TWO ESSAYS ON INSTITUTIONAL INVESTORS

by

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ABSTRACT

This dissertation consists of two essays investigating the trading by institutions and its impact on the stock market.

In the first essay, I investigate why changes in institutional breadth predict return. I first show that changes in breadth are positively associated with abnormal returns over the following four quarters. I then demonstrate that this return predictability can be attributed to the information about the firms' future operating performance. When I examine different types of institutions independently, I find that the predictive power varies across the population of institutions. More specifically, institutions that follow active management style are better able to predict future returns than the passive institutions, and their predictive power appears to be associated with information about future earnings growth. These findings are consistent with the information hypothesis that changes in breadth of institutional ownership can predict return because they contain information about the fundamental value of firms.

In the second essay, I examine institutional herding behavior and its impact on stock prices. I document that herds by institutions usually last for more than one quarter and that herds occur more frequently for small and medium size stocks. I find that after herds end, there are reversals in stocks returns for up to four quarters. The magnitude of reversals is positively related to the duration of herding, and negatively related to the price impact of current herding activity. This pattern in returns prevails for all sub-periods examined and is concentrated in small and medium size stocks. My findings suggest that institutional herding may destabilize stock prices.

To

my caring parents, Huy Nguyen and Lan Nguyen

my beloved wife, Thuy Nguyen

my daughter, Phuong Nguyen, and the newborn baby girl Linh Nguyen

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CHAPTER ONE: INTRODUCTION

Institutions are long believed to be sophisticated investors whose trading contains information about future performance of stocks. As the number of institutions and the size of the assets under their management increase significantly over time, their trading could influence stock prices through its impact on the market supply and demand. Therefore, it is important to understand the institutional trading behavior and its relation with stock returns.

It is documented in the literature that current aggregate trading by institutions could predict the future stock returns for up to four quarters. In the following chapter, I evaluate three hypotheses that could potentially explain this returns predictability, namely short sale constraint, information and investor recognition. Taking advantage of the relation between stock returns and the future operating performance of firms, I document that return predictability appears to be associated with the superior information institutions possess at the time they trade.

In the second part of the dissertation, I examine the tendency that institutions follow each other in their trades, or herd in trades. This behavior could increase the volatility of stock prices, especially, when herds are not associated with information. So far, the literature has focused on the trading by institutions within a single quarter and found very limited evidence for such behavior. Employing a time dependent technique to identify herds, I find that it is common for institutions to engage in multi-quarter herds and that herding may destabilize stocks prices.

CHAPTER TWO: CHANGES IN BREADTH OF OWNERSHIP AND INFORMATION

2.1. Introduction

Several recent studies have documented that changes in institutional ownership can predict returns for up to twelve months. For example, Wermers (1999) documents that stocks that mutual funds buy outperform stocks they sell by four percent during the following six months. Chen, Jegadeesh, and Wermers (2000) find that a strategy to short stocks that mutual funds sell most and long stocks they buy most generates an abnormal return of six percent in the next four quarters. Chen, Hong, and Stein (2002) document that future stock returns and changes in breadth of mutual fund ownership are positively correlated, and that the difference in 12-month returns between stocks with the largest increases and those with the largest reductions in breadth is about five percent.[1]

While the return predictability by changes in institutional ownership in general, and by changes in institutional breadth in particular, is not subject to much controversy, there is no agreement on the reason for this predictive power. Three different explanations have been proposed. The information explanation is formed naturally on the extensive literature on the sophistication of institutional investors.[2] Formally, it proposes that because institutions are smart and trade on information about firm, changes in their ownership predict return. The second explanation is proposed by Lehavy and Sloan (2005) who argue that return predictability by changes in institutional breadth is due to the combination of Merton (1987)'s investor recognition

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[1] Breadth of institutional ownership is defined as the proportion of the universe of institutions holding a long position in a particular stock.
[2] See Sias, Starks, and Titman (2006), Chen, Jegadeesh, and Wermers (2000), and Gibson, Safieddine, and Sonti (2004) for discussion on institutions' sophistication.

effect and the autocorrelation in changes in breadth. They document that after controlling for the future changes in institutional ownership, current changes in breadth is negatively related to future returns. Finally, Chen, Hong, and Stein (2002) attribute this predictability to the potential impact that changes in breadth have on the short sale constraint on a stock. However, they explicitly acknowledge the possibility that the information advantages of institutions can be the reason behind the observed results. In this paper, I investigate this possibility, and try to distinguish the three different hypotheses. Specifically, I simultaneously examine return of stocks and operating earnings growth of firms around the quarter of changes in breadth.

