASDAQ 100 stocks and find that institutions were primarily responsible for the rise and fall of NASDAQ 100 from September 1999 to 2001[4]. There are 4 important differences between our study and these studies. (1) Even though these studies are indicative of institutional herding they do not directly measure the level of institutional herding. We directly measure herding for each category of institutional investor in new economy stocks using the Lakonishok, Shleifer, and Vishny (1992) measure. (2) These studies do not have a broad sample of institutions or internet stocks. Brunnermeier and Nagel's sample of hedge funds accounts for less than one third of one percent of high price-to-sales NASDAQ stocks. Griffin, Harris and Topaloglu (2003) use only the NASDAQ 100 stocks. In contrast, our sample of aggregate institutional holdings in the period 1998-2001 ranges from 37% to 59% of the new economy stocks and includes all large institutional investors like mutual funds, banks, insurance companies, etc. While it may not be all that surprising for hedge funds to be riding the internet bubble, it is very surprising that institutions like banks and insurance companies, university endowments and foundations contributed to the internet bubble. (3) Griffin, Harris and Topaloglu (2003) base their conclusions on daily and intra-daily trading patterns and find that institutional buying was driven by positive feedback trading. Our results, which are based on quarterly institutional holdings for all institutions, suggest that institutions herded not just into internet stocks with high returns, but also into internet stocks that were poor performers

[4]Griffin, Harris and Topaloglu (2003) divide the trades into institutional and individual trades based on the originating brokerage house, and this classification, though right on average, will unavoidably make classification errors. In contrast, our results are based on actual institutional holdings.

in the prior period. Thus institutional herding in new economy stocks is not purely a result of momentum trading by some institutions. (4) Brunnermeier and Nagel (2003) and Griffin, Harris and Topaloglu (2003) do not test whether the price pressures created by the buying behavior of the institutions were destabilizing by examining returns in subsequent quarters. Our evidence of return reversals in the quarter subsequent to institutional herding and the negative relationship between the return reversal and institutional herding in the prior quarter provide clear evidence on the destabilizing nature of institutional herding.

In the next section of the paper, we discuss various theories and empirical evidence on herding. In section 3 of the paper, we describe the data and sample of firms. In section 4 of the paper, we describe the methodology used to detect herding and related issues. The section 5 of the paper describes the return performance of new economy stocks and presents some preliminary results. The main results of the study are presented in section 6 of the paper. We conclude the paper in section 7.

2. Herding Models and Empirical Evidence

2.1. Herding Models

The first set herding of models is called *Information-Based Herding and Cascades.* These models, attributed to Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992), are based on the simple idea that agents gain useful information from observing the actions of previous agents, to the point that they optimally and rationally completely ignore their own private information. In such situations, the agents are said to be in an informational cascade. However, when agents know that they are in a cascade, they also know that the cascade is based on little or no information. Therefore, any new arrival of public information or better informed agents or shifts in the underlying value of actions, could result in the dissolution of the cascade. Thus, fragility is one key characteristic of a cascade.

The second set of models known as *Information Acquisition Herding* models are proposed by Froot, Scharfstein and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994). The common theme in these models is that investors decide to follow the same set of stocks or same sources of information. In the Froot, Scharfstein and Stein (1992) model, the focus is on short-term horizon of investors, which leads to positive informational spillovers. In this model, an informed investor wishing to liquidate his position in an asset stands to gain only if other people acting on the same information trade in that asset. This leads to these investors following the sources of information which are likely to be also used by other investors.

Hirshleifer, Subrahmanyam, and Titman (1994) consider early informed and late informed investors. The early informed investors trade aggressively in the initial period and reverse their position in the next period to reduce long-term risk, while the late informed investors cause the price to reflect early informed investors' information. The early informed investors make greater profits the larger the number of late informed investors that trade. Therefore, if investors do not know whether they are early informed or late informed, their ex ante utility increases in the total number of investors collecting information.

The third set of models termed *Principal-Agent Models of Herding* were developed by Scharfstein and Stein (1990).These models are based on the idea that when principals are uncertain of agents' ability to pick the right stocks, it makes sense for agents to mimic the decisions of other agents to preserve the principal's uncertainty about the agents' ability. Similarly, Maug and Naik (1995) demonstrate that an explicit relative performance clause, which is written by principals to mitigate the problem of moral hazard (for example, to induce the agent to do private research), and adverse selection (for example, to differentiate between good and bad managers) may lead to herding. They suggest that a compensation scheme which increases with a money manager's performance and decreases in the performance of other money managers, provides an additional incentive for herding.

Fourth, institutional investors may share aversion/preference to stocks with certain characteristics like liquidity, riskiness, and size (Falkenstein (1996); Del Guercio (1996); Gompers and Metrick (2001)). As a result of their preference for securities with similar characteristics, they may appear to follow each other into and out of the same stocks.

Finally, investors could exhibit herding as a consequence of fads (Friedman (1984); Dreman (1979)), or where positive feedback traders invest at a style level, and chase relative style returns. This practice targets funds into higher relative returns stocks, and moves the prices away from fundamentals (Barberis and Shleifer (2003)).

2.2. Empirical Evidence

In one of the earliest studies, Kraus and Stoll (1972) analyze monthly trades for 229 mutual funds or bank trusts for the period starting January 1968 and ending September 1969. Though they find significant imbalances between purchases and sales, they attribute it to chance, rather than herding by investors.

More recently, six important studies have analyzed herding in the context of institutional investors. The first study by Lakonishok, Shleifer, and Vishny (hereafter LSV) (1992) uses 769 US tax-exempt equity funds' (mostly pension funds) quarterly ownership of shares data for the period 1985-1989. LSV (1992) conclude that money managers do not display economically significant levels of herding. Even in the small stocks and technology stocks with uncertain cash flows, they find little evidence of herding. They find even less herding at the industry level than at the stock level. This paper also introduced the basic herding measure used by later studies.

The second study by Grinblatt, Titman, and Wermers (hereafter GTW) (1995) uses the quarterly ownership data on portfolio changes of 274 mutual funds between 1974 and 1984. Using the LSV (1992) measure, they find similar levels of herding as found by LSV (1992). Relating it to momentum trading, GTW find more herding by investors in buying past winners than investors selling past losers. To control for significant heterogeneity in the mutual funds, they differentiate funds according to their investment objectives: aggressive growth funds, balanced funds, growth funds, growth-income funds, income funds. They find even less herding after controlling for objectives.

Wermers (1999) performed the most comprehensive study to date using quarterly holdings data for virtually all mutual funds in existence between 1975 and 1994. Using the LSV (1992) measure of herding, Wermers finds little herding taking place in an average stock. He finds greater herding in small stocks, in general. However, small stocks are not typically the preferred holdings of mutual funds. He also finds higher levels of herding in growth-oriented funds than income-oriented funds, which he attributes to smaller stocks being dominant in growth funds. In contrast to GTW (1995), he finds more herding on the sell side than on buy side. By looking at the differential between contemporaneous returns and returns after 6 months on the stock bought by the herds relative to the stocks sold by the herd, he concludes herding is 'rational' and helps bring about incorporation of news into securities prices and is, therefore, stabilizing. This last finding, which, Wermers (1999) asserts is the most important contribution of his study, is also consistent with an alternative explanation. Continuing trends in the prices could also mean that, as institutional investors herd even more, they drive the prices away from fundamentals. Only if the price trends continue in the subsequent longer period, unaccompanied by herding, can we accept his claim.

Jones, Lee and Weis (hereafter JLW) (1999) study herding by institutional investors using quarterly holding data for 1984-1993, and find negligible level of herding for an average stock. They also document a positive relation between observed institutional demand and subsequent returns. Therefore, similar to Wermers (1999), they conclude that trading by institutional investors contributes to long-run market efficiency. In a recent study, Sias (2003) using quarterly holding data of institutional investors for 1983-1997, finds a strong positive relation between fraction of institutions buying over adjacent quarters. Consistent with Wermers (1999), he finds the strongest evidence of herding in the small stocks. Sias (2003) also documents that institutional demand is more strongly related to lagged institutional demand than lagged return. Lastly, Sias (2003) examines institutional demand and future returns, and documents the absence of a negative relationship. Pirinsky (2002) tests for herding by institutional investors by examining time-series correlation for individual securities in changes in the fraction of shares by institutional investors. Similar to Sias (2003), he documents a positive relation between current quarter change in fractional ownership and previous quarter change in factional ownership. Pirinsky (2002) finds greater evidence of herding, when institutional investors initiate (terminate) a position in a security. He also documents significant herding in growth and volatile stocks. In contrast to Wermers (1999), JLW (1999), and Sias (2003), he finds herding to be destabilizing, since stocks bought (sold) by institutional investors in herds tend to under-perform (outperform) over the following year.

Two recent studies investigate institutional trading in technology stocks during 1998-2000. Although neither of the studies directly measures herding, their results are suggestive of the notion that institutional investors rode the internet bubble. Brunnermeier and Nagel (2003) examine the technology stocks holdings of hedge funds and find that hedge funds portfolios were overweighted in (overpriced) technology stocks during 1998-2000.Brunnermeier and Nagel (2003) also find that these hedge funds reduced their exposure to technology stocks in the quarter prior to price peaks of individual stocks. Griffin, Harris and Topaloglu (2003) find during 1999-2001 that both institutional ownership levels and volume on NASDAQ were high. Institutions bought shares from individuals on net the day after price increases and institutions sold on net following price drops. They conclude that institutions contributed more than individuals to the NASDAQ rise and fall.

3. Data and Sample Selection

3.1. Identifying Internet Stocks

There is no strict definition of what constitutes an internet firm, since any company, especially a technology company, could perform both ‘internet-related’ and non-internet related (‘old economy’) activities. Furthermore, there is no unique SIC code associated with internet firms. Our initial sample of internet firms comes from two sources. Our first sample of firms comes from a previous study by Hand (1999). His sample consists of 271 firm reported on the Internet Stock List™ of www.internet.com as of 11/1/1999 plus 3 other firms which were earlier listed but no longer traded as of 11/1/1999 (Excite, Geocities and Netscape Communications). The parent company of this website, Internet.com Corp., itself is listed on NASDAQ under the ticker symbol INTM. To some degree, this website follows an intuitive criterion for a firm to be included in its Internet Stock List. For a firm to be included in the list, it should have 51% or more of its revenue generated from or because of the internet. There is no minimum market capitalization, trading volume, or shares outstanding requirements imposed on the firms to be included in the list. More often than not, however, these companies tend be the more recognized and larger companies in the e-commerce field.

The second source of internet firms comes from Morgan Stanley Dean Witter’ Internet Company Handbook v.2. This list reports primary financial characteristics for 383 internet firms that existed on 6/1/2000. The basic criterion used to include firms in this list is that they should be pure internet firms. Thus firms like Cisco, which have both internet-related and non-internet businesses will not be part of the list. These firms are further classified into 11 categories related to the internet sector – (i) portals, (ii) infrastructure companies, (iii) infrastructure services, (iv) software, (v) commerce, (vi) consulting and applications, (vii) financial services, (viii) multi-sector, (ix) vertical portals, (x) marketing and advertising services, and (xi) B2B commerce.

We start examining firms in December 1997, and continue to follow them to the end of 2001. There were 66 internet firms at the beginning of this period. As more new firms came to the market during 1998-2000, the number of internet firms in the sample increased to 470 by the end of March 2000. Our initial sample consists of the 470 firms, that are included in either of the two lists (187 firms are common to both the lists). We merge these 470 firms with CRSP files to extract their CUSIP (NCUSIP) numbers. We find information on CRSP for 434 firms. These 434 firms constitute our final sample[5]. Many of these firms were delisted or merged with other firms by the end of 2001. By identifying internet firms from end of 1999 and middle of 2000, our sample of internet firms include the firms that were subsequently delisted, and therefore, we are able to reduce the survivorship bias.

3.2. Institutional Investors Holdings

A 1975 amendment to the Securities and Exchange Act of 1934 requires all institutional investors, with greater than $100 million of securities under discretionary management, to report their holdings to the SEC. The holdings are to be reported on form 13-F on a quarterly basis for all exchange-traded or NASDAQ-quoted equity securities within 45 days of the end of each quarter. A further requirement is that equity positions should be greater than either 10,000 shares or $200,000 in market value. For the 434 internet firms, we used Thomson Financial (earlier called CDA Spectrum) 13-F filing data to get the quarterly holdings of the institutions for the period starting end of 4th Quarter of 1997 to end of 4th Quarter of 2001. We also extract holdings data for other stocks held by these institutions. The aggregate holdings of all institutional investors for each quarter represents total institutional holdings in each of these stocks, and the remainder is held by individual investors and small institutions. Thomson Financial classifies the institutions into 5 'types' according to Standard and Poor's definition of the institution's primary line of business: (1) bank trust departments, (2) insurance firms, (3) investment companies (mutual funds), (4) independent investment advisors (includes most of the large

[5] A complete list of these firms with names and ticker symbols is available on request.

brokerage firms) and (5) others (which encompasses foundations, university endowments, ESOPs, internally managed pension funds, and individuals who invest others' money but not otherwise categorized). These classifications are not always precise especially between investment companies and independent investment advisors. For example, if a brokerage firm's mutual fund assets constitute more than 50% of its total assets, it could be categorized as investment company (mutual fund), and as independent investment advisor, otherwise. It is also possible for an institution to be reclassified over time, if its primary business has changed. In addition, as discussed in Appendix A, certain reclassifications are erroneous. In order to reduce the reclassification errors, we make the necessary corrections as described in the Appendix.

4. Methodology and Portfolio Turnover

4.1. LSV (1992) Measure of Herding

To detect herding, we compute the most commonly used measure, attributed to LSV (1992), which essentially examines "the extent to which money managers end up on the same side of the market in a given stock in a given quarter, relative to what is expected if managers trade independently."

For a given quarter t, the herding measure is computed as follows:

$$\mathrm{H}(\mathrm{i},\mathrm{t}) = \left|\mathrm{p}(\mathrm{i},\mathrm{t}) - \mathrm{p}(\mathrm{t})\right| - \mathrm{AF}(\mathrm{i},\mathrm{t}) \tag{1}$$

Where

$$\mathrm{p}(\mathrm{i},\mathrm{t}) = \frac{\mathrm{B}(\mathrm{i},\mathrm{t})}{[\mathrm{B}(\mathrm{i},\mathrm{t}) + \mathrm{S}(\mathrm{i},\mathrm{t})]} \tag{2}$$

$$\mathrm{p}(\mathrm{t}) = \frac{\sum_{i=1}^{\mathrm{i}=\mathrm{N}_{\mathrm{it}}} \mathrm{B}(\mathrm{i},\mathrm{t})}{\left[\sum_{\mathrm{i}=1}^{\mathrm{i}=\mathrm{N}_{\mathrm{it}}} \mathrm{B}(\mathrm{i},\mathrm{t}) + \sum_{\mathrm{i}=1}^{\mathrm{i}=\mathrm{N}_{\mathrm{it}}} \mathrm{S}(\mathrm{i},\mathrm{t})\right]} \tag{3}$$

$$AF\ (i, t) = E\{|p\ (i, t) - p\ (t)|\} \tag{4}$$

B (i, t) = number of institutional investors that are net buyers of stock i in quarter t

S (i, t) = number of institutional investors that are net sellers of stock i in quarter t

p (t) = total number of institutional investors buying in quarter t relative to the total number of institutional investors active in quarter t aggregated across all stocks

AF (i, t) = an adjustment factor that accounts for the fact that under the null hypothesis of no herding the expected value of $|$ p (i, t) - p (t) $|$ will be greater than zero.

N_{it} = number of stocks traded by at least one institutional investors in quarter t

p (i, t) is the fraction of active managers buying stock i in quarter t. | p (i, t) – p (t) | can be interpreted as excess buying or selling in the stock i relative to an average stock bought or sold by institutional investors in quarter t and AF (i, t) is the expected value of | p (i, t) – p (t) |. Since B (i, t) and S (i, t) are outcomes of a binomial process, this expected value can be computed based on number of the traders[6]. As the number of active traders increase in a stock-quarter t, unaccompanied by herding, we expect that the fraction of traders, who are buyers and sellers, will tend to become equal. Thus if there is no herding, for a large number of traders in a quarter, p (i, t) will tend to p (t), and AF (i, t) will be close to zero. For small number of traders, AF (i, t) will be larger. Positive values of H (i, t) will occur when | p (i, t) – p (t) | is greater than AF(i, t), and these would occur when the extent of buy or sell herding is greater than its expected value under the assumption that traders are buying or selling independently. These positive values of H(i, t) would be consistent with herding. Negative values of H (i, t) will occur when | p (i, t) – p (t) | is less AF (i, t), and these would occur when the extent of buy or sell herding is less than its expected value under the assumption that traders are buying or selling independently. These instances of negative values of H (i, t) should not be considered as

[6] For instance if there are 2 traders in a stock in a quarter t, then AF (i, t) assuming p (t) =0.5 is 0.25*|0/2-0.5|+0.5*|1/2-0.5|+0.25*|2/2-0.5|=0.250. The probabilities are computed as ${}^2C_0 * (0.5)^0*(0.5)^2=0.25$, ${}^2C_1 * (0.5)^1*(0.5)^1=0.5$ and ${}^2C_2 * (0.5)^2*(0.5)^0=0.25$ respectively. Similarly with 5 traders in a stock-quarter AF (i, t) could be shown to equal to 0.188.

evidence of herding. Prior studies have included these negative herding values along with positive herding values to compute the mean herding. For the purpose of our study, we need to separate stocks in each quarter into three groups: stocks that were buy herded, stocks that were sell herded, and stocks for which there was no herding. We consider the stocks for which H (i, t) is negative as stocks with no herding, and exclude them in computing the mean herding for the stocks in which there was buy or sell herding. However, for comparison with prior studies, we also compute mean herding including these stocks with negative values of H (i, t). To further determine, whether herds form on the buy-side or sell side, we use following modified measures:

$$BH\ (i, t) = H\ (i, t) \mid p\ (i, t) > p\ (t) \text{ for buy-side herding and,}$$
$$SH\ (i, t) = H\ (i, t) \mid p\ (i, t) < p\ (t) \text{ for sell-side herding.}$$

We compute H (i, t) across all stock-quarters and average them for a sub-period (or a type of investor) to compute different herding measures. We refer to the average H (i, t) as the *herding intensity*. In describing the herding, we will report the average herding intensity and the number of stocks that were herded. The number of stocks indicates how pervasive herding was (or the breadth of herding). Together these two aspects of herding will measure the extent of herding.

While computing p (i, t) and p (t), appropriate adjustments are made to account for stock-splits and stock dividends. Furthermore, as a new stock comes to the market in a quarter, most investors will be net buyers thus inflating p (i, t). To mitigate this problem, we compute herding measures for only those stocks which existed in the previous quarter. Of course, the reverse is also true for those quarters when stocks go out of existence due to merger and acquisition, delisting, etc. To correct for this, we exclude the last quarter from herding computation if a stock exits the sample prior to December 2001.

4.2. Portfolio Turnover and the use of Quarterly Holdings Data

One possible drawback of using quarterly holdings data to detect herding is that it may fail to capture any intra-period buy or sell herding that is reversed in the same quarter. However, if it takes time to know what other investors are doing, it may actually increase the chances of detecting herding. The magnitude of this problem of using quarterly data would be a function of the portfolio turnover of institutional investors. To examine the portfolio turnover for our sample of institutional investors, we follow the CRSP mutual funds database, Wermers (2000), and Brunnermeier and Nagel (2003) and define turnover as the minimum of the absolute values of buys and sells of a manager in a given quarter, divided by the total stock holdings. As noted in Brunnermeier and Nagel (2003), this method of calculating turnover captures only the trading that is unrelated to inflows or outflows. We find that, for an average institutional investor, the portfolio turnover is 70% on an annualized basis. This is slightly lower than Wermers's (2000) 72.8% for mutual funds for 1994, and substantially lower than Brunnermeier and Nagel's (2003) 100% for hedge funds for 1998-2000. Mutual funds and brokerage firms average 71% each. Banks and insurance firms have the lowest turnover of 56% and 59%, respectively. The "others" category which includes hedge funds, university endowments, foundations and internally managed pension funds have the highest portfolio turnover ratio of 77%. On average, only about 18% of the portfolio is turned over in a quarter. Since a substantial part of the holdings survive from one quarter to the next, we agree with the prior studies that the use of quarterly holdings data does not pose a significant problem in detecting herding.

5. Internet Firms and Preliminary Results

5.1. Internet Firms and Stock returns

Although some firms like Cisco and AOL have existed for many years, most of the firms in our sample came into existence after 1996. The highest number of firms entering the market was 254 in the year 1999. As a result, most of the firms in our sample are quite young. By the end of 2001, 160 of these firms were either delisted or merged with other companies. At the peak of internet boom in March 2000, these firms had combined market capitalization of $1.63 trillion, accounting for more than 15.7% of the entire market capitalization of all stocks listed on NYSE/AMEX/NASDAQ. At the same time, average market capitalization of stocks was $ 2.80 billion, and the median was $ 0.250 billion. However, consistent with Ofek and Richardson (2003), our sample of stocks is distributed over all NYSE size quintiles.

Figure 1 graphs a return index for an equally-weighted portfolio of internet firms. To compute the quarterly returns, monthly returns from CRSP files are compounded. For comparison purposes, index levels associated with NASDAQ and S&P 500 are also plotted. The most striking fact that emerges from the figure is the stratospheric level of the internet index. $100 invested in internet index at the start of 1998, grew to yield approximately $824 in March of 2000. While $100 invested in S&P 500 Index would have grown to 'only' $153 during the same period. Although $100 invested in NASDAQ Index also would have grown to $291, it was just slightly more than a quarter of what internet firms yielded. As Ofek and Richardson (2003) point out, in order to justify these valuations for internet firms, they had to perform better than the best 2 % of the existing firms for several decades while having a zero % cost of capital!! Although, it is very difficult to prove whether these valuations reflected or violated internet firms' fundamentals, we use the popular terminology to designate the period from the beginning of 1998 to March 2000 as the *bubble-period*.

The poor performance of the internet stocks after March 2000 is also evident in Figure 1. By the end of December 2001 they had lost more than 77% of their March 2000 valuations. Although NASDAQ and S&P 500 Index had also declined in the same period, their decline was much more modest in comparison. NASDAQ and S&P 500 lost 51% and 23%, respectively of their March 2000 valuations. This period is referred to as the *post-bubble* period.

5.2. Portfolio Weights and Dollar-ratios

To investigate the trading behavior of institutional investors in internet stocks, we aggregate the holdings of all institutional investors at the end of each quarter, and compute the percentage of their holdings in internet firms. This portfolio weight for institutional investors in internet firms is compared with the ratio of the internet firms' market capitalization to the market capitalization of all stocks. This simple comparison sheds light on institutional investors' inclination to overweight (underweight) internet firms in their portfolio. Figure 2 shows this comparison by following the evolution of internet portfolio weight versus market portfolio weight. The most striking feature of this comparison is that commencing December 1997, institutional investors underweighted the internet portfolio relative to the market portfolio. For example, at the peak of internet bubble in March 2000, they held 7.85% (approximately $0.74 trillion) of their total holdings in internet firms when these firms accounted for 15.7% of the market portfolio. Although not shown, we get the same picture when we plot the portfolio weight of different investor types, e.g., banks, insurance firms, and mutual funds, etc.

Another interesting observation from Figure 2 is that, although institutional investors did not overweight internet firms relative to the market portfolio for most of the bubble-period, their internet firms holdings kept rising through out the period and started declining only after the bubble burst in March of 2000. To measure the excess demand for internet stocks, we compute the D-ratio (dollar ratio) for a particular stock-quarter t as

$$\text{D-ratio (t)} = \frac{\left[\sum_{i=1}^{i=N} \$\text{Buy (i)} - \sum_{i=1}^{i=N} \$\text{Sell (i)}\right]}{\left[\sum_{i=1}^{i=N} \$\text{Buy (i)} + \sum_{i=1}^{i=N} \$\text{Sell (i)}\right]} \qquad \textbf{(5)}$$

Where, \$Buy (i) is dollar increases by all institutional investors in internet stock i, and \$Sell (i) is dollar decreases in the internet stock (i) in holdings. N is the total number of internet stocks bought and sold in the same quarter. To control for changes in holdings resulting from price changes, we use the average of the prices at the beginning and end of the quarter. Consequently, our measure of the D-ratio captures the dollar increase (decrease) in the internet holdings of institutions resulting from purchase (sale) of these stocks, and not from price changes. The results are reported below.

	Jan'98-Dec'01			Jan'98-March'00			April'00-Dec'01		
	obs[7]	**Mean**	**t Value**	**obs**	**Mean**	**t Value**	**obs**	**Mean**	**t Value**
D-Ratio	3464	-3.74%	-3.74	1267	16.69%	11.50	2197	-15.70%	-12.45

For the bubble-period the mean D-ratio is 16.69 % (t-statistic of 11.50) signifying substantial excess demand and inflow of funds into internet stocks. In the post-bubble period D-ratio is in excess of – 15.70 % suggesting swift outflow of funds[8].

Overall, there is no evidence that institutional investors engaged in any trading behavior to counteract the bubble. If we assume that institutional investors were aware of the bubble (though it is possible that they were not), institutions' trading actions supported the bubble by perhaps, riding it. The only other possibility is that smart money managers resorted to short-selling the internet stocks, which is not evident in our long position data. Ofek and Richardson (2003) suggest that short-selling was difficult for 'special' stocks since lock-up periods acutely restricted the supply of internet stocks. While this explanation may be valid for certain stocks, Geczy, Musto, and Reed (2002) argue that it does not apply to a large majority of stocks, including internet stocks. Additionally, Lamont and Thaler (2003) suggest that high shorting costs can explain why a rational arbitrageur fails to short the overpriced stocks, but not why anyone buys the overpriced security. Furthermore, Brunnermeier and Nagel (2003) find that for the highest priced NASDAQ stocks, hedge funds, which were not restricted from short-selling, did not take enough short positions during the period of 1998-2000 to counter their long position.

[7] obs refers to stock-quarters used to compute d-ratios.

[8] This is consistent with Barberis and Shleifer (2003) explanation for the findings of Chan, Karceski, and Lakonishok (2001) as to why despite having good earnings for 1998-1999 period, value stocks performed badly. According to Barberis and Shleifer (2003) extraordinary performance of growth stocks during 1998-1999 period could have generated substantial flow of resources out of value stocks and into growth investing thereby depressing the prices of value stocks.

6. Herding Results

6.1. Overall Herding Results

In Table I we present the results of overall herding exhibited by institutional investors in our sample of internet firms for the overall period and both sub-periods, the bubble-period (Jan’98-March’00) and the post-bubble (April’00-Dec’01). In panel A, we present mean (median) herding measures across our sample of firms, traded by at least 1 institutional investor. For the overall period, our average herding intensity for internet stocks is 6.76%. Although not shown in the table, we also document that the mean herding intensity is 3.86% for an average stock during the same period. Perhaps, the unprecedented returns earned by stocks prompted all money managers to invest in equity markets, in general, and in new economy stocks, in particular. The mean herding measure of 6.76% (3.86%) implies that if 100 institutional investors trade in the average stock-quarter, then 6.76 (3.86) more investors traded on the same side of the market than would be expected, if these investors made their trading decisions randomly and independently of one another. Our measure is more than twice the figure of 2.7%, 2.5%, and 3.4% reported by LSV (1992), GTW (1995), and Wermers (1999), respectively. Our mean herding measure for internet stocks for the entire period is almost four times the 1.6% and 1.78% for an average stock reported in Jones, Lee and Weis (1999), and Sias (2003) respectively. Based on the comparisons with prior studies, we can conclude that (i) herding was higher in this period than in prior periods; and (ii) herding was higher in internet stocks than herding in an average stock.

An overall herding measure masks the direction of herding. For example, for the overall period a herding intensity of 6.76% in internet stocks does not tell us whether institutional investors were buying or selling in herds. To examine whether buy or sell herding was dominant, we separately compute buy and sell herding intensities. The mean buy herding for the overall period is 6.17% over 2129 stock-quarters. In contrast, the mean sell herding is more pronounced at 7.53% over 1653 stock-quarters. Thus, buy herding was less intense, but more pervasive. Conversely, sell herding was stronger in intensity, but less pervasive. Since the return performance of an average internet firm was quite different in the two sub-periods, the results are reported separately for the two sub-periods. Our mean herding intensity for the bubble-period is 7.26% with buy herding measure amounting to 8.47%[9] computed over 1036 stock-quarters, and sell herding amounted to only 3.62% measured over 346 stock-quarters. Quite clearly, buy herding is more pronounced than sell herding in the bubble-period. This difference is both economically and statistically significant. Interestingly, the number of stock-quarters for buy herding is also almost three times that of sell herding. Both these observations indicate that institutional investors herded far more and over larger set of stock-quarters on the buy side, rather than on the sell side during the bubble-period.

In the post-bubble period, overall herding intensity drops to 6.48% with buy and sell herding being 3.99% and 8.56%, respectively. The number of stock-quarters used to compute buy and sell herding are also quite different from each other (1093 for buy versus 1307 for sell). Thus in the post-bubble period, buy herding diminished as compared to the bubble-period, and over smaller number of stock-quarters. However, sell herding had become more important in the post-bubble period and accounted for a larger number of stock-quarters.

Our median herding intensities for both buy (sell) herding and for all periods, are similar to the mean herding intensities. In contrast to LSV (1992), and Wermers (1999), who report much lower median herding measures, we find medians only slightly less than the corresponding mean. This indicates that our results are not driven by a minority of stocks. In further herding analysis, we report only mean herding intensities.

Next, as discussed in section 4.1, we exclude the stock-quarters with negative herding intensities, where the extent of buy or sell herding was less than what could be expected at random. Predictably, our herding intensities are much higher but with fewer numbers

[9] Plausibly, new additions to S&P 500 index and seasoned equity offerings could induce buy herding by institutional investors. We find only 4 stocks from our sample of firms added to the S&P 500 index by end of 2000. Similarly, using CRSP data we estimated only 28 possible seasoned equity offerings for our sample of stocks during the entire period of 1998-2001.

of stock-quarters. Overall, herding numbers after removing stock-quarters with negative herding measures are qualitatively similar to unadjusted herding intensities. We use only stock-quarters with positive herding measures for our further analysis on herding from table II onwards.

We aggregate our herding measures regardless of the number of traders in a stock-quarter. However, it is likely that the level of herding may be affected by the number of traders in a particular stock-quarter. It could also be argued that herds by definition consist of more than 1 institutional investor. In order to examine whether the level of herding is affected by number of traders, we present herding results when there were at least 20 traders in each stock in Panel B. Most of the herding intensities (unadjusted) in Panel B are slightly higher than in Panel A (although with fewer stock-quarters). This is consistent with the notion that bigger herds make for stronger herds. But as discussed in section 4.1, this could also be due to the decline in the adjustment factor with greater number of traders. However, the herding intensity adjusted for negative herding are slightly lower than what they were for one trader. Overall, the differences in the results between Panels A and B are quite small. In further analysis, we do not see substantial differences in the results based on the number of traders. Hence we only report results for stock-quarters, where at least 1 trader was present.

In order to examine how herding related to the bubble-period price run-up and the post-bubble crash, we look at the quarterly herding intensity for buy and sell herding in Table II. The buy herding column shows an upward trend during 1998-1999, peaking in Septemeber-1999 at 15.34% and staying high till March 2000. Another useful way of examining at the extent of herding is the percentage of stocks buy or sell herded out of the total number of stocks traded by institutional investors in a particular quarter. During 1998-1999, the percentage of stocks buy herded by institutional investors was much larger than the percentage of stocks that were sell herded (approximately 60% versus 15%). After March 2000, the buy herding intensity started declining, reaching a modest 7.52 % by December 2001. On the other hand, sell herding, though significant, was confined to a much smaller number of stocks during the bubble-period. However, it began trending up and spreading to half of all internet stocks in the middle of 2001 in the post-bubble period.

Lakonishok, Shleifer, Thaler, and Vishny (hereafter LSTV) (1991) suggest that institutional investors 'window dress' their portfolios at the end of every quarter, and especially at the end of the year by adding past winners and selling past losers, so that they can impress their sponsors. Consistent with Wermers (1999), we find no evidence of 'window dressing' by money managers. In the bubble-period, when most of the internet stocks were experiencing huge price gains, buy (sell) herding measures are not necessarily the highest in December. Even in the post-bubble period we do not see buy (sell) herding measure peaking in December. Perhaps with quarterly evaluation of money managers' performance, end of year 'window dressing' is no longer important.

6.2. Herding and Age of the Stock

The public float of new stocks goes up at the end of the lock-up period of 180 days after an IPO, when insiders are no longer restricted from selling their shares. Although not necessary, there may be greater buy herding by institutional investors in the 3rd quarter after an IPO[10]. Thus, it is possible that our results for higher intensities of herding are driven by greater buying in the 3rd quarter, when the lock-up period expires. To control for this, we separately compute the herding in the 3rd quarter of every stock's age. To proxy for a stock's age, we use the number of quarters from the time the since stock's return is available on CRSP files. We report the results in Table III. Although herding is generally quite high in terms of its intensity (13.36%) in the 3rd quarter, it is restricted to a relatively small number of stocks (215 stock-quarters)[11]. Additionally, the herding intensity is high both before and after the 3rd quarter and with a substantial number of stock-quarters. Thus, we conclude that our results are not purely a manifestation of the increased public float for these stocks after the expiration of the lock-up period.

[10] Individual investors and small institutions may also buy the stocks sold by insiders.
[11] One may argue that buying in 215 stocks out of possible 370 new stocks since January 1st 1998 is quite substantial. However, of the approximately 1500 stock-quarters subjected to buy-herding, only 215 are from 3rd quarter.

Furthermore, if herding is primarily driven by informational cascades, then we expect that herding will be more pronounced in younger stocks for which information is scarce and noisy (possibly because of lower analyst coverage, and more uncertainty about cash flows). Alternatively, if institutional investors have similar preferences/aversions for certain stock characteristics, then conceivably, as stocks age and have larger market capitalization, they could attract the attention of institutional investors. In order to examine the variation in the herding levels as stocks age, we compare herding for old and new stocks by splitting our sample of stocks in two different age groups, one group with age of less than or equal 2 quarters (new-stocks) and another group with age more than 3 quarters (old stocks). For both the overall period and the bubble-period, we find that buy herding intensity is higher for new stocks than for old stocks. Additionally, both buy and sell herding intensity are significant with a larger number of stock-quarters for old stocks. Thus our results are only weakly consistent with the Informational Cascades models. It is also possible that institutional investors were simultaneously selling old stocks (or buying less of old stocks) and buying more of new stocks to capitalize on the post-offering returns of internet firms. The pattern of buy and sell herding in the bubble-period for new stocks versus old stocks is somewhat consistent with this notion. Institutional investors are sell herding more and in larger number of old stocks, than in new stocks. However, the intensity of buy herding is much larger than intensity of sell herding, and was greater in new stocks, though confined to a smaller number of stock-quarters. In the post-bubble period buy (sell) herding is mostly confined to old stocks. This observation is consistent with at least two possible explanations. This could be the result of diminishing euphoria over the dotcoms, which in turn accounted for fewer number of new internet firms coming to the market. This could also be due to better performance of old stocks, or new stocks not having the preferred characteristics for institutional investors.

6.3. Herding by Different Investor Types

In this section, we explore the relative contribution of different types of institutional investors to herding in internet firms. Since Thomson Financial data for 13-F aggregates all long positions for a particular institution, we cannot determine the impact of specific performance objectives and investment horizons for institutions on their herding behavior. Nevertheless, we attempt to make some general observations about these institutions, which give us some idea about their trading strategies.

The five categories of institutional investor could face different incentives and thus exhibit different tendencies to herd. Banks are primarily involved in external pension fund management and trust operations. Insurance firms invest on their own accounts in stocks, and also do a substantial business in external pension fund management. Although their external fund management performance is monitored by a plan sponsor, JLW (1999) suggest that fund managers pursue strategies which are easily defensible ex-post. They have little incentive for superior performance, and they just try to do no worse than average. Peter Lynch (1991) states that "worst camp-following (herding) takes place in bank pension-fund departments and in insurance companies, where stocks are bought and sold from pre-approved lists." For mutual funds, Khorana (1996) shows that fund managers are likely to be fired after 6-8 quarters of poor performance. This gives them incentive to follow momentum based strategies, which are likely to pay off in the short run. This positive feedback trading strategies may look like unintentional herding. In contrast, since pension fund members cannot withdraw their funds due to poor performance and have long-term objectives, it is likely that they may follow different trading strategies. Brokerage firms, in addition to mutual funds business, also exercise control over customized accounts of large individual investors. Thus, their incentives for herding are similar to those of mutual funds. Furthermore, Dreman (1979) suggests that clients have a tendency to withdraw funds from accounts, if their investment advisors do not invest in stocks that are in 'fashion'. Thus, it could be argued that brokerage firms too have reasons to herd. The category 'other' consists of a wide variety of institutions; e.g., foundations, university endowments, ESOPs, internally managed pension funds, and individuals who invest others' money. It is plausible that they have different investment objectives and holding periods. As a result, it is difficult to say what trading styles are followed by them.

In Table IV, we report the results for different institution types for the overall period, the bubble-period and the post-bubble period. In the overall period, buy herding intensity ranges from 11% to 15% for different institutions. Brokerage firms have the lowest herding intensity of approximately 11%. However, brokerage firms herded in a relatively higher number of stock-quarters. During this period of 1998 to 2001, sell herding intensity (approximately 13-15%) is also significant for most of the institutions types, but over a much smaller number of stock-quarters. In addition, sell herding is similar across institutions. Overall, there is little cross-sectional difference in the buy and sell herding across institution types during the overall period. The herding results are qualitatively similar during the bubble-period. In the post-bubble period, buy herding intensity is lower, and over smaller number of stock-quarters, compared to bubble-period. Moreover, sell herding intensity became much more pronounced and over a greater number of stock-quarters relative to buy herding. While Brunnermeier and Nagel (2003) find that hedge funds tilted their portfolio towards overpriced technology stocks, surprisingly more conservative investors like banks, insurance firms, pension funds, some hedge funds, university endowments and foundations also behaved no differently. Overall, we can conclude that all institutions of different types contributed equally to the herding in both the bubble and post-bubble periods.

One could argue that a number of internet related mutual funds came to the market during the bubble-period. Therefore, possibly part of buy herding (especially by mutual funds) could be attributed to retail investors. However, given little differences in herding measures across different institutions types, flow of funds by retail investors to internet related mutual funds alone cannot entirely explain the observed herding.

6.4. Herding and Stock Size

The Information-Based Herding and Cascades models predict that herding is more likely to occur when private information is more difficult to obtain and to evaluate (due to more noise). Wermers (1999) suggests that for small capitalization stocks (with large information asymmetry) investors are more likely to suppress their own beliefs, and put greater weight on what others are doing. Herding in small capitalization stocks is also consistent with Scharfstein and Stein's (1990) agency model of herding, in which money managers may sell small stocks with bad past performance, but might hold on to large capitalization stocks regardless of their past performance. On the other hand, if herding results from Information Acquisition models, then Sias (2003) conjectures that cross-sectional correlation between signals is likely to be stronger in large stocks (due to investors following the same indicators) with less noisy signals. In his view, larger stocks should have greater herding. Furthermore, because of institutional investors' preference for liquidity and size (Falkenstein (1996); Gompers and Metrick (2001)), we may observe greater herding in large capitalization stocks.

To examine herding based on size, we divide the universe of all NYSE stocks into quintiles based on market capitalization at the beginning of every quarter from 1998 to 2001. Internet firms traded by institutional investors are assigned to quintiles and updated quarterly. The results are reported in Table V. During the overall period of 1998 to 2001, buy herding intensity of 13.61% was the greatest in the smallest size quintile, versus 10.28% in the largest size quintile. This is consistent with Information-Based Herding and Cascades Models. In addition, the results are also consistent with Wermers (1999), and Sias (2003), who document greater herding levels in smaller stocks than in larger stocks. However, the number of stock-quarters with herding for small stocks is much smaller – 121 stock-quarters for smallest size quintile versus 336 stock-quarters for the largest size quintile. In addition, the proportion of stock-quarters herded into in the smallest size quintile is much smaller than the largest size quintile (18% versus 64%). The buy herding intensity in the largest size quintile, though lower in comparison to the smallest size quintile is still substantial at 10.28%. The buy herding in larger stocks is consistent with information acquisition models, and institutional investors' preference for larger and more liquid stocks. The buy herding results are similar in both the bubble and post-bubble period as well. In summary, we observe that buy herding is similar across stock size quintiles.

The intensity of sell herding in the overall period of 1998 to 2001 is the highest in the smallest size quintile – approximately 17% in the smallest size quintile versus 7% in the largest size quintile. The number of stock-quarters (and proportion) traded is also the largest in the smallest size quintile - 288 (43.44%) in the smallest size quintile versus 91 (17.23%) in the largest size quintile. We find similar results in both the bubble and the post-bubble periods. The post-bubble period sell herding is consistent with LSTV (1991) finding of more window dressing in small stocks. Overall, sell herding results are consistent with the notion that, since institutions have preference for large stocks, they hold onto bigger stocks, but imitate others in selling the smaller stocks due to information reasons. Overall, we conclude that buy herding is pervasive across all stocks, though sell herding is the greatest in the smaller stocks.

6.5. Herding and Momentum Trading

Recent papers by GTW (1995), Wermers (1999), Wermers (2000), Nofsinger and Sias (1999), JLW (1999), and Sias, Starks, and Titman (2001) suggest that institutional investors are momentum investors. Momentum based trading strategies are also consistent with LSTV (1991) arguments of "window-dressing". In order to investigate, the relationship between herding and momentum trading (unintentional herding), we partition our sample of stocks into return quintiles on the basis of one quarter lagged NYSE/AMEX/NASDAQ return break points[12], which are updated quarterly. The results are reported in Table VI[13]. Although, we report results for the entire period of 1998-2001, given different return performance of internet sector in two sub-periods, we focus our analysis on bubble and post-bubble periods separately. During the bubble-period, we find some evidence of a relationship between momentum trading and herding. On the buy side, more stock-quarters are being traded in the highest quintile (391 in R5, versus 119 in R1) with a herding intensity of 12.37%. However, even in the lowest two quintiles (R1 and R2), the herding intensities (10.94% and 10.84%, respectively), as well as the

[12]We also did the analysis using NYSE return breakpoints. Our results are qualitatively similar.
[13]R5 is the quintile with the highest return in the prior quarter and R1 is the quintile with the lowest return.

proportion of stocks-quarters (38% and 51%, respectively) are quite large. The buy herding results are similar in the post-bubble period though the largest number of stock-quarters is in the lowest return quintile (due to poor return performance of internet stocks in general). Overall, institutional investors were buying internet stocks in herds, even the stocks with poor or average performance in the prior quarters, during the overall period from 1998 to 2001. Thus, the previously documented results on herding are not entirely an artifact of momentum trading strategies being employed by some institutions.

On the sell-side there is more evidence of stocks being dumped in the lowest return quintile in the bubble-period. There is little evidence of contrarian trading in that just around 7% of stock-quarters were sold in the highest quintile. In the post-bubble period, stocks continue to be dumped in the lowest return quintile with the greatest herding intensity. Although not reported in Table VI, sell herding in the lowest quintile was primarily associated with small stocks. Additionally, greater stock-quarters and proportion were being sold than bought in the post-bubble period in the lowest return quintile. Thus, sell herding appears to be largely related to momentum. We could conclude, that after the bubble had burst, the fascination with internet stocks had diminished somewhat on the buy side, and selling had become more wide-spread over larger number of stocks, especially the poor performing ones.

While Griffin, Harris and Topaloglu (2003) document that institutions were essentially chasing trends in prices at the daily horizon, we find that on the buy-side, institutions bought stocks even with average and below-average performance (at longer previous quarter interval). Possibly, entire new economy sector appeared attractive regardless of its past performance. Overall, we find strong evidence of institutional investors buy herding in internet stocks especially in the bubble-period, which can not be fully explained by simple momentum trading strategies.

6.6. Herding and Price-Book Ratio

The evidence discussed above suggests that institutional investors herded into internet stocks across all size and prior period return categories. Potentially, this herding occurred because of highly uncertain future cash flows of internet firms and because of greater difficulty in valuing internet firms than more established stocks. Yet another possibility is that money managers were so excessively excited by the huge opportunities offered by internet stocks, that they were willing to buy any internet stock regardless of its price. This could be also justified as 'rational' if institutional investors with short-horizons expect to find more investors in future, who are even more enthusiastic about these stocks, even at inflated prices.

As discussed in section 5.1 of this paper, internet stocks were priced so high relative to other stocks, that any classification of them using traditional accounting based proxies for growth (mispricing) like Price-Book, Price-Earnings or Price-Sales, according to NYSE/AMEX break points would result in their falling in the top quintile. Therefore, to proxy for relative growth (mispricing) differences, we categorize our sample of firms into quintiles on the basis of their own lagged one quarter price-book ratio, which are updated quarterly[14]. The results are reported in Table VII. During the bubble-period, the intensity of buy herding was more or less uniform across the price-book quintiles. However, the largest number of stock-quarters was in the highest price-book quintile – 189 stock-quarters in the highest price-book quintile versus 92 for the lowest price-book quintile. The results are consistent with both herding being dominant in relatively more growth-oriented stocks, and with mispricing. We observe similar results for buy herding in the post-bubble period, though buy herding intensity was the largest in the highest price-book quintile. In the bubble-period, the intensity of sell herding was similar to buy herding, except that the largest number of stocks-quarters was in the lowest price-book quintile. Moreover, smaller proportions of stocks were sold in each price-book quintile than

[14] Book-Value of the firms is extracted from COMPUSTAT data. We also do the analysis using Price-Sales (past 6 months) ratio and find similar results. Since most of these stocks had very little or negative earnings, classification on the basis of Price-Earning ratio was not considered to be appropriate.

bought (approximately 15% sold versus 60% bought). We observe similar results in the post-bubble period except that the proportion of stock-quarters of sell herding was much higher in comparison to the bubble-period. In conclusion, institutions bought all internet stocks in herds, possibly because there were more difficult to value than ordinary stocks. It is also plausible that some institutions expected to find more buyers in the future for these high priced stocks, consistent with the 'Greater Fool Theory'.

6.7. Herding, Price Impact and Subsequent Returns

Two important questions related to institutional herding are whether the institutional herding had an impact on prices, and whether the price changes resulting from herding were justified based on current or subsequent information. If institutional herding created price pressures, we should observe abnormal returns in the quarter of herding, and these abnormal returns should be related to the level of herding[15]. If these abnormal returns related to institutional herding were justified based on current or subsequent information, we should not observe price reversals in the subsequent quarters, and the absence of reversal suggests that the price pressures exerted by institutional herding were not destabilizing and improved the informativeness of the prices. However, if there is a reversal in subsequent quarters, and if this reversal is directly related to the extent of institutional herding in the prior quarter, then the reversal suggests that the price pressures were not related to information, and were destabilizing[16].

[15] Nofsinger and Sias (1999) find that the decile of NYSE stocks, which experiences the largest annual increase in institutional ownership outperform the decile of stocks that have had the largest decrease in institutional ownership. Similarly, GTW (1999) and Wermers (1999) find a similar relationship for quarterly changes in mutual funds holdings and stock returns.

[16] If the positive relationship between contemporaneous returns and institutional demand relationship is not based on superior information, then principal-agent models of herding of Scharfstein and Stein (1990) and fad models of (Friedman (1984); Dreman (1979)) and Barberis and Shlieifer (2003) suggest that we should observe subsequent return reversals.

In order to examine price changes related to institutional herding and whether or not there were subsequent reversals, we first classify the stocks herded into by institutional investors into buys and sells (the stocks, which were traded but not herded are ignored). We further classify the buy and sell herded stocks into groups of high and low buy and sell herded stocks, respectively, on the basis of herding intensity for the overall period from 1998 to 2001. In order to examine whether the price pressures created by herding were justified based on current or subsequent information, we examine the performance of these stocks in the subsequent quarter. However, if these stocks continue to be herded on either the buy or sell side by the institutional investors in the subsequent quarter, we cannot unambiguously attribute the abnormal return of the subsequent quarter to the prior quarter's herding, since it would be contaminated by the herding that is still continuing. This is a significant problem, since buy and sell herding, on average, persists for 1.7 and 1.9 quarters, respectively. In order to unambiguously determine if there is return (or price) reversal in the subsequent quarter, we further subdivide each of the four herding groups into three sub-groups based on the herding in that quarter (subsequent to herding): no herding, and buy and sell herding. The abnormal return in the subsequent quarter for the stocks that continue to be buy or sell herded will continue to be affected by the institutional herding. However, the examination of the abnormal returns of the sub-groups that exhibit no herding in the subsequent quarter will allow us determine if there were return reversals, and whether these were related to the level of herding in the prior quarter.

For each stock-quarter, we first compute AR_c, and AR_a as mean industry-adjusted contemporaneous abnormal return and one quarter ahead abnormal return. To compute abnormal returns, the internet stocks' average (equally-weighted) quarterly industry return is subtracted from each firm's quarterly return. The period for computing the abnormal returns is from March 1998 to March 2002.

The results are reported in Table VIII. Due to significant skewness of the firms' returns, there are large differences in the means and the medians of the abnormal returns, and we base our conclusions on the level of median returns. For the overall period of 1998-2001, reported in panel A, stocks with high buy herding in the current quarter have median contemporaneous returns of 14.39%, while stocks with low herding in the current quarter have contemporaneous abnormal returns of 2.03%. Similarly, higher sell herding in the current quarter is associated with more negative abnormal returns (-19.19% vs. -14.58%), as compared to the abnormal returns for the low sell herding stocks. The differences are statistically significant (p value for buy herding difference in the median abnormal return is 0.0001 and for sell herding is 0.06). These results are consistent with the notion that institutional herding exerts price pressures that are related to the intensity of herding.

Examining the one quarter ahead returns for the sub-groups that exhibited no herding in the subsequent quarter, we find reversals (negative abnormal returns) for both low and high buy herding groups. Moreover, the reversal is more negative for the high buy herding group (median = -13.11%) in the prior quarter, as compared to the low buy herding group (median = -7.10%) in the prior quarter. The difference in the median abnormal return is statistically significant with p-value of 0.0184. Buy herding results are similar in both the bubble and post-bubble period in panels B and C. In summary, reversal of abnormal returns in subsequent quarter is consistent with price destabilization in the quarter of herding, and that the institutional trading was not based entirely on superior information.

On the sell-side also, we observe a price impact of sell herding in the contemporaneous quarter returns. However, the price impact is confined to the post-bubble period when sell-herding was more pronounced. The greater sell herded stocks experience larger negative contemporaneous quarter returns in both the overall and the post-bubble period. Both mean and median abnormal returns are statistically different with p value less than 0.01 for high versus low sell herded group stocks. In the subsequent quarter, stocks that were sold in the largest herds have less negative returns than the stocks sold by them the least. However, the difference is statistically not significant. Thus sell herding appears to be consistent with institutional herding being based on information.

Overall, we conclude that institutional herding had a large price impact on the buy-side and that institutional trading was not entirely based on information. However, institutional sell herding seems to be based on information. These results put a new spin on the Wall Street dictum -"Buy on rumors and sell on information".

7. Conclusion

This paper investigates correlated trading by institutional investors in the new economy stocks during 1998-2001. In contrast to previous research, we find considerable evidence of herding by institutional investors in an average stock, in general, and internet stocks, in particular during this period. Our results are consistent with our intuitive understanding that herds (crowds) emerge and become dominant, whenever we observe substantial price movements in the markets. In addition, herds are more easily formed in the stocks that are considered to be 'hot'. During the entire bubble-period of January 1998 to March 2000, institutional investors were net buyers in new economy stocks. We find that all categories of institutional investors like banks, insurance firms, mutual funds, brokerage houses, hedge funds, university endowments, and foundations etc. herded into new economy stocks, suggesting that this herding was not just a manifestation of retail investors channeling funds into new economy related funds. They bought in herds all internet stocks, regardless of their size and past performance. Institutional buy herding exerted price pressures, as we find consistent evidence of positive relationship between herding and contemporaneous excess return. Institutional investors' buying exerted temporary price pressure, with subsequent quarters' return reversal provide evidence that the herding was destabilizing and not based on information. However, sell herding results are consistent with the explanation that institutional trading helped impound information into stock prices.

Either institutions were unaware of the bubble or rode it to generate profits. If individual investors were also buying these stocks during the bubble-period, then we could surmise that small institutions and insiders were on the other side of the market. However, small institutions and insiders' trading did not have much influence on the price movements.

Our strong results of herding in an average stock during the period are indicative of market-wide herding, when money managers followed each other in market-timing strategies. Institutional investors' particular fascination with internet stocks could be explained by Barberis & Shleifer (2003) model of style investing.

References

Banerjee, A., 1992, "A Simple Model of Herd Behavior," *Quarterly Journal of Economics* 107, 797-817.

Brunnermeirer, Markus, K., and Stefan Nagel, 2003, "Arbitrage at its Limits: Hedge Funds and the Technology bubble," Forthcoming *Journal of Finance*.

Barberis, N. and A. Shleifer, 2003, "Style Investing," *Journal of Financial Economics* 68, 161-199.

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

Bikhchandani, S., and Sunil Sharma, 2000, "Herd Behavior in Financial Markets: A Review," Working Paper, International Monetary Fund.

Chan L., Karceski J., and J. Lakonishok, 2000, "A New Paradigm or the Same Old Hype?" The Future of Value Versus Growth Investing," *Financial Analysts Journal* 56, 23-36.

Christie, William G., and Roger D. Huang, 1995, "Following the Pied Piper: Do Individual Returns Herd Around the Market?" *Financial Analysts Journal*, (July-August), 31-37.

Del Guercio, D., 1996, "The Distorting Effect of the Prudent-man Laws on Institutional Equity Investment," *Journal of Financial Economics*, 40, 31-62.

Dreman, D., 1979, "Contrarian Investment Strategy: The Psychology of Stock Market Success," Random House, N.Y.

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

Friedman, B.M., 1984, "A Comment: Stock Prices and Social Dynamics," *Brookings Papers on Economic Activity*, 2, 504-508.

Froot, A, Kenneth, David S. Scharfestein, and Jeremy Stein, 1992, "Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation," *Journal of finance*, 47, 1461-1484.

Geczy, Christopher, David K. Musto, and Adam V. Reed, 2002, "Stocks are Special, too: An Analysis of the Equity Lending Market," *Journal of Financial Economics* 66, 241-269.

Gompers, P. and A. Metrick, 2001, "Institutional Investors and Equity Prices," *Quarterly Journal of Economics*, 116, 229-260.

Griffin, John M., Jeffrey H. Harris, and Selim Topaloglu, 2003, "Investor Behavior over the Rise and Fall of NASDAQ", Yale ICF Working Paper No. 03-27

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior" *American Economic Review* 85, 1088-1105.

Hand, John R.M., 2000, "Profits Losses and the Non-linear Pricing of Internet Stocks," Working Paper, University of North Carolina at Chapel Hill

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

Jones, S., D. Lee, and E. Weis, 1999, "Herding and Feedback Trading by Different Types of Institutions and the Effects on Stock Prices," Working Paper, Indiana University – Indianapolis Campus, Kennesaw State University, and Merrill Lynch.

Khorana, Ajay, 1996, "Top Management Turnover: An Investigation of Mutual Fund Managers," *Journal of Financial Economics* 40, 403-427.

Kraus, Alan and Hans R. Stoll, 1972, "Parallel Trading by Institutional Investors," *Journal of Financial and Quantitative Analysis* 7, 2107-2138.

Lakonishok, Josef, Andrei Shleifer and Robert W. Vishny, 1992, "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics*, 312, 23-43.

Lakonishok, Josef, Andrei Shleifer, Richard Thaler, and Robert W. Vishny, 1991, "Window Dressing by Pension Fund Managers," *American Economic Review*, Papers and Proceedings 81, 227-231.

Lamont, O., and R. Thaler, 2003, "Can the Market Add and Subtract? Mispricing in Tech Stock Carve outs," *Journal of Political Economy*, 111, 227-268.

Lynch, Peter, 1989, "One Up On Wall Street", (Simon and Schuster, New York, NY).

Maug, Ernst, and Narayan Naik, 1995, "Herding and Delegated Portfolio Management: The Impact of Relative Performance Evaluation on Asset Allocation," Working Paper, Duke University and London Business School

Nofsinger, John R., and Richard W. Sias, 1999, "Herding and Feedback Trading by Institutional Investors", *Journal of Finance*, 54, 2263-2316.

Ofek, Eli, and Mathew Richardson, 2003, "Dotcom Mania: The Rise and Fall of Internet Stock Prices," *Journal of Finance* 58, 1113-1137.

Oehler, Andreas and George Goeth-Chi Chao, 2002, "Institutional Herding in Bond Markets," Working Paper, SSRN

Pirinsky, C., 2002, "Herding and Contrarian Trading of Institutional Investors," Working Paper, Texas A&M University.

Scharfstein, David and Jeremy Stein, 1990, "Herd Behavior and Investment," *American Economic Review*, 80, 465-479.

Schwartz, Robert and James Shapiro, 1992, "The Challenge of Institutionalization for the Equity Market", Working Paper, New York University, New York, NY.

Shiller, Robert, 2000, "Irrational Exuberance" *Princeton University Press*, Princeton NJ

Shleifer A., and R. Vishny, 1997, "The Limits of Arbitrage," *Journal of Finance* 52, 35-55.

Sias, Richard, W., "Institutional Herding," 2003, Forthcoming, *Review of Financial Studies*.

Sias, R., L. Starks, and S. Titman, 2001, "The Price Impact of Institutional Trading," Working Paper, Washington State University and The University of Texas.

Strozinsky, R., 1998, "Inside the Stock Market," Website (www.stanford.edu/~stoz/)

Teo, Melvin, and Sung-Jun Woo, 2002, "Style Effects," Working Paper, Harvard University

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

Figure 1: Index Levels

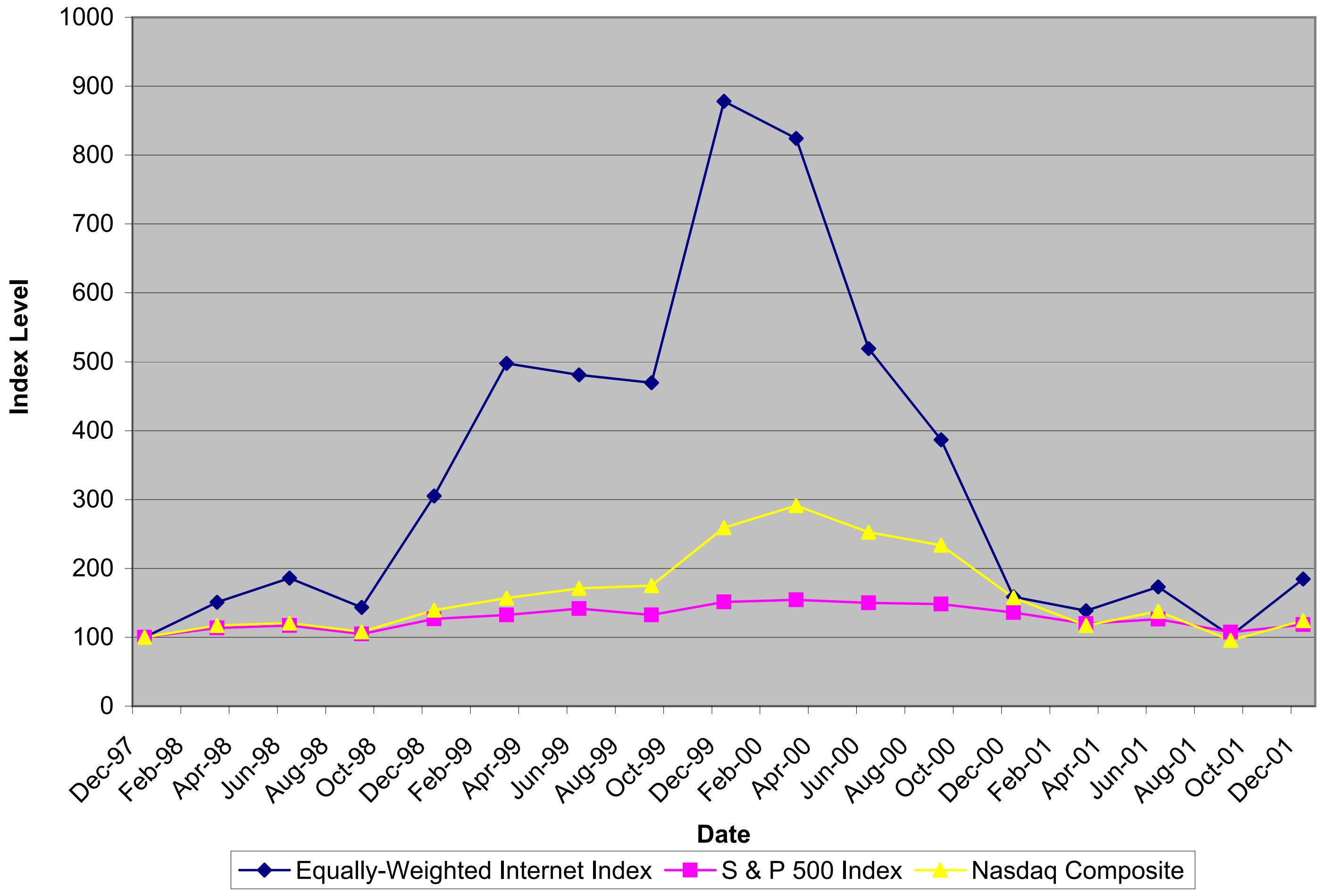

Figure 2: Index Level & Investor Holdings

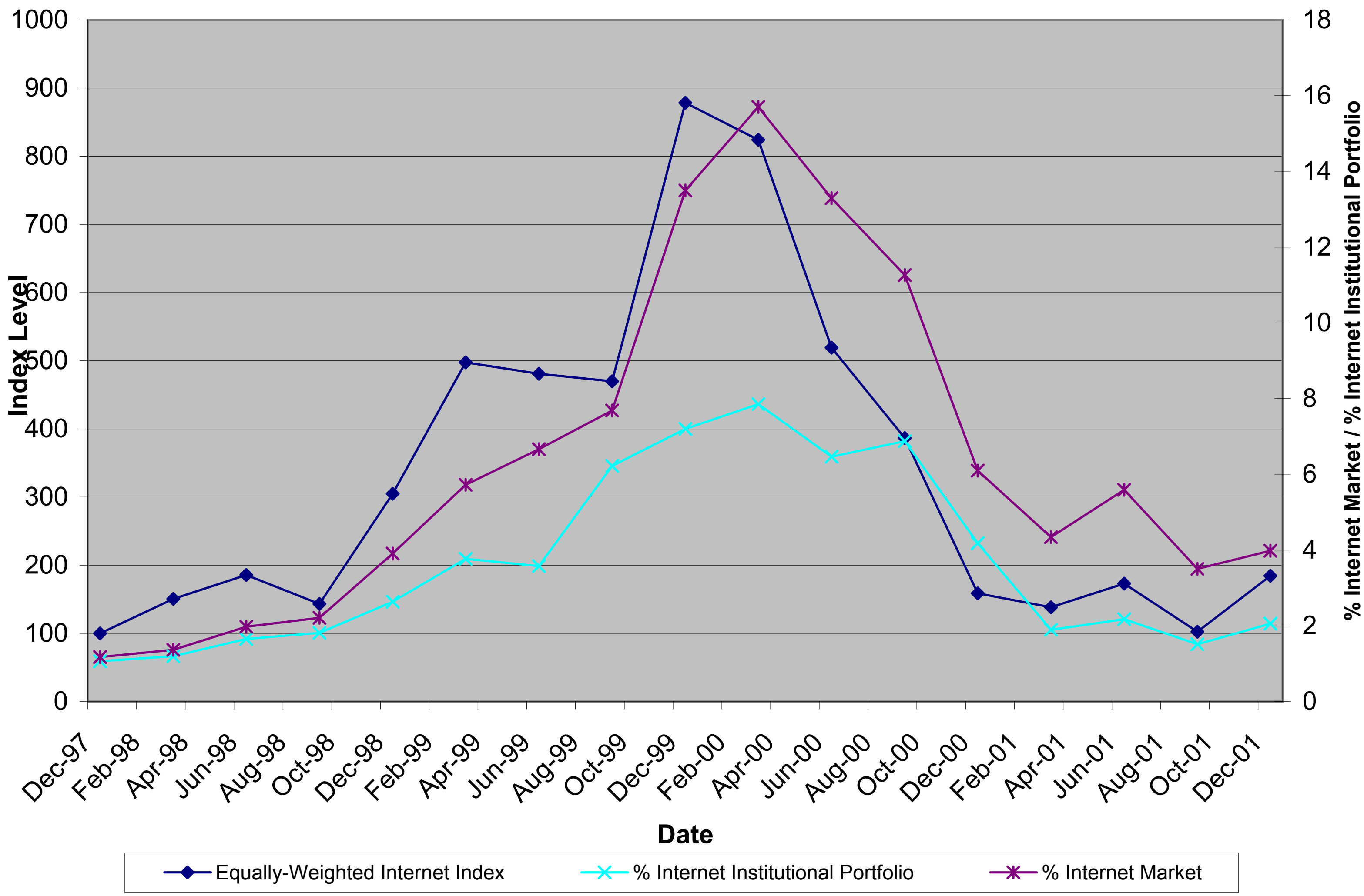

Table I
Overall Herding Measures

The herding measure H (i,t), for a given stock-quarter equals |p (i,t)-p (t)|-E||p (i,t)-p (t)||, where p (i,t) is the proportion of institutional investors trading the stock (i) quarter t are buyers. The p (t) is expected proportion of institutional investors being buyers averaged across all stocks traded by them in the quarter t. The overall herding H (i,t) is the average of all H (i,t) during the period indicated in the top row of the tables. The buying herding is computed as the average of H (i, t) where p (i, t) > p (t). Similarly sell herding is measured as average of H (i,t), where p (i, t) < p (t). Buy herding* and Sell Herding* are recomputed for those stock-quarter pairs, where H (i,t) is positive. The median herding measures are given in parentheses under mean. The stock-quarters used to compute Buy Herding* and Sell Herding* are listed under observation (obs) column. Total obs (observation) refers to stock-quarters traded by at least one institutional investor.

Panel A
Herding measure with at least 1 Trader in a stock-quarter pair

	Jan'98-Dec'01			Jan'98-March'00			April'00-Dec'01		
Herding	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Overall Herding	3782	6.76% (4.74%)	35.35	1382	7.26% (5.98%)	24.81	2400	6.48% (4.06%)	25.92
Buy Herding	2129	6.17% (4.94%)	28.3	1036	8.47% (7.43%)	26.79	1093	3.99% (2.83%)	13.97
Sell Herding	1653	7.53% (4.51%)	22.47	346	3.62% (2.13%)	5.6	1307	8.56% (5.88%)	22.38
Buy Herding*	1517	10.59% (8.82%)	50.87	801	12.12% (10.36%)	40.47	716	8.89% (7.03%)	32.48
Sell Herding*	1115	13.79% (10.33%)	38.97	199	10.65% (7.05%)	14.27	916	14.47% (11.20%)	36.58

Panel B
Herding measure with at least 20 Trader in a stock-quarter pair

	Jan'98-Dec'01			Jan'98-March'00			April'00-Dec'01		
Overall Herding	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Overall Herding	2590	7.50% (5.48%)	38.17	1032	8.37% (6.92%)	28.08	1558	6.92% (4.51%)	26.7
Buy Herding	1633	7.56% (6.10%)	34.97	815	9.41% (8.32%)	29.1	818	5.70% (4.28%)	20.99
Sell Herding	957	7.41% (4.12%)	19.32	217	4.45% (2.46%)	6.67	740	8.27% (4.76%)	18.35
Buy Herding*	1290	10.27% (8.65%)	47.38	684	11.72% (9.87%)	37.25	606	8.62% (6.83%)	30.81
Sell Herding*	665	11.97% (8.70%)	26.82	132	9.40% (6.56%)	11.19	533	12.61% (9.56%)	24.57

Table II
Quarterly Herding measures with at least 1 Trader in a stock-quarter pair

The herding measure H (i,t), for a given stock-quarter equals |p (i,t)-p (t)|-E||p (i,t)-p (t)||, where p (i,t) is the proportion of institutional investors trading the stock (i) in quarter t are buyers. The p (t) is expected proportion of institutional investors being buyers averaged across all stocks traded by them in the quarter t. The buying herding is computed as the average of H (i,t) conditioned on p (i,t) > p (t) and H (i, t) >0. Similarly sell herding is measured as average of H (i,t), conditioned on p (i,t) < p (t) and H (i,t) >0. The stock-quarters used to compute H (i, t) are listed under observation (obs) column. Total obs (observation) refers to stock-quarters traded by at least one institutional investor. Obs as % of total obs is listed in obs column in parentheses. The total of buying herding % and sell herding % is less than 100% in each row as some of the stock-quarters do not qualify for meaningful herding.

Date	Total Obs	Quarterly Buy Herding			Quarterly Sell Herding		
		Obs	mean	t Value	Obs	mean	t Value
31-Mar-98	61	36 (59.02%)	10.27%	8.61	11 (18.03%)	12.01%	5.17
30-Jun-98	70	34 (48.57%)	10.90%	7.25	9 (12.86%)	8.92%	4.62
30-Sep-98	77	41 (53.25%)	8.64%	8.64	15 (19.48%)	14.43%	4.95
31-Dec-98	94	51 (54.26%)	11.44%	12.19	10 (10.64%)	8.73%	3.17
31-Mar-99	103	65 (63.11%)	12.74%	11.41	14 (13.59%)	3.41%	4.72
30-Jun-99	140	59 (42.14%)	10.81%	10.24	23 (16.43%)	8.77%	5.07
30-Sep-99	216	139 (64.35%)	15.34%	19.05	28 (12.96%)	15.54%	4.70
31-Dec-99	281	196 (69.75%)	12.99%	23.45	30 (10.68%)	12.43%	6.22
31-Mar-00	340	180 (52.94%)	10.47%	16.37	59 (17.35%)	9.25%	9.44
30-Jun-00	388	168 (43.30%)	10.43%	18.12	102 (26.29%)	16.49%	10.38
30-Sep-00	383	159 (41.51%)	9.80%	16.75	95 (24.80%)	9.62%	11.14
31-Dec-00	371	87 (23.45%)	6.97%	10.56	160 (43.13%)	11.45%	16.99
31-Mar-01	351	81 (23.08%)	7.11%	9.22	133 (37.89%)	12.59%	11.69
30-Jun-01	326	71 (21.78%)	9.76%	9.81	173 (53.07%)	15.57%	17.87
30-Sep-01	309	67 (21.68%)	8.25%	8.24	163 (52.75%)	18.45%	21.32
31-Dec-01	272	83 (30.51%)	7.52%	12.17	90 (33.09%)	16.15%	11.23

Table III
Herding Measures As Stocks Age with at least 1 Trader in a stock-quarter pair

The herding measure H (i,t), for a given stock-quarter equals |p (i,t)-p (t)| - E||p (i,t)-p (t)||, where p (i,t) is the proportion of institutional investors trading the stock (i) in quarter t are buyers. The p (t) is expected proportion of institutional investors being buyers averaged across all stocks traded by them in the quarter t. The buying herding is computed as the average of H (i,t) conditioned on p (i,t) > p (t) and H (i, t) >0. Similarly sell herding is measured as average of H (i,t), conditioned on p (i,t) < p (t) and H (i,t) >0. The stock-quarters used to compute H (i, t) are listed under observation (obs) column. The age of the stocks is given in parentheses measured as the quarters since the stock's return are available on CRSP tapes.

Herding	**Jan'98-Dec'01**			**Jan'98-March'00**			**April'00-Dec'01**		
Buy Herding	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Stocks (=< 2 qtrs)	201	13.77%	20.98	174	14.39%	20.06	27	9.78%	7.12
Stocks (in 3rd qtr)	215	13.36%	22.8	154	13.99%	19.63	61	11.75%	11.86
Stocks (> 3 qtrs)	1101	9.47%	42.01	473	10.67%	30.37	628	8.57%	29.69
Sell Herding	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Stocks (=< 2 qtrs)	86	8.87%	8.23	62	7.49%	8.35	24	12.44%	4.13
Stocks (in 3rd qtr)	50	14.18%	7.28	16	11.06%	4.09	34	15.64%	6.13
Stocks (> 3 qtrs)	979	14.20%	37.76	121	12.22%	11.55	858	14.48%	36.05

Table IV
Herding Across Type with at least 1 Trader in a stock-quarter pair

The herding measure H (i,t), for a given stock-quarter equals |p (i,t)-p (t)|-E||p (i,t)-p (t)||, where p (i,t) is the proportion of institutional investors of a type trading the stock (i) quarter t are buyers. The p (t) is expected proportion of institutional investors being buyers averaged across all stocks traded by them in the quarter t regardless of the type. The buying herding is computed as the average of H (i,t) conditioned on p (i,t) > p (t) and H (i, t) >0. Similarly sell herding is measured as average of H (i,t), conditioned on p (i,t) < p (t) and H (i,t) >0. The stock-quarters used to compute H (i, t) are listed under observation (obs) row.

Period	Herding	Statistic	Banks	Insurance Firms	Mutual Funds	Brokerage Firms	Others
Jan'98-Dec'01	Buy Herding	Mean	13.90%	14.63%	13.58%	10.50%	13.52%
		t-Value	49.69	43.93	47.51	42.94	49.19
		Obs	1154	879	1081	1145	1105
	Sell Herding	Mean	13.87%	14.79%	14.59%	13.29%	14.06%
		t-Value	34.80	34.46	35.06	38.79	31.43
		Obs	835	714	776	1097	644
Jan'98-March'00	Buy Herding	Mean	14.96%	15.35%	14.79%	11.66%	15.65%
		t-Value	39.86	32.54	36.05	34.47	34.86
		Obs	583	391	541	644	447
	Sell Herding	Mean	12.22%	13.19%	11.68%	11.38%	12.47%
		t-Value	13.28	15.64	14.24	15.92	14.27
		Obs	155	183	164	211	159
April'00-Dec'01	Buy Herding	Mean	12.82%	14.06%	12.35%	9.00%	12.07%
		t-Value	31.18	30.24	31.60	26.49	36.02
		Obs	571	488	540	501	658
	Sell Herding	Mean	14.24%	15.34%	15.37%	13.74%	14.58%
		t-Value	32.29	30.88	32.35	35.50	28.12
		Obs	680	531	612	886	485

Table V
Herding with at least 1 Trader in a stock-quarter pair based on Lag Size

The herding measure H (i,t), for a given stock-quarter equals |p (i,t)-p (t)|-E||p (i,t)-p (t)||, where p (i,t) is the proportion of institutional investors trading the stock (i) quarter t are buyers. The p (t) is expected proportion of institutional investors being buyers averaged across all stocks traded by them in the quarter t. The buying herding is computed as the average of H (i,t) conditioned on p (i,t) > p (t) and H (i, t) >0. Similarly sell herding is measured as average of H (i,t), conditioned on p (i,t) < p (t) and H (i,t) >0. The stock-quarters used to compute H (i,t) are listed under observation (obs) column. Total obs (observation) refers to stock-quarters traded by at least one institutional investor. Obs as % of total obs is listed in obs column in parentheses. The total of buying herding % and sell herding % is less than 100% in each row as some of the stock-quarters do not qualify for meaningful herding. The stocks are classified into quintiles on the basis of lagged NYSE size (market capitalization) break points and updated quarterly.

			Buy Herding			Sell Herding		
Period	**Size Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Jan'98-Dec'01	**S1 (Smallest)**	663	121 (18.25%)	13.61%	15.37	288 (43.44%)	16.99%	26.76
	S2	652	211 (32.36%)	11.35%	19.80	232 (35.58%)	13.10%	20.27
	S3	657	342 (52.05%)	9.99%	24.94	132 (20.09%)	9.93%	10.08
	S4	701	407 (58.06%)	10.72%	27.65	106 (15.12%)	10.61%	9.00
	S5 (Largest)	528	336 (63.64%)	10.28%	24.43	91 (17.23%)	6.75%	7.98
Period	**Size Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Jan'98-March'00	**S1 (Smallest)**	179	61 (34.08%)	15.41%	13.21	34 (18.99%)	15.55%	8.39
	S2	248	122 (49.19%)	12.23%	15.65	44 (17.74%)	11.60%	8.02
	S3	300	183 (61.00%)	11.60%	19.27	43 (14.33%)	8.64%	5.55
	S4	347	243 (70.03%)	12.28%	23.35	33 (9.51%)	9.53%	4.81
	S5 (Largest)	257	187 (72.76%)	10.74%	18.98	28 (10.89%)	7.52%	5.65
Period	**Size Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
April'00-Dec'01	**S1 (Smallest)**	484	60 (12.40%)	11.78%	9.04	254 (52.48%)	17.18%	25.41
	S2	404	89 (22.03%)	10.14%	12.30	188 (46.53%)	13.46%	18.64
	S3	357	159 (44.54%)	8.13%	17.19	89 (24.93%)	10.55%	8.42
	S4	354	164 (46.33%)	8.42%	16.30	73 (20.62%)	11.09%	7.59
	S5 (Largest)	271	149 (45.98%)	9.71%	15.45	63 (23.25%)	6.40%	5.97

Table VI
Herding with at least 1 Trader in a stock-quarter pair based on Past Return

The herding measure H (i,t), for a given stock-quarter equals |p (i,t)-p (t)|-E||p (i,t)-p (t)||, where p (i,t) is the proportion of institutional investors trading the stock (i) quarter t are buyers. The p (t) is expected proportion of institutional investors being buyers averaged across all stocks traded by them in the quarter t. The buying herding is computed as the average of H (i,t) conditioned on p (i,t) > p (t) and H (i, t) >0. Similarly sell herding is measured as average of H (i,t), conditioned on p (i,t) < p (t) and H (i,t) >0. The stock-quarters used to compute H (i, t) are listed under observation (obs) column. Total obs (observation) refers to stock-quarters traded by at least one institutional investor. Obs as % of total obs is listed in obs column in parentheses. The total of buying herding % and sell herding % is less than 100% in each row as some of the stock-quarters do not qualify for meaningful herding. The stocks are classified into quintiles on the basis of lagged NYSE/AMEX/NASDAQ return break points and updated quarterly.

			Buy Herding			Sell Herding		
Period	**Return Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Jan'98-Dec'01	**R1 (Worst)**	1374	350 (25.47%)	10.00%	23.75	570 (41.48%)	14.00%	30.01
	R2	407	183 (44.96%)	9.40%	17.17	96 (23.59%)	12.49%	9.99
	R3	224	122 (54.46%)	9.80%	16.02	35 (15.63%)	12.01%	6.66
	R4	279	166 (59.50%)	10.03%	16.34	41 (14.70%)	10.46%	6.99
	R5 (Best)	841	540 (64.21%)	11.88%	33.48	115 (13.67%)	10.93%	10.54
Period	**Return Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Jan'98-March'00	**R1 (Worst)**	309	119 (38.51%)	10.94%	15.37	78 (25.24%)	11.32%	9.33
	R2	115	59 (51.30%)	10.84%	10.23	20 (17.39%)	11.90%	4.24
	R3	106	62 (58.49%)	11.47%	13.81	9 (8.49%)	12.23%	3.96
	R4	172	114 (66.28%)	11.20%	14.10	13 (7.56%)	12.49%	3.91
	R5 (Best)	528	391 (74.05%)	12.37%	29.63	35 (6.63%)	8.39%	4.88
Period	**Return Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
April'00-Dec'01	**R1 (Worst)**	1065	231 (21.69%)	9.51%	18.29	492 (46.20%)	14.43%	28.69
	R2	292	124 (42.47%)	8.72%	13.94	76 (26.03%)	12.65%	9.00
	R3	118	60 (50.85%)	8.07%	9.49	26 (22.03%)	11.94%	5.40
	R4	107	52 (48.60%)	7.46%	9.33	28 (26.17%)	9.52%	5.84
	R5 (Best)	313	149 (47.60%)	10.60%	15.94	80 (25.56%)	12.03%	9.45

Table VII
Herding with at least 1 Trader in a stock-quarter pair based on lag Price-Book Ratio

The herding measure H (i,t), for a given stock-quarter equals |p (i,t)-p (t)|-E||p (i,t)-p (t)||, where p (i,t) is the proportion of institutional investors trading the stock (i) quarter t are buyers. The p (t) is expected proportion of institutional investors being buyers averaged across all stocks traded by them in the quarter t. The buying herding is computed as the average of H (i,t) conditioned on p (i,t) > p (t) and H (i, t) >0. Similarly sell herding is measured as average of H (i,t), conditioned on p (i,t) < p (t) and H (i,t) >0. The stock-quarters used to compute H (i, t) are listed under observation (obs) column. Total obs (observation) refers to stock-quarters traded by at least one institutional investor. Obs as % of total obs is listed in obs column in parentheses. The total of buying herding % and sell herding % is less than 100% in each row as some of the stock-quarters do not qualify for meaningful herding. The stocks are classified into quintiles on the basis of their lagged Price-Book Ratio and updated quarterly.

			Buy Herding			Sell Herding		
Period	**Price-Book Ratio Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Jan'98-Dec'01	**PB1 (Lowest)**	548	141 (25.73%)	10.91%	16.46	211 (38.50%)	14.07%	18.60
	PB2	575	185 (32.17%)	9.03%	16.43	195 (33.91%)	13.24%	18.30
	PB3	574	270 (47.04%)	9.83%	21.59	135 (23.52%)	11.10%	12.58
	PB4	586	305 (52.05%)	10.27%	24.30	112 (19.11%)	10.86%	10.59
	PB5 (Highest)	581	362 (62.31%)	11.23%	27.06	99 (17.04%)	10.39%	10.95
Period	**Price-Book Ratio Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
Jan'98-March'00	**PB1 (Lowest)**	228	92 (40.35%)	11.52%	14.26	47 (20.61%)	11.22%	7.97
	PB2	237	109 (45.99%)	9.86%	12.71	48 (20.25%)	10.52%	7.91
	PB3	239	144 (60.25%)	10.94%	17.51	34 (14.23%)	7.66%	5.69
	PB4	239	163 (68.20%)	11.58%	19.84	22 (9.21%)	7.34%	4.24
	PB5 (Highest)	237	189 (79.75%)	12.35%	21.27	16 (6.75%)	12.54%	5.33
Period	**Price-Book Ratio Quintile**	**Total obs**	**obs**	**mean**	**t Value**	**obs**	**mean**	**t Value**
April'00-Dec'01	**PB1 (Lowest)**	320	49 (15.31%)	9.77%	8.49	164 (51.25%)	14.89%	16.97
	PB2	338	76 (22.49%)	7.84%	10.79	147 (43.49%)	14.13%	16.71
	PB3	335	126 (37.61%)	8.56%	13.19	101 (30.15%)	12.25%	11.49
	PB4	347	142 (40.92%)	8.76%	14.86	90 (25.94%)	11.72%	9.84
	PB5 (Highest)	344	173 (50.29%)	10.00%	17.24	83 (24.13%)	9.97%	9.61

Table VIII
Abnormal Return with at least 1 Trader in a stock-quarter pair based on Herding

The herding measure H (i,t), for a given stock-quarter equals |p (i,t)-p (t)|-E||p (i,t)-p (t)||, where p (i,t) is the proportion of institutional investors trading the stock (i) quarter t are buyers. The p (t) is expected proportion of institutional investors being buyers averaged across all stocks traded by them in the quarter t. The buying herding is computed as the average of H (i,t) conditioned on p (i,t) > p (t) and H (i, t) >0. Similarly sell herding is measured as average of H (i,t), conditioned on p (i,t) < p (t) and H (i,t) >0. The stock-quarters used to compute H (i, t) are listed under observation (obs) column. The stocks are first classified into buy and sell and then they are classified into 2 groups on the basis of herding measure for the entire period of 1998-2001. AR_c, and AR_a refer to mean industry-adjusted contemporaneous abnormal return and 1 quarter ahead abnormal return. No herding refers to stocks which had negative herding intensity in the subsequent quarter. To compute abnormal returns internet stocks' average quarterly industry return is subtracted from their quarterly raw returns. The period for abnormal return is from end of 1997 to March of 2002. The p value for mean (t-test) and median (Sign-Rank test) are given in parentheses.

Panel A

Subsequent Quarter Abnormal Return Conditioned on Current Quarter Buy Herding for the Period Jan-1998 to Dec-2001												
	Current Quarter			**Buy Herding**			**No Herding**			**Sell Herding**		
Buy Herding	**Obs**	**Mean AR_c**	**Median AR_c**	**Obs**	**Mean AR_a**	**Median AR_a**	**Obs**	**Mean AR_a**	**Median AR_a**	**Obs**	**Mean AR_a**	**Median AR_a**
Low	526	9.62	2.03	200	21.57	13.49	178	-4.51	-7.10	148	-13.18	-17.72
		(0.004)	(0.141)		(0.000)	(0.000)		(0.158)	(0.010)		(0.000)	(0.000)
High	508	24.24	14.39	224	11.76	3.73	161	-13.63	-13.11	123	4.08	-5.76
		(0.000)	(0.000)		(0.002)	(0.018)		(0.000)	(0.000)		(0.412)	(0.357)
Subsequent Quarter Abnormal Return Conditioned on Current Quarter Sell Herding for the Period Jan-1998 to Dec-2001												
	Current Quarter			**Buy Herding**			**No Herding**			**Sell Herding**		
Sell Herding	**Obs**	**Mean AR_c**	**Median AR_c**	**Obs**	**Mean AR_a**	**Median AR_a**	**Obs**	**Mean AR_a**	**Median AR_a**	**Obs**	**Mean AR_a**	**Median AR_a**
Low	553	-9.21	-14.58	115	24.84	9.79	139	-6.04	-12.07	299	-12.63	-19.13
		(0.000)	(0.000)		(0.003)	(0.004)		(0.111)	(0.010)		(0.000)	(0.000)
High	544	-11.53	-19.19	128	21.37	14.20	141	8.21	-6.16	275	-7.81	-15.64
		(0.000)	(0.000)		(0.000)	(0.001)		(0.271)	(0.207)		(0.010)	(0.000)

Panel B

Subsequent Quarter Abnormal Return Conditioned on Current Quarter Buy Herding for the Period Jan-1998 to March-2000												
	Current Quarter			Buy Herding			No Herding			Sell Herding		
Buy Herding	Obs	Mean AR_c	Median AR_c	Obs	Mean AR_a	Median AR_a	Obs	Mean AR_a	Median AR_a	Obs	Mean AR_a	Median AR_a
Low	213	-6.85 (0.157)	-15.29 (0.000)	109	20.91 (0.060)	1.08 (0.216)	58	-14.00 (0.014)	-7.43 (0.007)	46	-18.40 (0.058)	-30.48 (0.009)
High	288	21.35 (0.000)	4.69 (0.000)	174	8.01 (0.083)	-0.14 (0.483)	43	-27.43 (0.000)	-27.86 (0.000)	71	10.87 (0.156)	2.38 (0.551)
Subsequent Quarter Abnormal Return Conditioned on Current Quarter Sell Herding for the Period Jan-1998 to March-2000												
	Current Quarter			Buy Herding			No Herding			Sell Herding		
Sell Herding	Obs	Mean AR_c	Median AR_c	Obs	Mean AR_a	Median AR_a	Obs	Mean AR_a	Median AR_a	Obs	Mean AR_a	Median AR_a
Low	63	-13.82 (0.100)	-23.76 (0.003)	25	10.57 (0.423)	4.17 (0.647)	21	-31.74 (0.007)	-28.91 (0.002)	17	-30.51 (0.017)	-18.60 (0.030)
High	79	-15.88 (0.041)	-15.78 (0.025)	41	4.93 (0.520)	-7.64 (0.873)	23	-1.39 (0.933)	-20.68 (0.066)	15	-14.54 (0.145)	-31.49 (0.120)

Panel C

Subsequent Quarter Abnormal Return Conditioned on Current Quarter Buy Herding for the Period April-2000 to Dec-2001												
	Current Quarter			Buy Herding			No Herding			Sell Herding		
Buy Herding	Obs	Mean AR_c	Median AR_c	Obs	Mean AR_a	Median AR_a	Obs	Mean AR_a	Median AR_a	Obs	Mean AR_a	Median AR_a
Low	313	20.82 (0.000)	9.79 (0.000)	91	22.35 (0.000)	20.33 (0.000)	120	0.08 (0.984)	-6.53 (0.169)	102	-10.83 (0.000)	-16.16 (0.000)
High	220	28.02 (0.000)	22.65 (0.000)	50	24.83 (0.000)	20.13 (0.000)	118	-8.60 (0.006)	-10.53 (0.000)	52	-5.20 (0.332)	-9.39 (0.010)
Subsequent Quarter Abnormal Return Conditioned on Current Quarter Sell Herding for the Period April-2000 to Dec-2001												
	Current Quarter			Buy Herding			No Herding			Sell Herding		
Sell Herding	Obs	Mean AR_c	Median AR_c	Obs	Mean AR_a	Median AR_a	Obs	Mean AR_a	Median AR_a	Obs	Mean AR_a	Median AR_a
Low	490	-8.62 (0.000)	-13.85 (0.000)	90	28.80 (0.004)	10.09 (0.001)	118	-1.47 (0.705)	-6.36 (0.141)	282	-11.55 (0.000)	-19.26 (0.000)
High	465	-10.79 (0.000)	-19.65 (0.000)	87	29.12 (0.000)	22.30 (0.000)	118	10.08 (0.226)	-4.79 (0.522)	260	-7.42 (0.019)	-15.62 (0.000)

Appendix

An examination of the Thomson Financial 13-F data of the institutions classified as banks, insurance companies, investment companies/mutual funds, and independent investment advisors/brokerage firms (types 1, 2, 3 and 4) reveals that the number of these institutions have declined dramatically over time, while the number of institutions classified as ‘Others’ (type 5) have increased correspondingly. For example, Panel A of Table A-1 reveals that number of institutions classified as mutual funds in the Thomson Financial 13-F data decrease from 64 in September 1998 to 1 in December 1998, and the number of brokerage firms decreased from 626 in December 1998 to 125 in March 1999. And these decreases are accompanied with corresponding increases in the number of institutions classified as ‘Others’. These changes cannot be possibly explained by objective classification. According to Thomson Financial during the integration with former Technimetrics, the institutional classification mapping was changed and merged with the mappings from Technimetrics. This resulted in a mapping error. Consequently, numerous institutions were reclassified to type 5 that should not have been. The problem seems to magnify in December 1998 and remains in the data till the end of December 2001. Although, classification errors are spread across all types, it affects the mutual funds and brokerage houses categories the most. Consequently, the Thomson Financial 13-F data used in all other studies may suffer from this misclassification error.

We further investigate this classification error by taking a sample of 100 institutions whose classification changed over time. We find that in 95 out of these 100 cases the reclassification to type 5 occurred when an institution’s name was recorded marginally differently. For example, as reported in Panel A of Table A-2, when a comma was inserted into the name of A R Asset Management Inc, the classification was changed from type 4 (independent investment advisor/ brokerage firm) to type 5 (others). And when the word ‘The’ was added to the name of Adams Express Co, the classification was changed from type 3 to type 5. Similarly, when the word ‘Partners’ was abbreviated for Artisan Partners, the classification was changed from type 4 to type 5. It appears that in mapping two databases, whenever there was a less than a perfect match of the name of the institution, the institution was reclassified as type 5. And this occurs for 95% of the reclassifications we examined. These reclassifications are clearly erroneous.

The remaining 5 reclassifications that we examine occur without any change in the manner in which the name is recorded. Two of these examples are provided in Panel B of Table A-2. Even in these few cases, it appears that the classification change to type 5 may not have been justified, and that the original classification was correct.

To correct these reclassification errors, if an institution is reclassified form types 1, 2, 3, or 4 to type 5, we reassign an institution to its original classification. We realize that this correction may wrongly classify a very small percentage of institutions. However, it corrects for much greater number of misclassifications. A time series of the number of institutions of various types after the correction is provided in Panel B of Table A-1. An examination of these corrected time series and a comparison of these with the uncorrected time series makes evident that the correction significantly improves the classification of institutions.

Table A-1

Panel A: Original Institution Type Count By Quarter

Institution Type (Number)	Dec-97	Mar-98	Jun-98	Sep-98	Dec-98	Mar-99	Jun-99	Sep-99	Dec-99	Mar-00	Jun-00	Sep-00	Dec-00	Mar-01	Jun-01	Sep-01	Dec-01
Banks (1)	145	147	150	154	152	134	138	148	148	145	101	103	98	141	123	126	127
Insurance Firms (2)	52	57	58	54	51	15	17	18	20	19	18	24	22	21	19	18	16
Mutual Funds (3)	65	66	66	64	1	1	2	14	16	14	13	12	10	10	12	9	12
Brokerage Firms (4)	522	564	628	626	626	125	93	92	181	191	88	111	156	152	149	137	111
Others (5)	51	58	48	60	288	767	870	940	1013	1017	1217	1229	1266	1172	1179	1162	1093
Total	**835**	**892**	**950**	**958**	**1118**	**1042**	**1120**	**1212**	**1378**	**1386**	**1437**	**1479**	**1552**	**1496**	**1482**	**1452**	**1359**

Panel B: Corrected Institution Type Count By Quarter

Institution Type (Number)	Dec-97	Mar-98	Jun-98	Sep-98	Dec-98	Mar-99	Jun-99	Sep-99	Dec-99	Mar-00	Jun-00	Sep-00	Dec-00	Mar-01	Jun-01	Sep-01	Dec-01
Banks (1)	145	147	150	154	154	150	155	166	166	166	166	177	169	162	148	148	147
Insurance Firms (2)	52	57	58	55	59	50	55	55	57	53	53	55	56	55	52	51	47
Mutual Funds (3)	65	67	66	66	70	66	68	69	71	69	66	67	63	61	64	60	58
Brokerage Firms (4)	522	566	629	630	745	647	683	714	803	812	822	821	846	811	813	793	740
Others (5)	51	55	47	53	90	129	159	208	281	286	330	359	418	407	405	400	367
Total	**835**	**892**	**950**	**958**	**1118**	**1042**	**1120**	**1212**	**1378**	**1386**	**1437**	**1479**	**1552**	**1496**	**1482**	**1452**	**1359**

Table A-2

Panel A: Reclassification with Trivial Change in the Name

Date	Manager Code	Manager Name	Type
3/31/1999	110	A R ASSET MANAGEMENT INC	4
6/30/1999	110	A R ASSET MANAGEMENT, INC.	5
Date	**Manager Code**	**Manager Name**	**Type**
12/31/1998	260	ADAMS EXPRESS CO	3
3/31/1999	260	THE ADAMS EXPRESS COMAPANY	5
Date	**Manager Code**	**Manager Name**	**Type**
6/30/1998	4719	ARTISAN PARTNERSS L P	4
3/31/1999	4719	ARTISAN PTNR L. P.	5

Panel B: Reclassification without Any Change in the Name

Date	Manager Code	Manager Name	Type
3/31/2000	5955	BANK ONE CORPORATION	1
6/30/2000	5955	BANK ONE CORPORATION	5
Date	**Manager Code**	**Manager Name**	**Type**
9/30/1999	7905	BARCLAY BK PLC –NY BRNCH	1
12/31/1999	7905	BARCLAY BK PLC –NY BRNCH	5

Chapter 2

Intra-Day Trading: Herding versus Market Efficiency

1. Introduction

Financial commentators and investors often say that herding in the financial markets is rampant[17]. In the extreme form, it manifests itself when investors act as a herd and flock to the same stock by buying (selling) at the same time even if there is no fundamental information supporting their actions. In such circumstances investors' actions are destabilizing and induce excess volatility in the financial markets. In more benign cases, their actions could be justified as ex post rational if price trends did not quickly reverse following a rapid run up. In such situations, their actions could be justified if they were based on independent private information. In the latter case, investors, by acting in a herd might help impound fundamental news into each security's price. However, in the absence of access to their private information, it is still difficult to say as to whether they acted independently on the same fundamental piece of information, or if they resorted to imitative behavior as suggested by many herding theories.

There is a rich theoretical literature suggesting both rational and irrational explanations for herding by investors. Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992) and Welch (1992) argue that investors infer information by observing the trades of others, and end up in informational cascades. Froot, Scharfstein and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994), attribute herding to investors following the same sources of information. Scharfstein and Stein (1990) and Trueman (1994), advance the

[17]"Institutions are herding animals. We watch the same indicators and listen to the same prognostications. Like lemmings, we tend to move in the same direction at the same time. And that naturally, exacerbates price movements."- A Pension Fund Manager (Wall Street Journal (October 17, 1989))
"Who really did do the panicking at the bottom? We found what we had long suspected. The real pasties were the large institutional traders who's congenitally shaky nerves get so much sensationalized media attention."- Louis Rukeyser in Wall $treet Week-Quoted by Richard Strozinsky (1998)

idea of reputation costs arising out of acting differently from others as a cause of herding. Investors may also exhibit herding because they unintentionally get attracted to securities with similar attributes, e.g. past returns, size, and liquidity etc. (Falkenstein (1996); Del Guercio (1996); Gompers and Metrick (2001)). Lastly, investors could exhibit herding as a consequence of fads (Friedman (1984); Dreman (1979; Barberis and Shleifer (2003)).

The majority of the rational herding models assume that prices of financial assets are fixed; that is the demand for stock is perfectly elastic. In financial markets, however, asset prices are flexible and are affected by the actions of traders. Avery and Zemsky (1998) study the theoretical relations between herding (an informational cascade) and the informational efficiency of the market. They consider a setup where each agent receives an independent, but noisy, signal of the true value of a financial asset. Herding occurs if the agents ignore their signal and decide to buy or sell based on the trend in past trades. However, if market prices are not fixed, and if the financial asset market is informationally efficient in the sense that the price of an asset reflects all publicly available information, then asset prices will adjust up or down with no undershooting or overshooting in response to each agent's buy or sell action. Thus, in the informationally efficient markets case, agents will buy or sell based upon their signal because they are facing conditionally correct prices, with the result that there is no herding. More generally, Avery and Zemsky (1998) show that in a market where the informed traders engage in rational herd behavior, this cannot cause long-run mispricing of financial assets.

Despite the perceptions of market watchers and herding theorists, empirical evidence that supports herding is almost non-existent. Lakonishok, Shleifer, and Vishny (1992) find no evidence of herding by pension funds in the stock market. Their paper also introduced the basic herding measure used by later studies. Similarly, Grinblatt, Titman, and Wermers (1995) document economically insignificant level of herding by mutual funds. Wermers (1999) finds only weak evidence of herding by mutual funds.

Most of the above studies[18] apply the Lakonishok, Shleifer, and Vishny (hereafter LSV) (1992) measure[19] of herding to quarterly holdings data of institutional investors. As a result of this low sampling rate, any herding by investors at intra-day, daily, weekly or monthly intervals is not captured. Furthermore, if institutional investors have high portfolio turnovers, then any lack of herding found in these studies could also be interpreted as evidence of low power in the test. Moreover, it is plausible that individual investors herd more than institutional investors. Thus by analyzing institutional investors only, we cannot comment on herding by individual investors. Lastly, at an intuitive level, herding implies a follow-the-leader relationship with regard to trading. Given only snapshots of quarterly holdings data of institutional investors, it is difficult to judge who imitates whom.

This paper makes a number of important contributions. To the best of our knowledge, this is the first paper examining herding at the intra-day level using a new methodology based on runs tests and correlation between interarrival trade times. Rather than asking whether institutional investors herd or not, we endeavor to ask if herding occurs in an average stock. This paper attempts to detect herding in financial markets using a set of two methodologies based on runs test and dependence between interarrival trade times. Our first and the most important finding is that markets function efficiently and show no evidence of any meaningful herding in general. Second, herding seems to be confined to very small subset of small stocks. Third, dispersion of opinion among investors does not have much of an impact on herding. Fourth, analysts' recommendations do not contribute to herding. Last, the limited amount of herding on price increase days seems to be destabilizing but on the price decrease days, the herding helps impound fundamental information into security prices thus making markets more efficient. Our results are consistent with Avery and Zemsky (1998) model's prediction that flexible financial asset prices prevent herding from arising.

[18] Christie and Huang (1995) is an exception, who measure herding by examining cross-section dispersion in assets returns during times of large price movements. They find that dispersion around markets return is higher and interpret this as evidence against herding.
[19] LSV (1992) measure of herding essentially examines "the extent to which money managers end up on the same side of the market in a given stock in a given quarter, relative to what is expected if managers trade independently."

In the next section of the paper, we discuss various theories and empirical evidence on herding. In section 3 of the paper, we describe the research methodology and sample. The main results of the study are presented in section 4 of the paper. We conclude the paper in section 5.

2. Herding Models and Empirical Evidence

2.1 Herding Models

Although herding could result from several phenomena such as investor psychology, interpersonal communication, or contagion of interest, ideas which are studied in the 'irrational' or 'near rational' herding literature, we summarize here the most important rational herding models. The first set of models fall under the heading *Information-Based Herding and Cascades.* These models, attributed to Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992) and Welch (1992), are based on the idea that agents gain useful information from observing the actions of agents who traded previously, to the point that they optimally and rationally completely ignore their own private information. In such situations, the agents are said to be in an informational cascade. However, when agents know that they are in such a cascade, they also know that the cascade is based on little or no information. Therefore, any new arrival of public information, or better informed agents, or shifts in the underlying value of action, could result in the dissolution of the cascade. Thus, fragility is one key characteristic of a cascade.

The second set of models known as *Information Acquisition Herding* models are due to Froot, Scharfstein and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994). The common theme in these models is that investors decide to study the same set of stocks or same sources of information. In the Froot, Scharfstein and Stein (1992) model, the focus is on the short-term horizon of investors, which leads to positive informational spillovers. In this model, an informed investor, who wants to liquidate his long position (initiated early) in an asset stands to gain only if other people acting on the same information trade in that asset. This leads to informed investors studying the sources of information which are likely to be also used by other investors.

Hirshleifer, Subrahmanyam, and Titman (1994) consider “early informed” and “late informed” investors. The early informed investors trade aggressively in the initial period and reverse their position in the next period to reduce long-term risk, while the late informed investors cause the price to reflect early informed investors’ information. The early informed investors make more profits if late informed investors trade. Therefore, if investors do not know that they are early informed or late informed, their ex ante utility increases in the total number of investors collecting information.

The third set of models termed *Principal-Agent Models of Herding* were developed by Scharfstein and Stein (1990) and Trueman (1994).These models are based on the idea that when principals are uncertain of agents’ ability to pick the right stocks, it makes sense for agents to mimic the decisions of other agents to preserve the principal’s uncertainty about the agents’ ability. Similarly, Maug and Naik (1995) demonstrate that an explicit relative performance clause, which is written by principals to mitigate the problem of moral hazard (for example, to induce the agent to do private research), and adverse selection (for example, to differentiate between good and bad managers) may lead to herding. They suggest that a compensation scheme which increases with a money manager’s performance and decreases in the performance of other money managers, provides an additional incentive for herding.

Fourthly, institutional investors may share aversion/preference to stocks with certain characteristics like liquidity, riskiness, and size (Falkenstein (1996); Del Guercio (1996); Gompers and Metrick (2001)). As a result of their preference for securities with similar characteristics, they may appear to follow each other into and out of the same stocks.

Lastly, investors could exhibit herding as a consequence of fads (Friedman (1994); Dreman (1979)), or where positive feedback traders invest at a style level, and chase relative style returns. This practice targets funds into higher relative returns stocks, and moves the prices away from fundamentals (Barberis and Shleifer (2003)).

2.2. Empirical Evidence

In one of the earliest studies, Kraus and Stoll (1972) analyze monthly trades for 229 mutual funds or bank trusts for the period starting January 1968 and ending September 1969. Though they find significant imbalances between purchases and stocks, they attribute it to chance, rather than herding by investors.

More recently, six important studies have analyzed herding in the context of institutional investors. The first study by LSV (1992) uses 769 US tax-exempt equity funds' (mostly pension funds) quarterly ownership of shares data for the period 1985-1989. LSV (1992) conclude that money managers do not display economically significant levels of herding. Even in the small stocks and technology stocks with uncertain cash flows, they find little evidence of herding. They find even less herding at the industry level than at the stock level. This paper also introduced the basic herding measure used by later studies.

The second study by Grinblatt, Titman, and Wermers (hereafter GTW) (1995) uses the quarterly ownership data on portfolio changes of 274 mutual funds between 1974 and 1984. Using the LSV (1992) measure, they find similar levels of herding as found by LSV (1992). Relating it to momentum trading, GTW find more herding by investors in buying past winners than investors selling past losers. To control for significant heterogeneity in the mutual funds, they differentiate funds according to their investment objectives: aggressive growth funds, balanced funds, growth funds, growth-income funds, income funds. They find even less herding after controlling for objectives, than in the total sample.

Recently, Wermers (1999) performed the most comprehensive study to date using quarterly holdings data for virtually all mutual funds in existence between 1975 and 1994. Using the LSV (1992) measure of herding, Wermers finds little herding taking place in an average stock. He finds greater herding in small stocks, in general. However, small stocks are not typically the preferred holdings of mutual funds. He also finds higher levels of herding in growth-oriented funds than income-oriented funds, which he attributes to smaller stocks being dominant in growth funds. In contrast to GTW (1995), he finds more herding on the sell side than on buy side. By looking at the differential between contemporaneous returns and returns after 6 months on the stocks bought by the herds relative to the stocks sold by the herd, he concludes herding is 'rational' and helps bring about incorporation of news into securities prices and is, therefore, stabilizing. This last finding, which, Wermers (1999) asserts is the most important contribution of his study, is also consistent with an alternative explanation. Continuing trends in the prices could also mean that, as institutional investors herd even more, they drive the prices away from fundamentals. Only if the price trends continue in the subsequent longer period, unaccompanied by herding, can we accept his claim.

Jones, Lee and Weis (hereafter JLW) (1999) study herding by institutional investors using quarterly holding data for 1984-1993, and find negligible level of herding for an average stock. They also document a positive relation between observed institutional demand and subsequent returns. Therefore, similar to Wermers (1999) conclusion, they conclude that trading by institutional investors contributes to long-run market efficiency. In a recent study, Sias (2002) using quarterly holding data of institutional investors for 1983-1997, finds a strong positive relation between fractions of institutions buying over adjacent quarters. Consistent with Wermers (1999), he finds the strongest evidence of herding in the small stocks. Sias (2002) also documents that institutional demand is more strongly related to lagged institutional demand than lagged return. Lastly, Sias (2002) examines institutional demand and future returns, and documents the absence of a negative relationship. Pirinsky (2002) tests for herding by institutional investors by examining time-series correlation for individual securities in changes in the fraction of shares by institutional investors. Similar to Sias (2002), he documents a positive relation between current quarter change in fractional ownership and previous quarter change in factional ownership. Pirinsky (2002) finds greater evidence of herding, when institutional investors initiate (terminate) a position in a security. He also documents significant herding in growth and volatile stocks. In contrast to Wermers (1999), JLW (1999), and Sias (2002), he finds herding to be destabilizing, since stocks bought (sold) by institutional investors in herds tend to under-perform (outperform) over the following year.

3. Research Methodology

Bikhchandani, Hirshlieifer, and Welch (1998) describe how, in terms of micro-market behavior, an information cascade (that is herd behavior) can start. Suppose individuals face an investment decision under uncertainty. Each investor receives a noisy signal about the future value of a security (G means good, the price will go up, and B indicates bad, the price will fall). The probability that the signal is correct, is p, which is greater than 0.5. If p were equal to 1.0, then the signal would be perfect, which is to say the signal would be noise free. Each investor can observe the trade decisions made by other investors, but not the signal received by others.

In this model investors decide in sequence whether or not to invest in the security. The payoff to investing is V, which is either +1 or -1. The probability of either outcome is the same; that is 0.5. If V=+1, then the probability that the signal is a G is equal to p, and the probability of a B is 1-p. Bikhcandani, Hirshlieifer, and Welch (1992) use Baye's rule to show that the posterior chance of V=+1 after receiving a G signal is

$$\Pr ob[V=+1 \mid G] = \frac{\Pr ob[G \mid V=+1] * \Pr ob[V=+1]}{\Pr ob[G \mid V=+1] * \Pr ob[V=+1] + \Pr ob[G \mid V=-1] * \Pr ob[V=-1]}$$

$$= \frac{p * 0.5}{p * 0.5 + (1-p) * 0.5} = p > 0.5$$

The first investor in the sequence, I#1, will follow his signal: buy if the signal is G and not invest if it is B. I#2 observes behavior of I#1, and will determine I#1's signal based upon I#1's action. If I#2's signal is G and he had observed that I#1 bought, then I#2 will also buy. If I#2 receives a B signal, but observed that I#1 did not invest then it can be shown using Baye's rule that I#2's posterior probability that V=+1 is 0.5. In this case I#2 flips a coin in order to deciding whether or not to buy. If both I#1 and I#2 both buy, then I#3 will infer that I#1 received a G and that I#2 is more likely to have received a G signal.

Hence, I#3 will buy even if his signal is B. The next investor in the sequence, I#4, will learn nothing about I#3's signal based upon I#3's decision to buy. As a consequence, I#4 is in the same position as I#3, and will buy regardless of his own signal. And so on with I#5, I#6, I#7$\cdots$. A reject cascade begins if I#1 and I#2 both decide not to buy.

In general, Bikhcandani, Hirshlieifer, and Welch (1998) show that there will be a buy cascade if and only if the number of predecessors who invest exceeds the number of predecessors who do not invest by two or more. A parallel statement holds for the case where the predecessors do not choose to invest (buy). The important point is that there is a high probability of a cascade starting after the first few investors' have made their decisions. If an investment cascade starts then we would expect to observe long sequences of buy or sell trades. In particular, we would expect to see fewer buy or sell runs than we would in the case where each investor followed his or her own signal. Below we introduce two tests of herding: (1) the herding intensity statistic, and (2) the interarrival time test.

3.1 Herding Intensity Statistic

Our first new measure of herding based upon a runs test. As explained above, if investors herd with regard to their buying (selling) decisions, then in a fixed interval, we expect to see longer sequences of buy (sell) trades, rather than what would be expected if investors made their buying (selling) decisions independently of each other. The data on buy-sell trades is generally not available. However, a growing literature on microstructure offers many methodologies to infer the direction of trade using intra-day trading data. We use a tick-test[20] with respect to traded prices to infer if a trade is buyer or seller initiated. In particular, a trade is classified as buyer-initiated, if the current trade price is higher than the previous trade price (up-tick). Similarly, a trade is classified as seller-initiated, if the current trade price is lower than the previous trade price (down-tick). If there is no change in the current trade price with respect to the previous trade price (zero-tick) then the trade is classified using the last trade price, which differs from current trade price. However, as the sequence of zero-ticks gets longer, it may be difficult to justify the use of above method to classify zero-tick trades. Therefore, we separate the zero-ticks from up-ticks and down-ticks. Thus trades are classified as buyer or seller initiated only if current trade price differs from the previous trade price. Admittedly this biases against finding long sequences or buyer or seller initiated trades. Therefore as a test of robustness, we also use the conventional way of combining zero-tick trades as continuation of previous buyer or seller initiated trades. It is important to note that separating out the zero-tick trades from buyer-seller initiated trades biases against finding any evidence of herding. In contrast, grouping zero-tick trades as continuation of buyer or seller initiated trades biases in favor of herding. The greater the fraction of zero-tick trades, the more severe is the problem[21]. We calculate the statistical significance of the number of runs test using a statistic similar to Mood (1940) with a discontinuity adjustment suggested by Wallis and Roberts (1956) as follows.

If x (i, j, t) denotes a type of run (buy /sell/zero-tick) in a stock j on date t then the random variables

$$x(i,j,t) = \frac{(r_i + 1/2) - np_i(1-p_i)}{\sqrt{n}} \quad i = 1,2,\cdots,k$$

---

[20] Alternately, one could use a quote-method to classify trades. In this method, if the current trade price is greater (lower) than the midpoint of the bid-ask price, then the trade is categorized as buyer (seller) initiated. However, this method fails when the trade price is equal to the midpoint of the bid-ask price. Lee and Ready (1991) propose a hybrid method in which they switch to the tick-test when quote-method fails. Most of the studies have applied the Lee and Ready (1991) technique to classify trades. However, in a recent study, Finucane (2000) finds that tick-test performs better with respect to classifying trades.

[21] In our sample as described later, the average fraction of zero-tick trades in the top and bottom decile stocks is approximately 56%.

are asymptotically normally distributed with zero means and variances

$$\sigma^2(i,j,t) \;= p_i(1-p_i) - 3p_i^2(1-p_i)^2$$

It is to be noted that if we separate out the buyer-seller-initiated trades from zero-tick trades, then k =3. Alternatively, if we combine zero-tick trades with buyer-seller initiated trades, then k=2.

Where,
r_i = actual number of runs of type i
$\frac{1}{2}$ = a discontinuity adjustment
n=total number of trades in stock j on date t
p_i = probability of buy/sell/zero-tick run

Let H (i, j, t) be a measure of herding intensity of a type of run i (buyer, seller initiated or zero-tick runs) for stock j in on date t:

$$H(i,j,t) = \frac{x_i(j,t)}{\sqrt{\sigma_i^2(j,t)}} \quad \text{i=buyer-initiated, seller-initiated, zero-tick trade}$$

For large samples, H (i, j, t) is normally distributed with mean 0 and variance 1. If investors herd, then actual number of buyer-initiated or seller initiated runs would be lower than what is expected, this would result in a statistically significant negative H (i, j, t). Therefore, the more negative H (i, j, t), the greater is the probability of herding.

3. 2 Interarrival Time Test for Trades

Stock market trades occur at discrete points in time. A stochastic process called a *counting process* is a natural way to model the occurrence times of market trades. In the language of Poisson point processes (see Synder 1975) the occurrence of a trade is referred to as a *point,* and $N_{s,u}$ represents the number of points (counted) in the interval from s to u, including any point at s but not at u. We define a stochastic process $\{N_t; t \geq t_0\}$ according to

$$N_t \triangleq N_{t_0} + N_{t_0,t}$$

where N_{t_0} is a nonnegative integer that usually is set to zero. If graphed as a function of time (t), $\{N_t; t \geq t_0, N_{t_0} = 0\}$ has a unit jump at the occurrence of each point.

The Poisson counting process has independent increments which means that the numbers of points in nonoverlapping intervals are statistically independent no matter how large or small the intervals and no matter how close or distant they may be located on the time line. The expected number of points on the interval $[s,t)$ is evaluated as

$$E\left(N_{s,t}\right) = \sum_{n=0}^{\infty} n \Pr\left[N_{s,t} = n\right] = \Lambda_t - \Lambda_s$$

for the Poisson counting process. The parameter $\Lambda_t - \Lambda_s$ has the limit

$$\lim_{\delta \to 0} \delta^{-1}(\Lambda_{t+\delta} - \Lambda_s) = \lambda_t$$

where λ_t is a nonnegative function of t *for* $t \geq t_0$ and is referred to as the *intensity function* of the process. If the intensity function λ_t is independent of time, then the Poisson process is said to be *homogeneous.*

The two important aspects of a point process are the counting statistics, which were explained above, and the *location characteristics*. The latter refers to the point locations and the interpoint spacings. The sequence $\{\upsilon_n\}$ is called the *occurrence time* sequence, and the related sequence $\{t_n\}$ is known as the *interarrival time* sequence. Therefore, t_n is the nth interarrival time and is the random time between the (n-1) st and nth occurrence times. The interarrival times are independently and identically distributed, *iid,* under the assumption that the counting process is Poisson and homogeneous. Therefore, it follows directly that $\{t_n\}$ is an uncorrelated sequence.

Suppose, however, that the number N_t and occurrence times $\upsilon_1, \upsilon_2, \cdots, \upsilon_n$ for points realized before some time t can influence the number and occurrence times for points arriving subsequent to t. This is a general definition of a *self-exciting point process.* A self-exciting point process can be thought of as a modified inhomogeneous Poisson process where the intensity parameter λ_t is not only a function of time but also the past of the point process. The sequence of interarrival times is no longer *iid,* but exhibit some form of dependence, such as autocorrelation. Although autocorrelation of the interarrival times implies a self-exciting point process, the converse is not true: uncorrelated interarrival times do not imply that the interarrival times are *iid.* A characteristic of an informational cascade is that agents trade because others are trading, which implies that trade times do not occur at random, but rather that trade times follow some sort of self-exciting point process.

Under the null hypothesis of no herding stock trades arrive at random if information arrives at random, which means that the sample correlation of observed interarrival times $\hat{r}(t_n)$ is not significantly different from zero. Therefore, the statistical analysis of $\hat{r}(t_n)$ is our second test of the no herding hypothesis. We carry out the test by regressing t_n on t_{n-1}. The slope coefficient from this regression is the sample correlation $\hat{r}(t_n)$. The t-statistics for the means of the slope coefficients are computed from the standard errors of the regression coefficients[22]. This measure of herding has two merits. First, this measure appeals to our intuitive understanding of how the information flows in the efficient markets. That is, in efficient markets random arrival of information should cause

[22] Using the simulated data as described in section 3.4 for top decile stock-days with zero dependence in trades, we find the average slope coefficient to be 0.00126 with t –statistic of -0.0328. The t-static has been computed using the standard errors of the slope coefficients. Thus this measure of herding has appropriate power.

interarrival times between trades to be *iid*. Any dependence in interarrival times indicates clustering of trades i.e. trade begets trade. Second, this measure is free from any potential bias that may be introduced by using herding intensity statistic as described in section 3.1. Third, this measure of herding is not affected by any microstructure issues like bid-ask bounce etc.

3.3 Sample

Investors are more likely to herd when markets are under stress. Consequently, we select 1998-2001 as the period for our study. It is evident from figure I that \$100 invested in the S&P 500 index at the beginning of 1998 grew to \$152 by the end of March 2000. During the same period \$100 invested in the NASDAQ composite grew to even greater \$282. However, by the end of 2001, the investment of \$100 in NASDAQ had fallen to \$120, and to \$117 in the S&P 500 index. Many market watchers refer to 1998-2000 as a *bubble* period. Second, according to Boni and Womack (2003) "late 1990s was recognized as the advent of the "day trader" due to convenient and inexpensive transactions services available via the Internet". Therefore this period provides a good setting to detect herding.

We use intra-day trading data of NYSE[23] stocks for analysis. The data source is the trade and quote data files (TAQ), and the period included is 1998-2001. In order to reduce the computational burden, we select on a random basis 50 trading days (approximately 20%) for each year of our study. We expect herding to be most evident in those stocks which experience large price run ups or run downs. Therefore, for each of the trading days selected at random, we categorize the common stocks[24] into top and bottom deciles in terms of daily returns. For further analysis, we randomly select 20 stocks from each of the categories (top and bottom deciles). Thus for each randomly selected trading day, we

[23] We restrict our sample to only NYSE stocks to avoid any possibility of results being influenced by differences in trading protocols.
[24] We expunge any assets with CRSP share code other than 10 or 11. Thus we exclude certificates, ADRs, shares in beneficial interest, unit investment trusts, companies incorporated outside the United States, Americus Trust components, closed-end funds, preferred stocks, and REIT.

have 40 stocks. In order to enhance the power of our tests, we restrict the sample to those stocks that have at least 200 trades on the day of trading[25]. In aggregate, we use 8,000 stock-days' trade data. (50 days x 4 years x 20 stocks x 2 categories). For each of the 8,000 stock-days, we extract trade data from the TAQ files. Next, we purge a trade for any of the following reasons: trades reported out of sequence, any trade reported before the open or after the closing time[26], and any trade with special conditions. In order to count the number of runs of different types, we sort the TAQ data for each return decile by ticker; then by date of the trade, and finally by time stamp.

Table I presents the daily descriptive statistics for our sample of firms. The mean return for top return decile stocks is 6.18%. The bottom return decile stocks experience an average return of -5.44%. On further analysis, we find that consistent with intuition, smaller stocks have greater absolute positive (negative) returns. For our 200 sample days, the average return of S&P 500 index was an inconsequential -1/2% per day. The mean size (market capitalization) of the stocks is $12.65 billion. The median is much lower at $3.83 billion. The mean (median) size of the firms is similar in top and bottom return deciles. The mean (median) closing price of the stocks on the previous day of trading was $37 ($32). Again, similar to size, mean (median) closing prices are similar in top and bottom return deciles. Quite predictably, the trade size is big and similar in top and bottom return deciles stocks.

For top decile stocks, our null hypothesis is that actual number of buyer-initiated runs is statistically no different from what is expected by random chance, i.e. price changes are a purely random process. Thus for top decile stocks, i=buyer-initiated runs. For top decile stocks, we compute H (i, j, t) for each stock-day and average them to get $\overline{H(i,j,t)}$. Likewise, for bottom decile stocks, our null hypothesis is that actual number of seller-initiated runs is statistically no different from what is expected at random. Accordingly for bottom decile stocks, i=seller-initiated runs. For bottom decile stocks, we compute H (i, j, t) for each stock-day and average them to get $\overline{H(i,j,t)}$.

[25] This could bias our sample towards larger stocks.
[26] Trades reported on TAQ files between 9:30 a.m. and 4:05 p.m.

3.4 Calibration of the Herding Statistic

As explained in Section 3.1 above, Mood (1940) shows that the herding statistic H (i, j, t) is distributed as a normal random variable. In deriving his result, Mood assumed that the variable under study is *iid* and continuously distributed. Stock prices inherently are generated by marked point processes. That is, when the point (a trade) occurs there is a drawing from the mark distribution (log normal in the case of stocks) which determines the new price. Furthermore, stock prices are discretized to the nearest unit of permitted price change (1/8, 1/16, or a penny). The discretization of prices implies that the H (i, j, t) variable has a mean and variance different from the mean and variance calculated by Mood. Thus, while H (i, j, t) is asymptotically distributed as a normal random variable, it is necessary to estimate its mean and variance. In this sub-section we develop a Monte Carlo method that calibrates H (i, j, t) such that the test statistic has the appropriate size (the "size" of a test refers to it's probability of a Type I error).

Our Monte Carlo method consists of a simulation of stock market prices with Poisson generated trade times and discretization of prices to the nearest $1/16^{th}$ of a dollar. The mark process is distributed log normal with a specified mean and variance. In particular, when the point occurs, the simulation produces a price for that selected time point by selecting the corresponding price at same that time point from an underlying log normal continuous time price process. The Poisson intensity parameter λ was chosen to produce an average of 800 trades per day, which in our judgment is a good compromise as the mean and median of the real data are approximately 1000 and 500 respectively. The log normal prices were generated by exponentiating a normally distributed rate of return process. The rates of return are uncorrelated in order to correspond to a null of no herding. For purposes of the simulation, the variance of the daily rate of return was set to 1.28% per day which is equivalent to about 20% per year[27]. We generated 1000 days of

[27]Experimentation with simulation shows that as the variance of returns increases, with the level of discretization fixed, the distribution of the herding test statistic moves towards the unit normal. For the actual data, intra-day volatility (standard deviation) for the top and bottom decile stocks averages around 11.2% and 16.11% respectively on an annualized basis. Thus our specification of

prices to simulate the case of the top decile of our sample where the stocks were moving up in price and another 1000 days for the case of the bottom decile where stock prices were falling. Consider the simulation of the top decile. The mean returns were chosen at random from the set of 4000 sample means observed in the top return decile of our sample. For a particular day the mean rate of return was chosen with replacement from the sample set using a uniform random number generator. The means for the bottom decile of simulated days were chosen in a similar manner.

The critical values for the herding test statistic were selected from the lower tails of the empirical distributions of H (i, j, t) observed in the simulations of the top and bottom decile of the sample data using two different ways of classifying the trades. In one case zero-tick trades are separated from buyer and seller initiated trades. The table A below displays the mean, median and 1%, 5%, 10% fractiles (the herding test is a one sided test for fewer buyer-initiated runs than expected) of the distribution for the top decile simulation, and the mean, median and critical values for the bottom decile (the herding test is a one sided test for fewer sell runs than expected) using this method.

Table A: Zero-tick trades separated from buyer-seller initiated trades

Mean	Mean	Median	1%	5%	10%
Top Decile	1.619315	1.628248	-0.205607	0.329796	0.645651
Bottom Decile	1.706234	1.716395	-0.0457759	0.5246229	0.7974518

Table B below repeats the exercise by clubbing zero-tick trades with buyer and seller initiated trades as described earlier.

Table B: Zero-tick trades grouped with buyer-seller initiated trades

Mean	Mean	Median	1%	5%	10%
Top Decile	-9.7677	-10.1037	-12.899422	-12.171157	-11.729883
Bottom Decile	-10.3532	-10.5322	-13.059000	-12.274073	-11.914086

20% standard deviation used in the simulation makes our tests more conservative as greater variance makes the distribution approach standard unit normal.

In both the tables, note that the critical values are roughly similar between the entries in for top and bottom decile. This is hardly surprising because the herding test is applied to the first difference in the prices which is equivalent to detrending the data. So, the results of applying the herding test to the real data as presented below in Section 4 will be evaluated using the critical values shown in Tables A and B.

In order to gain some appreciation of the power of the herding test we also repeated the simulations using returns that are positively correlated at either 20% or 50% using both the methodologies for classifying the trades in the top and bottom return deciles. For example, we separate the zero-tick trades from buyer or sellers initiated trades and calculate the percentage of H (i, j, t) test statistics falling at or below a particular critical value. For example, for the top quintile simulation with +20% correlation, 60% of the H (i, j, t) s for buyer-initiated runs were equal to or less than -0.205607, the 1% critical value shown in Table A, which is strong evidence against the null of zero correlation (no herding). Similar results were found for the bottom decile, with 50% correlation and using the conventional way of classifying trades. In Section 4, we will display the results of applying the herding test to real data.

4. Herding Results

4.1 Overall Herding

To investigate herding in an average stock, we classify trades into buyer and seller initiated by tick-test. In panel A of Table II, we report the herding intensity $\overline{H(i,j,t)}$ by separating out the zero-tick trades from buyer or seller initiated trades. Panel B shows the results using conventional tick-test of classifying trades into buyer and seller initiated. In panel A, the mean (median) herding intensity for top decile stock is 2.52 (2.00). The mean (median) herding intensity for bottom decile stock is 2.22 (1.75). Using the critical values obtained from simulation described earlier in the text, these herding intensities are not significantly different from zero, and therefore indicate that there is no evidence of herding by investors in an average stock experiencing very large price increase (decreases). However, it is plausible that a small subset of stocks in these groups might have experienced statistically significant herding. To investigate this, we sort the stock-days in terms of herding intensity for each return decile. We find 314 stock-days in the top return decile with herding intensity significant at 5% (again using the critical values derived from simulation tests). However, this is only slightly bigger than 200 stock-days, we would expect by random chance, which is due to sampling error. On the other hand for the bottom return decile, the number of stock-days for which the herding intensity is significant at the 5% level is 610. This is more than 3 times, what is expected by random chance. Thus a small set of stocks do experience a significant herding statistic and the herding seems to be more pronounced in bottom decile return stocks[28]. Since zero-tick trades are combined with buyer or seller initiated trades in panel B, this result in longer sequences of buying and selling sprees. Consequently, the results in panel B are stronger than in panel A but qualitatively similar.

In panel C, we regress the interarrival time between trades on lag interarrival time to examine any correlation between trades. The mean (median) for top decile is 0.11 (0.11) approximately. The mean correlations for bottom decile are also similar. Thus in half of the stock-days, correlation between interarrival trade time greater than 0.11. Although mean correlations are statistically significant at 1%, it is difficult to interpret the magnitude as being rather big or small.

In summing up, we find only limited evidence of herding by investors in an average stock. Though, there is strong evidence of herding in a small subset of stocks. Thus markets appear to be functioning in a manner largely consistent with the Efficient Markets Hypothesis (EMH).

---

[28] However one could argue that statistically significant herding in this subset of stocks could be purely due to random chance. For example in a sample of randomly selected 100 stock-days, at 5% significance level, 5 of the stock-days could exhibit significant herding due to sampling error. In our sample of stock-days for which the herding intensity statistic appears significant is very close to what is expected by random chance for the top decile stocks, but random chance is much less likely to explain the results for the bottom decile.

4.2 Herding and Stock Size

The Information-Based Herding and Cascade models predict that herding is more likely to occur when private information is more difficult to obtain and hard to evaluate (due to high noise). Wermers (1999) suggests that for small capitalization stocks (with large information asymmetry) investors are more likely to suppress their own beliefs, and put greater weight on what others are doing. Herding in small capitalization stocks is also consistent with Scharfstein and Stein's (1990) agency model of herding, in which money managers may sell small stocks with bad past performance, but might hold on to large capitalization stocks regardless of their past performance. On the other hand, if herding results from Information Acquisition models, then Sias (2002) posits that cross-section correlation between signals is likely to be stronger in larger stocks (due to investors following the same indicators) with less noisy signals. In his view, larger stocks should have greater herding. Furthermore, because of institutional investors' preference for liquidity and size (Falkenstein (1996); Gompers and Metrick (2001)), we may observe greater herding in large capitalization stocks.

To examine herding based on size, we divide the universe of all NYSE stocks into quintiles based on market capitalization at the beginning of every day from 1998 to 2001. Then we assign each firm in our sample into the appropriate quintile and update daily. The herding intensity results are reported in Table III and Panel A and B. During the overall period of 1998 to 2001, for both top and bottom return deciles, the average herding intensity was statistically not different from zero in any of the size quintiles.
In panel C, we report the mean[29] correlations between interarrival times of trades for each size quintiles. They are statistically significant in each quintile with slightly higher correlation in the smallest 2 quintiles. Thus, herding seems more pronounced for smaller stocks.

We acknowledge that our sample is biased towards larger capitalization stocks, which may be more efficiently priced and thus reducing the chances of detecting herding.

[29] Median correlations were very close to mean. Therefore, we do not report them in tables.

Consequently, in the smallest 2 quintiles, we do find some evidence of herding. In summary, herding is primarily present in small stocks probably due to less efficient pricing.

4.3. Herding and Dispersion of Opinions

Prior research suggests that heterogeneity of beliefs or dispersion of opinion among investors affects stock prices. Miller (1977) argues that in presence of short sales constraints, systematic security overvaluation occurs because the most optimistic investors set the prices. In contrast to Miller (1977), Merton (1987) and Varian (1985) suggest that in the absence of short sale constraints, dispersion of opinion denotes more risk and is priced relatively at a discount. We posit that dispersion of opinion and herding are correlated. However, the correlation could be either positive or negative. On one hand, if a greater degree of beliefs' dispersion arises from noisy information (information asymmetry) then investors could herd as they infer information from others' actions leading to positive correlation. On the other hand, a greater degree of beliefs' dispersion may prevent formation of cascades.

Shalen (1993) and Harris & Raviv (1993) present theoretical models correlating dispersion beliefs with asset time series volatility and trading volume. In recent studies Gephardt, Lee and Swaminathan (2001) and Diether, Malloy and Scherbina (2002) use share turnover as a proxy for dispersion of opinion. We also use share turnover on each sample day for each firm as a proxy of dispersion of opinion. To compute herding based on share turnover, we classify H (i, j, t) for the stocks in our sample in each return decile, into quintiles on the basis of share turnover. The herding intensity results are presented in table IV Panel A and Panel B. In none of the share turnover quintiles is the average herding intensity statistically significant.

When we compute the mean correlation interarrival times of trades of each share turnover quintile in Panel C, we find greater correlation in the higher share turnover quintile stocks. This is consistent with the hypothesis that greater dispersion in opinion leads to greater herding. In summary, a greater degree of dispersion amongst investors has only a limited impact on herding in an average stock.

4.4. Herding and Analysts Recommendations

Investors often listen to analysts' recommendation, thus receiving correlated information. If they act accordingly, herding may occur. In order to examine whether or not analysts' recommendations have any meaningful impact on herding, we use IBES/First Call analysts' recommendations dataset. Each record of the database has, among other items, the date of the recommendation, identifiers for the brokerage house giving the recommendations and the analyst writing the report (if analyst's identity is known) and a rating of 1 to 5. A rating of 1 reflects a strong buy, 2 a buy, 3 a hold, 4 an underperform and 5 a sell. These are the 5 points generally used by analysts. Womack (1995) and Barber, Lehavy, Mcnichols and Trueman (2001) find that stocks, which are upgraded (downgraded), experience abnormal returns on the day of the recommendation in the direction of recommendation. We identify the stocks from the top return decile, which were upgraded on the day we measure the herding intensity. To be included in this group, stocks must have a recommendation that changed from 'buy to strong buy', hold to strong buy/buy', 'underperform to strong buy/buy', or 'sell to strong buy/buy'. We also include those stocks which had new initiations of strong buy or buy. Likewise we identify the stocks from bottom return deciles, which were downgraded on a sample day. Similar to upgraded stocks, we include in this category all stocks with recommendation changes to underperform/sell, or new initiations of underperform/sell. The total stock-days with and without recommendations do not add up to 4000 as only recommendation changes are included (all reiterations are excluded). We then compute the mean herding intensity for the group of stocks with an upgrade (downgrade) and without any recommendations. The herding intensity results are presented in table V. As shown in the Panel A and Panel B, we do not find any meaningful difference in herding intensities between upgrades (downgrades) and stocks with no recommendations.

In Panel C, we report the mean correlations of interarrival times of trades for the upgraded and downgraded stocks and those without any recommendation change. In the upgraded stocks, there is slight evidence of more herding. However, the magnitude is not substantially very different form stocks without recommendation. Thus analysts' recommendations do not appear to have much explanatory power on herding. Possibly, analysts' recommendations lead to greater trading soon after the announcement and the market quickly incorporates this new information into security valuations. This is consistent with Avery and Zemsky's (1998) argument that with flexible price adjustment, investors do not have any incentive to herd.

4.5. Herding, Price Impact and Subsequent Returns

Recently, a number of studies have documented a positive cross-sectional relationship between returns and herding by investors. Nofsinger and Sias (1999) find that the top decile of NYSE stocks, that experience the largest annual increase in institutional ownership outperform the bottom decile of stocks that have had the largest decrease in institutional ownership. Similarly, GTW (1999) and Wermers (1999) find a similar relationship for quarterly changes in mutual funds holdings and stock returns. This positive relationship between herding and contemporaneous returns is consistent with the following three hypotheses: (1) because of price pressure, trading by investors contemporaneously affects prices; (2) investors tend to be short-term momentum investors and (3) investors have information that allows them to time their trades. If this positive relationship is not based on fundamental information, and in the absence of further herding into these stocks, then the principal-agent models of herding of Scharfstein and Stein (1990) and Trueman (1994), and fad models of (Friedman (1994); Dreman (1979)) and Barberis and Shlieifer (2003) suggest that we should observe subsequent return reversals.

In order to examine whether or not herding by investors affected price changes in a particular day (and if herding was related to information), we first classified the stocks in each return decile into quintiles on the basis of our herding measure for the entire period from 1998 to 2001. for each stock-day, we compute four measures of abnormal returns;

AR_c is a mean market-adjusted contemporaneous abnormal return, AR_{a1} is one-day ahead abnormal return (the abnormal return on the day following the herding day), AR_{a2} is two-day ahead abnormal return (the abnormal return on the second day following the herding day) and AR_{a3} is three-day ahead abnormal return (the abnormal return on the third day following the herding day). To compute abnormal returns, the return on a value weighted portfolio of all NYSE/AMEX/NASDAQ stocks' daily industry return is subtracted from each firm's daily return[30].

The results of applying our herding tests to this data are reported in Table VI. During the entire period from 1998 to 2001, except the top decile in Panel A, herding intensity statistics do seem to be related with the excess contemporaneous returns $AR_{c.}$ In Panel C, mean correlations between interarrival trades times are clearly correlated to excess contemporaneous returns AR_c. The more the correlations between interarrival trade times, the greater is absolute amount of abnormal return. Thus there is some evidence of contemporaneous return results being consistent with the either price pressure hypothesis or information driven trading[31].

In order to consider whether herding was destabilizing, we examine the subsequent three days' abnormal returns. For the highest herded stocks in the top or bottom return decile, 1-day ahead abnormal return is statistically not different from zero. 2-Days and 3-days ahead returns are statistically slightly negative. Thus herding in the top return decile stocks does provide some evidence of price destabilization. However, in the bottom decile 1-day, 2-days and 3-days ahead abnormal returns are not reliably different from zero. For the bottom return decile stocks, we do not observe any reversals. On the contrary, investors by acting in herds may help incorporate fundamental information into stock prices. Overall, we conclude that herding seems to destabilize prices on the steep

[30]We also computed size-adjusted abnormal return for our sample of firms'. To compute average size-adjusted return, we match our sample of firms with same size decile from the universe of all NYSE/AMEX/NASDAQ stocks. Then we subtract the average return for the corresponding size decile from the raw daily return for our sample of firms.

[31]However, it should be noted that herding intensity is statistically meaningful only for the very highest herded stocks. Although, not shown in the table, on further analysis we find that this pattern is most pronounced for the lowest 2 size quintiles of stocks. Thus controlling for size, we see the highest impact of herding on the smallest quintile stocks.

price increase days. However, herding on the price decline days is consistent with the notion that investors act the basis of information and helps to improve market efficiency.

5. Conclusion

This paper investigates herding by investors in a random selection of 8,000 NYSE stock-days during 1998-2001. We find no significant evidence of herding by investors in an average stock. There is, however, strong evidence of herding in a subset of small stocks with very large daily price increases (decreases). Herding, if present, is more pronounced on price decline days than price increase days. We also document that dispersion of opinion amongst investors has not much impact on our measures of herding. Our herding intensity is largely unrelated to analysts' recommendations. The limited amount of herding on price increase days appears to be slightly destabilizing. But when there are steep price declines, we believe that the evidence shows that investors by acting in herds help impound information, thus enhancing the market efficiency. Overall markets seem to be functioning in a manner reasonably consistent with the Efficient Markets Hypothesis (EMH). Our results are consistent with Avery and Zemsky (1998) model's prediction that flexible financial asset prices prevent herding from arising.

Although, we do not document herding in an average stock listed on NYSE during 1998-2001, it is possible that NASDAQ stocks, which experienced much greater volatile returns during the period, were subjected to herding. The second possibility is that perhaps it takes time for investors to infer what other investors are during. Consequently, intra-day period may be too short an interval to detect herding. Future research should possibly explore longer frequency like days, weeks or monthly data to examine the presence of herding. Lastly, we do not rule the possibility that herding may be present amongst a small subset of investors, such as institutional investors, who have somewhat similar objectives and follow correlated signals.

References

Avery, Christopher and Peter Zemsky, 1998, "Multidimensional Uncertainty and Herd Behavior in Financial Markets," *American Economic Review*, v88 (4, Sep), 724-748.

Banerjee, A., 1992, “Simple Model of Herd Behavior,” *Quarterly Journal of Economics* 107, 797-817.

Barberis, N. and A. Shleifer, 2003, “Style Investing,” Forthcoming *Journal of Financial Economics.*

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

Bikhchandani, S., and Sunil Sharma, 2000, “Herd Behavior in Financial Markets: A Review,” Working Paper, International Monetary Fund.

Boni, L., and Kent Womack, 2003, “Analysts, Industries, and Price Momentum,” Working Paper, SSRN

Christie, William G., and Roger D. Huang, 1995, “Following the Pied Piper: Do Individual Returns Herd Around the Market?” *Financial Analysts Journal*, (July-August), 31-37.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, “Differences of opinion and the cross-section of stock returns,” *Journal of Finance*, forthcoming.

Del Guercio, D., 1996, “The Distorting Effect of the Prudent-man Laws on Institutional Equity Investment,” *Journal of Financial Economics*, 40, 31-62.

Dreman, D., 1979, “Contrarian Investment Strategy: The Psychology of Stock Market Success,” Random House, N.Y.

Fama, Eugene H., 1965 “The Behavior of Stock Market Prices,” *Journal of Business*, 38, 34-105

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

Finucane Thomas J., 2002, “A direct test of methods for inferring trade direction from intra-day data,” *Journal of Financial and Quantitative Analysis, 35, 553-557*

Friedman, B.M., 1984, “A Comment: Stock Prices and Social Dynamics,” *Brookings Papers on Economic Activity*, 2, 504-508.

Froot, A, Kenneth, David S. Scharfestein, and Jeremy Stein, 1992, “Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation,” *Journal of finance*, 47, 1461-1484.

Gebhardt, W. R., C. M. C. Lee and B. Swaminathan 2001. "Toward an Implied Cost of Capital." *Journal of Accounting Research* 39 (1): 135-176.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, “Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior” *American Economic Review* 85, 1088-1105.

Harris, M. and A. Raviv, 1993, “Differences of Opinion Make a Horse Race,” *Review of Financial Studies* 6, 473-506.

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

Jones, S., D. Lee, and E. Weis, 1999, "Herding and Feedback Trading by Different Types of Institutions and the Effects on Stock Prices," working paper, Indiana University – Indianapolis Campus, Kennesaw State University, and Merrill Lynch.

Kraus, Alan and Hans R. Stoll, 1972, "Parallel Trading by Institutional Investors," *Journal of Financial and Quantitative Analysis* 7, 2107-2138.

Lakonishok, Josef, Andrei Shleifer and Robert W. Vishny, 1992, "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics*, 312, 23-43.

Lee, C.M.C., and M.J. Ready, 1991, "Inferring Trade form Intraday data," *Journal of Finance*, 46, 733-746

Merton, Robert C., 1987, "A Simple Model of Capital Market Equilibrium with Incomplete Information," *Journal of Finance* 42, 483-510

Miller, E.M., 1977, "Risk, Uncertainty, and Divergence of Opinion," *Journal of Finance*, 32, 1151-1168.

Mood, A., 1940, "The Distribution Theory of Runs," Annals of Mathematical Statistics, 11, 367-392

Nofsinger, John R., and Richard W. Sias, 1999, "Herding and Feedback Trading by Institutional Investors", *Journal of Finance*, 54, 2263-2316.

Oehler, Andreas and George Goeth-Chi Chao, 2002, "Institutional Herding in Bond Markets," Working Paper, SSRN

Pirinsky, C., 2002, "Herding and Contrarian Trading of Institutional Investors," Working Paper, Texas A&M University.

Snyder, D. L., 1975, *Random Point Processes*, John Wiley & Sons, New York

Scharfstein, David and Jeremy Stein, 1990, "Herd Behavior and Investment," *American Economic Review*, 80, 465-479.

Shalen, C.T., 1993, "Volume, Volatility, and the Dispersion of Beliefs," *Review of Financial Studies* 6, 405-434.

Sias, Richard, W., "Institutional Herding," 2003, Forthcoming, *Review of Financial Studies*.

Sias, R., L. Starks, and S. Titman, 2001, "The Price Impact of Institutional Trading," Working Paper, Washington State University and The University of Texas.

Strozinsky, R., 1998, "Inside the Stock Market," Website (www.stanford.edu/~stoz/)

Teo, Melvin, and Sung-Jun Woo, 2002, "Style Effects," Working Paper, Harvard University

Truemann, B., 1994, "Analysts Forecasts and Herding Behavior", *Review of Financial Studies* 7, 97-124.

Varian, Hal R., 1985, "Divergence of Opinion in Complete Markets: A Note," *Journal of Finance* 40, 309-317

Wallis, W., and H. Roberts, 1956, "Statistics: A New Approach," Free Press, New York

Welch, Ivo, 1992, "Sequential Sales, Learning, and Cascades", *Journal of Finance* 47, 695-732.

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

Figure I:S&P 500 AND NASDAQ COMPOSITE DURING 1998-2001

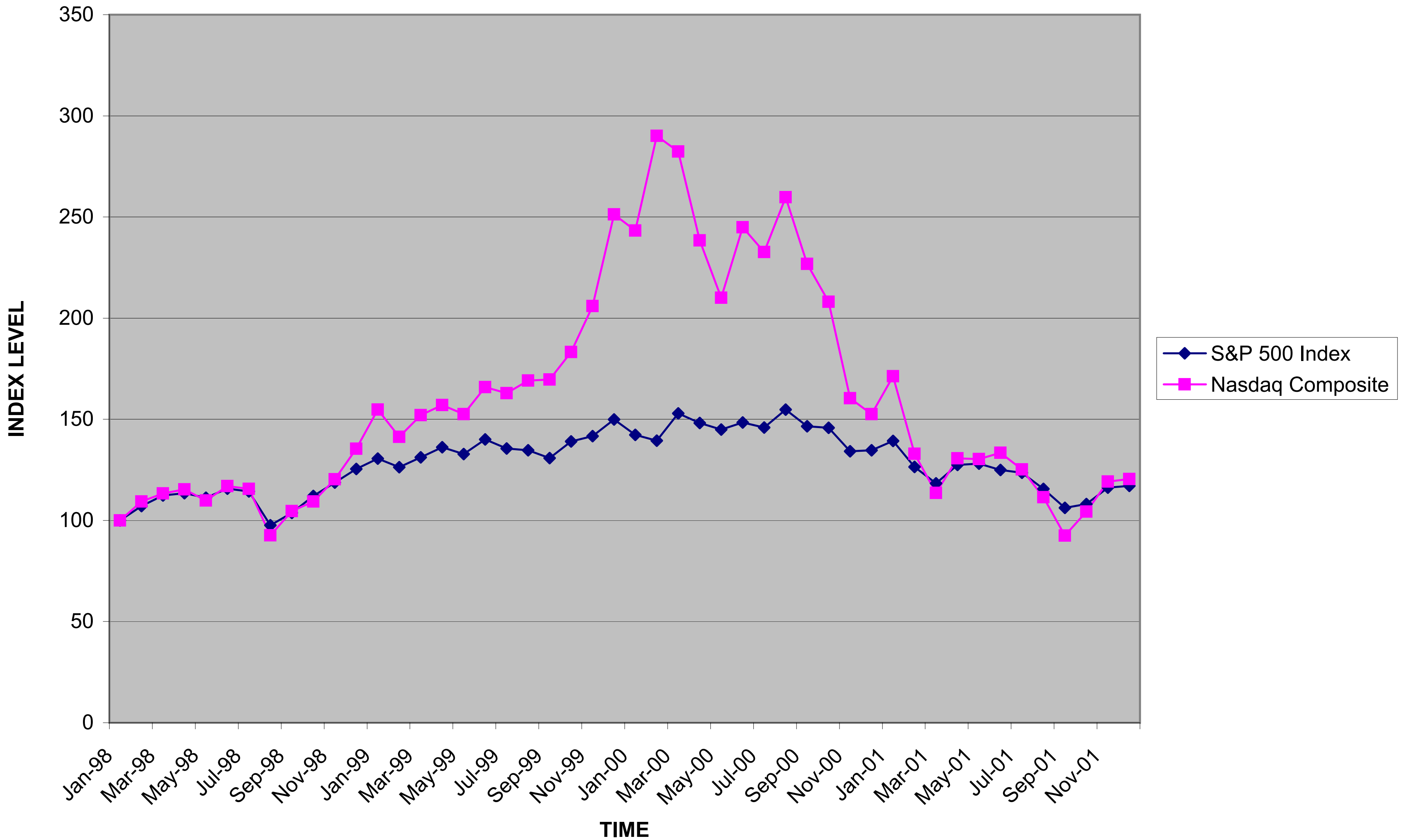

Table I
Descriptive Statistics

To construct our sample, we first randomly select 200 (50 from each year) days in the sample period of 1998-2001. Then we categorize the NYSE common stocks into top, middle and bottom deciles in terms of daily returns. For further analysis, we randomly select 20 stocks with at least 200 trades from each of the categories (top and bottom deciles). Thus for each randomly selected trading day, we have 40 stocks. Using the trade by trade data from TAQ for each of these firms, we calculate the herding intensity. In panel A, size refers to previous day market capitalization (shares outstanding X price) of firms in $ billions. Similarly price is the closing price on the previous day of trading from CRSP files. Trade size data are extracted from TAQ files for our firm. We only select those firms, which had 200 or more trades. Panel B reports the mean daily return (in %) for each return deciles. The t-statistics for returns are reported in parentheses under mean returns. Also reported is mean return (t-statistic) on the S&P 500 Index for our randomly selected days.

Panel A

Return Deciles	Stock-Days	Size ($Billions)		Price ($/Share)		Trade Size (Shares/Trade)	
		Mean	Median	Mean	Median	Mean	Median
Top	4000	9.994	2.587	33.586	28.844	1008	506
Bottom	4000	10.991	2.902	33.778	28.938	1041	503

Panel B

Return Deciles	Stock-Days	Return (%)
Top	4000	6.180 (54.27)
Bottom	4000	-5.443 (-73.69)
Return on S&P 500 Index		-0.052 (-2.56)

Table II
Overall Herding

The herding intensity H (i, j, t,) of type of run i (buyer or seller initiated trades) for a given stock j on day t is the z-statistic of the runs test. For top decile stocks, the z-statistic determines whether the actual total number of buyer-initiated runs is statistically different from what is expected by random chance. Similarly, for bottom decile stocks, the z-statistic determines whether the actual total number of seller-initiated runs is statistically different from what is expected by random chance. It should be noted that the smaller the herding intensity in magnitude, the greater is herding. First, we randomly select 200 (50 from each year) days in the sample period of 1998-2001. Then we categorize the NYSE common stocks into top and bottom deciles in terms of daily returns. For further analysis, we randomly select 20 stocks with at least 200 trades from each of the categories (top and bottom deciles). Thus for each randomly selected trading day, we have 40 stocks. Using the trade-by-trade data information from TAQ, we calculate the H (i, j, t,) and average across return deciles. Panel A separates zero-tick trades from buyer-initiated and seller-initiated trades. Panel B combines zero-tick trades with buyer- initiated or seller-initiated trades by comparing the current trade price with last different trade price. The critical values for Panel A and Panel B are computed separately using Monte-Carlo simulation method as described in the text. The median herding intensity is reported in parentheses under mean herding intensity. In Panel C, we regress inter-arrival time between each trade on lag inter-arrival time for each stock-day in each decile. Correlation reported is the average (median) beta slope from the regression equation for each stock-day. The t-statistic for the mean of slope coefficients is computed from the standard errors of regression coefficients. All mean correlations are statistically significant at 1%.

Panel A: Herding with Zero-ticks separted from Buyer & Seller initiated trades

Return Deciles	Stock-Days	Herding Intensity
Top	4000	2.520 (1.997)
Bottom	4000	2.221 (1.746)

Fraction of Herding Intensity Lower than one-tailed critical values		
	1%	5.00%
Top Decile	3.09%	7.85%
Bottom Decile	6.16%	15.25%

Panel B: Herding with zero-ticks trades grouped with Buyer & Seller initiated trades

Return Deciles	Stock-Days	Herding Intensity
Top	4000	-8.666 (-7.997)
Bottom	4000	-9.431 (-8.541)

Fraction of Herding Intensity Lower than one-tailed critical values		
	1%	5.00%
Top Decile	12.81%	16.16%
Bottom Decile	14.83%	18.88%

Panel C :Correlation Between Inter-Arrival Times of Trade

Return Deciles	Stock-Days	Mean Corrleation
Top	4000	0.118 ((0.1141)
Bottom	4000	0.117 (0.1142)

Fraction of Correlation Significant at the one-tailed critical values		
	1%	5%
Top Decile	61.80%	76.700%
Bottom Decile	61.37%	75.106%

Table III
Herding Based on Lag-Size

The herding intensity H (i, j, t,) of type of run i (buyer or seller initiated trades) for a given stock j on day t is the z-statistic of the runs test. For top decile stocks, the z-statistic determines whether the actual total number of buyer-initiated runs is statistically different from what is expected by random chance. Similarly, for bottom decile stocks, the z-statistic determines whether the actual total number of seller-initiated runs is statistically different from what is expected by random chance. It should be noted that the smaller the herding intensity in magnitude, the greater the herding. First, we randomly select 200 (50 from each year) days in the sample period of 1998-2001. Then we categorize the NYSE common stocks into top and bottom deciles in terms of daily returns. For further analysis, we randomly select 20 stocks with at least 200 trades from each of the categories (top and bottom deciles). Thus for each randomly selected trading day, we have 40 stocks. Using the trade-by-trade data information from TAQ, we calculate the H (i, j, t,) in each stock-day in both deciles. To compute herding based on size we classify all stocks in our sample into quintiles on the basis of lagged NYSE size (market capitalization) break points and updated daily. The H (i, j, t) are averaged across each quintile for mean herding intensity. The median herding intensity is reported in parentheses under mean herding intensity. Panel A separates zero-tick trades from buyer-initiated and seller-initiated trades. Panel B combines zero-tick trades with buyer- initiated or seller-initiated trades by comparing the current trade price with last different trade price. The critical values Panel A and Panel B are computed separately using Monte-Carlo simulation method as described in the text. In Panel C, we regress inter-arrival time between each trade on lag inter-arrival time for each stock-day in each decile. Correlation reported is the average beta slope from the regression equation for each stock-day in each size quintile. The t-statistic for the mean of slope coefficients is computed from the standard errors of regression coefficients. All mean correlations are statistically significant at 1%.

Panel A: Herding with Zero-ticks separted from Buyer & Seller initiated trades				
Size Quintile	**Top Decile**		**Bottom Decile**	
	Stock-Days	**Herding Intensity**	**Stock-Days**	**Herding Intensity**
S1 (Smallest)	156	1.632 (1.437)	158	1.278 (1.137)
S2	414	1.221 (1.142)	329	1.222 (1.184)
S3	688	1.224 (1.189)	713	1.222 (1.148)
S4	1269	1.471 (1.288)	1176	1.548 (1.370)
S5 (Largest)	1473	3.120 (2.277)	1623	3.188 (2.398)

Panel B: Herding with zero-tick trades grouped with Buyer & Seller initiated trades				
Size Quintile	**Top Decile**		**Bottom Decile**	
	Stock-Days	**Herding Intensity**	**Stock-Days**	**Herding Intensity**
S1 (Smallest)	156	-7.026 (-6.389)	158	-6.796 (6.464)
S2	414	-6.736 (-6.359)	329	-7.080 (-6.509)
S3	688	-7.180 (_6.745)	713	-7.617 (-7.192)
S4	1269	-8.407 (-7.842)	1176	-8.834 (-8.139)
S5 (Largest)	1473	-10.249 (-9.474)	1623	-11.373 (-10.390)

Panel C: Correlation Between Inter-Arrival times of trade				
Size Quintile	Top Decile		Bottom Decile	
	Stock-Days	Mean Correlation	Stock-Days	Mean Correlation
S1 (Smallest)	156	0.122	158	0.127
S2	414	0.119	329	0.126
S3	688	0.115	713	0.116
S4	1269	0.122	1176	0.114
S5 (Largest)	1473	0.114	1623	0.116

Table IV
Herding Based on Share Turnover

The herding intensity H (i, j, t,) of type of run i (buyer or seller initiated trades) for a given stock j on day t is the z-statistic of the runs test. For top decile stocks, the z-statistic determines whether the actual total number of buyer-initiated runs is statistically different from what is expected by random chance. Similarly, for bottom decile stocks, the z-statistic determines whether the actual total number of seller-initiated runs is statistically different from what is expected by random chance. It should be noted that the smaller the herding intensity in magnitude, the greater is herding. First, we randomly select 200 (50 from each year) days in the sample period of 1998-2001. Then we categorize the NYSE common stocks into top and bottom deciles in terms of daily returns. For further analysis, we randomly select 20 stocks with at least 200 trades from each of the categories (top and bottom deciles). Thus for each randomly selected trading day, we have 40 stocks. Using the trade-by-trade data information from TAQ, we calculate the H (i, j, t,). To compute herding based on share turnover, we classify H (i, j, t) for all stocks in our sample of different return deciles, into quintiles on the basis of share turnover. Then H (i, j, t,) are averaged across each share turnover quintile. The median herding intensity is reported in parentheses under mean herding intensity Panel A separates zero-tick trades from buyer-initiated and seller-initiated trades. Panel B combines zero-tick trades with buyer-initiated or seller-initiated trades by comparing the current trade price with last different trade price. The critical values for Panel A and Panel B are computed separately using Monte-Carlo simulation method as described in the text. In Panel C, we regress inter-arrival time between each trade on lag inter-arrival time for each stock-day in each decile. Correlation reported is the average beta slope from the regression equation for each stock-day in each share turnover quintile. The t-statistic for the mean of slope coefficients is computed from the standard errors of regression coefficients. All mean correlations are statistically significant at 1%.

Panel A: Herding with Zero-ticks separted from Buyer & Seller initiated trades				
Share Turnover Quintile	**Top Decile**		**Bottom Decile**	
	Stock-Days	**Herding Intensity**	**Stock-Days**	**Herding Intensity**
ST1 (Lowest)	800	2.506 (1.987)	800	2.251 (1.792)
ST2	800	2.404 (1.872)	800	2.183 (1.773)
ST3	800	2.239 (1.779)	800	2.053 (1.702)
ST4	800	2.430 (1.996)	800	2.040 (1.694)
ST5 (Highest)	800	3.022 (2.385)	800	2.579 (1.804)

Panel B: Herding with zero-tick trades grouped with Buyer & Seller initiated trades				
Share Turnover Quintile	**Top Decile**		**Bottom Decile**	
	Stock-Days	**Herding Intensity**	**Stock-Days**	**Herding Intensity**
ST1 (Lowest)	800	-7.784 (-7.342)	800	-8.011 (-7.475)
ST2	800	-8.238 (-7.638)	800	-8.793 (-8.091)
ST3	800	-8.491 (-7.784)	800	-9.233 (-8.461)
ST4	800	-8.667 (-8.277)	800	-9.580 (-8.926)
ST5 (Highest)	800	-10.058 (-9.116)	800	-11.490 (-10.231)

Panel C: Correlation Between Inter-Arrival Time Between Trades				
Share Turnover Quintile	**Top Decile**		**Bottom Decile**	
	Stock-Days	**Mean Correlation**	**Stock-Days**	**Mean Correlation**
ST1 (Lowest)	800	0.101	800	0.093
ST2	800	0.106	800	0.103
ST3	800	0.115	800	0.126
ST4	800	0.128	800	0.122
ST5 (Highest)	800	0.138	800	0.141

Table V
Herding Based on Analysts' Recommendations

The herding intensity H (i, j, t,) of type of run i (buyer or seller initiated trades) for a given stock j on day t is the z-statistic of the runs test. For top decile stocks, the z-statistic determines whether the actual total number of buyer-initiated runs is statistically different from what is expected by random chance. Similarly, for bottom decile stocks, the z-statistic determines whether the actual total number of seller-initiated runs is statistically different from what is expected by random chance. It should be noted that the smaller the herding intensity in magnitude, the greater is herding. First, we randomly select 200 (50 from each year) days in the sample period of 1998-2001. Then we categorize the NYSE common stocks into top and bottom deciles in terms of daily returns. For further analysis, we randomly select 20 stocks with at least 200 trades from each of the categories (top and bottom deciles). Thus for each randomly selected trading day, we have 40 stocks. Using the trade-by-trade data information from TAQ, we calculate the H (i, j, t,) and average across return deciles. To compute the impact of analysts' recommendations on herding, we identify the stocks from top deciles, which were upgraded on a sample day. Similarly, we identify the stocks from bottom deciles, which were downgraded on the day of herding. We use IBES/First Call analysts' recommendations data for identification purposes. The total stock-days with and without recommendations do not add up to 4000 as only recommendation changes are included. Then we compute mean herding intensity for the group of stocks with upgrade (downgrade) and without any recommendations. The median herding intensity is reported in parentheses under mean herding intensity. Panel A separates zero-tick trades from buyer-initiated and seller-initiated trades. Panel B combines zero-tick trades with buyer- initiated or seller-initiated trades by comparing the current trade price with last different trade price. The critical values for Panel A and Panel B are computed separately using Monte-Carlo simulation method as described in the text. In Panel C, we regress inter-arrival time between each trade on lag inter-arrival time for each stock-day in each decile. Correlation reported is the average beta slope from the regression equation for each stock-day in each group of stock-days. The t-statistic for the mean of slope coefficients is computed from the standard errors of regression coefficients. All mean correlations are statistically significant at 1%.

Panel A: Herding with Zero-ticks separted from Buyer & Seller initiated trades

Return Deciles	Recommendation Type	Stock-Days	Mean Herding Intensity
Top	Upgraded Recommendations	218	2.983 (2.247)
	No Recommendation	3701	1.938 (1.460)
Bottom	Downgraded Recommendations	19	3.148 (2.362)
	No Recommendation	3643	2.036 (1.573)

Panel B: Herding with zero-tick trades grouped with Buyer & Seller initiated trades			
Return Deciles	**Recommendation Type**	**Stock-Days**	**Mean Herding Intensity**
Top	Upgraded Recommendations	218	-10.124 (-9.255)
	No Recommendation	3701	-8.539 (-7.867)
Bottom	Downgraded Recommendations	19	-11.227 (-11.346)
	No Recommendation	3643	-9.161 (-8.364)

Panel C: Correlation Between Inter-Arrival time of trades			
Return Deciles	**Recommendation Type**	**Stock-Days**	**Mean Correlation**
Top	Upgraded Recommendations	218	0.146
	No Recommendation	3701	0.116
	Downgraded Recommendations	19	0.099
Bottom	No Recommendation	3643	0.116

Table VI
Price Impact versus Information Based Herding

The herding intensity H (i, j, t,) of type of run i (buyer or seller initiated trades) for a given stock j on day t is the z-statistic of the runs test. For top decile stocks, the z-statistic determines whether the actual total number of buyer-initiated runs is statistically different from what is expected by random chance. Similarly, for bottom decile stocks, the z-statistic determines whether the actual total number of seller-initiated runs is statistically different from what is expected by random chance. It should be noted that the smaller the herding intensity in magnitude, the greater the herding. First, we randomly select 200 (50 from each year) days in the sample period of 1998-2001. Then we categorize the NYSE common stocks into top and bottom deciles in terms of daily returns. For further analysis, we randomly select 20 stocks with at least 200 trades from each of the categories (top and bottom deciles). Thus for each randomly selected trading day, we have 40 stocks. Using the trade-by-trade data information from TAQ, we calculate the H (i, j, t,) and average across return deciles. Using the trade-by-trade data from TAQ, we calculate the H (i, t). for each stock in three return deciles. To compute impact of herding on stock returns, we first compute contemporaneous (AR_c), 1 day ahead (AR_{a1}), 2 days ahead (AR_{a2}) and 3 days ahead (AR_{a3}) abnormal return for each stock. To calculate abnormal returns, we subtract the same day return on a value weighted portfolio of all stocks included in NYSE/AMEX/NASDAQ from stock's return. Then we classify H (i, j, t) for all stocks in our sample of different return deciles, into quintiles and take the average of them. The *, **, and *** represent abnormal returns statistically significant at 1%, 5%, and 10%. For abnormal mean, we use t-test and for abnormal median, sign-rank test. Panel A separates zero-tick trades from buyer-initiated and seller-initiated trades. Panel B combines zero-tick trades with buyer- initiated or seller-initiated trades by comparing the current trade price with last different trade price. The critical values for herding statistic for Panel A and Panel B are computed separately using Monte-Carlo simulation method as described in the text. In Panel C, we regress inter-arrival time between each trade on lag inter-arrival time for each stock-day in each decile. Correlation reported is the average beta slope from the regression equation for each stock-day in each correlation quintile. The t-statistic for the mean of slope coefficients is computed from the standard errors of regression coefficients. All mean correlations are statistically significant at 1%.

Panel A: Herding with Zero-ticks separted from Buyer & Seller initiated trades											
Top Return Decile											
Herding Quintile	**Stock-Days**	**H (i,j,t)**		**AR_c**		**AR_{a1}**		**AR_{a2}**		**AR_{a3}**	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
H1 (Highest)	798	-0.004 *	0.156 **	6.258 *	4.643 *	0.294 **	0.064	-0.123	-0.213	0.025	0.090
H2	799	0.930	0.937	6.122 *	4.877 *	0.059	-0.275	-0.027	-0.258 **	-0.348 **	-0.238 **
H3	798	1.498	1.490	6.053 *	4.873 *	0.145	-0.093	-0.223	-0.257 **	-0.066	-0.228
H4	799	2.277	2.230	6.231 *	4.791 *	0.113	-0.276	0.100	-0.194	-0.145	-0.332 **
H5 (Lowest)	798	5.336	4.422	6.322 *	4.885 *	0.256	-0.125	-0.278 ***	-0.219 *	-0.255	-0.160

Bottom Return Decile												
Herding Quintile	Stock-Days	H (i,j,t)		AR_c		AR_{a1}		AR_{a2}		AR_{a3}	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
H1 (Highest)	797	0.172	0.341	-5.581	-4.415	0.114	0.101	0.030	0.068	0.038	0.016
		**	**	*	*						
H2	798	1.043	1.046	-5.437	-4.306	0.124	-0.104	-0.262	-0.413	-0.020	-0.162
				*	*				**		
H3	797	1.608	1.608	-5.326	-4.298	0.314	0.070	0.126	-0.070	0.208	0.106
				*	*	***					
H4	798	2.380	2.359	-5.221	-4.158	-0.138	-0.103	0.127	-0.170	0.137	-0.159
				*	*						
H5 (Lowest)	797	5.400	4.418	-5.440	-4.184	-0.026	-0.099	-0.081	-0.133	0.211	-0.061
				*	*						

Panel B: Herding with zero-tick trades gruped with Buyer & Seller initiated trades											
Top Return Decile											
Herding Quintile	Stock-Days	H (i,j,t)		AR_c		AR_{a1}		AR_{a2}		AR_{a3}	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
H1 (Highest)	798	-14.444	-12.928	6.472	4.923	0.162	-0.112	-0.301	-0.330	-0.244	-0.329
		*	*	*	*			**	*	***	*
H2	799	-9.785	-9.719	6.114	4.836	0.141	0.003	0.230	-0.061	-0.340	-0.135
				*	*					**	***
H3	798	-7.993	-7.978	6.185	4.765	0.148	-0.126	-0.263	-0.421	-0.174	-0.097
				*	*			**	*		
H4	799	-6.515	-6.550	6.224	4.734	0.362	-0.125	0.005	-0.040	-0.026	-0.241
				*	*	**					
H5 (Lowest)	798	-4.521	-4.759	5.991	4.856	0.055	-0.278	-0.223	-0.257	-0.008	-0.038
				*	*				**		

Bottom Return Decile												
Herding Quintile	**Stock-Days**	**H (i,j,t)**		**AR_c**		**AR_{a1}**		**AR_{a2}**		**AR_{a3}**	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
H1 (Highest)	797	-16.336 *	-14.463 *	-6.163 *	-4.654 *	0.053	-0.191	-0.075	-0.136	0.175	-0.077
H2	798	-10.687	-10.661	-5.320 *	-4.279 *	0.127	0.202	-0.267 **	-0.271 **	0.189	-0.041
H3	797	-8.567	-8.516	-5.262 *	-4.162 *	-0.136	-0.151	-0.005	-0.094	0.439 *	0.133 **
H4	798	-6.848	-6.863	-5.187 *	-4.044 *	0.219	0.072	0.226	-0.084	0.050	-0.094
H5 (Lowest)	797	-4.697	-4.874	-5.072 *	-4.225 *	0.125	-0.043	0.061	-0.160	-0.281	-0.280 **

Panel C: Correlation Between Inter-Arrival time of trades											
Top Return Decile											
Correlation Quintile	**Stock-Days**	**Mean Correlation**	**AR_c**		**AR_{a1}**		**AR_{a2}**		**AR_{a3}**	
		Mean	Mean	Median	Mean	Median	Mean	Median	Mean	Median
C1 (Lowest)	798	0.008 *	5.613 *	4.531 *	-0.112	-0.116	0.010	-0.039	-0.054	-0.104
C2	799	0.077 *	5.946 *	4.501 *	0.382 **	0.065	-0.327 **	-0.237 *	-0.086	-0.062
C3	798	0.115 *	5.799 *	4.842 *	0.079	-0.120	-0.077	-0.192 ***	-0.263 ***	-0.161 **
C4	799	0.153 *	6.232 *	5.075 *	0.207	-0.283	0.300	-0.346	-0.263	-0.396 *
C5 (Highest)	798	0.235 *	7.397 *	5.354 *	0.312 **	-0.130	-0.458 **	-0.313 **	-0.125	-0.123

Bottom Return Decile											
Correlation Quintile	**Stock-Days**	**Mean Correlation**	**AR_c**		**AR_{a1}**		**AR_{a2}**		**AR_{a3}**	
		Mean	Mean	Median	Mean	Median	Mean	Median	Mean	Median
C1 (Lowest)	797	0.008 *	-5.122 *	-4.034 *	-0.206	-0.104	-0.006	-0.057	0.089	0.064
C2	798	0.076 *	-4.863 *	-4.041 *	0.246	0.292 **	0.209	-0.004	-0.102	-0.192
C3	797	0.114 *	-5.408 *	-4.300 *	0.033	-0.050	-0.188	-0.312 **	-0.023	-0.257
C4	798	0.152 *	-5.606 *	-4.384 *	-0.032	-0.105	0.018	-0.154	0.449 *	-0.038
C5 (Highest)	797	0.235 *	-6.006	-4.637	0.347 ***	-0.057	-0.093	-0.288 ***	0.160	0.036

Vita

Vivek Sharma has an MBA from Indian Institute of Management, Lucknow (1992) and a B.Tech (Hons.) from Indian Institute of Technology, Kharagpur (1989). He worked for two years in the area of credit control and project management with companies like Tata Steel and Shriram Enterprises in India. After that, he taught finance at the MBA level at Birla Institute of Management Technology. He was also associated with the Chartered Financial Analyst Program in India. For almost five years he taught finance and accounting for the University of London in Singapore. During the summer of 2000, he worked as a Financial Consultant, designing "Financial Management Framework" for Info-Comm. Development Authority of Singapore. He has taught Investments, Derivative Pricing and International Finance to senior students at the Pamplin College of Business. His current areas of interest are investments and derivatives pricing.