There are advantages with the inclusion of earnings growth in my analysis. In fact, neither the short-sale constraint explanation by Chen, Hong, and Stein (2002) nor the investors-recognition argument by Lehavy and Sloan (2005) implies that changes in institutional ownership should have any direct effect on the future operating performance of firms. Conversely, the information hypothesis argues that institutions enter stocks of firms with better future performance and exit stocks of firms with poor prospects. Therefore, this hypothesis predicts a positive relation between changes in breadth and the firms' future operating performance. Thus, I expect that operating earnings growth can serve as an effective benchmark that helps me to distinguish information hypothesis from others.

Moreover, the inclusion of earnings growth provides us with a better understanding of the complicated relation between institutional trading and future returns. On one hand, institutions are believed to be sophisticated, which implies that their trading should be able to predict returns. On the other hand, institutions are documented to herd their own trades and the trades of others (see Sias, 2004, and Grinblatt, Titman, and Wermers, 1995), and the price pressure from herding can also result in return predictability. For example, if an institution enters (exits) a stock, others may follow to buy (sell) and thus push the stock price up (down) in the way predicted by the initial trade. Therefore, the causality question of whether expected returns make institutions trade or institutional trading moves prices can hardly be distinguished if I use stock returns alone. Unlike stock returns, earnings are not affected by trading activities and therefore they can be used to resolve the above causality problem. Specifically, if future earnings are found to be positively associated with changes in breadth, it will be evident that changes in breadth contain information. Moreover, as earnings are a fundamental source for returns, if both returns and future earnings show positive relations with changes in breadth, I am in a better position to argue that the return predictability is caused by information.

My findings support the information hypothesis. I document that changes in breadth, when applied to the universe of institutions, preserves its return predictive power, which is consistent with the findings of mutual funds in Chen, Hong, and Stein (2002). In the four quarters following the changes in breadth, on average, stocks in the highest decile of changes in breadth outperform the size/book-to-market/momentum benchmark portfolios by 2.38%, while those in the lowest decile underperform their benchmarks by 2.44%, leaving a difference of 4.82%. When the sample is partitioned based on market capitalization, the difference in returns is more pronounced for small and medium firms than for large firms.

I find evidence for the argument that institutions trade on information about future operating performance. Specifically, during the year of changes in breadth and the year after, stocks in the highest decile of changes in breadth outperform those in the lowest decile in terms of operating earnings growth by 1.48% and 1.97%, respectively. Moreover, in these two years, stocks in the top decile outperform their benchmark portfolios by 0.13% and 0.35%, while those in the bottom decile underperform their peers by 0.09% and 0.69%. Also, similar to the difference in returns, the difference in earnings growth between the two extreme deciles is systematically larger for small and medium size stocks than for large stocks.

I document that changes in breadth lose their predictive power once I control for the future earnings growth of firms in regression analysis. This result confirms the information argument that institutions can predict returns because they trade on information about future operating performance of firms. Thus, in the presence of the original source of information, the forecast value of changes in breadth is absorbed.

Next, I attempt to distinguish the two hypotheses by relying on the difference in the implication about variation in the ability of different institutions to predict returns. In Chen, Hong, and Stein's (2002) model, mutual funds are identical in terms of the short sale constraints they face. Therefore, there should be no difference in the predictive power of different types of institutions. If I allow for the possibility that mutual funds/institutions may face different degrees of short sale constraints, the model should predict that changes in the breadth of the institutions that are more likely to be short sale-constrained should be better able to predict returns. The information explanation, which allows for differential ability among institutions, predicts instead that the institutions that are more likely to be skilled should be better able to predict returns.

I first classify institutions based on their portfolio turnover ratios. Almazan, Brown, Carlson, and Chapman (2004) document that about one-third of mutual funds are allowed to take short positions. They also find that funds with higher turnover ratios are less likely to be constrained. The short sale constraint hypothesis should therefore predict that changes in breadth of institutions with high turnover ratios should have less ability to predict returns. On the other hand, the information hypothesis predicts that changes in breadth of high-turnover institutions, whose managers are supposed to be better informed (Chen, Jegadeesh, and Wermers, 2000, and Yan and Zhang, 2006), should have better predictive power.

Consistent with the information hypothesis, I find that changes in breadth of high-turnover institutions have greater predictive power over returns. In contrast, changes in breadth of low-turnover institutions exhibit no ability to predict returns. More importantly, when I examine how current changes in breadth are related to past and future abnormal earnings growth, I find that lower-turnover institutions appear to herd on past and contemporaneous growth, while high-turnover institutions seem to be more concerned about future information, lending additional support for the information hypothesis.

I then examine the relative predictive power of five types of institutions as classified by Thompson Financial. This examination is motivated by the fact that changes in breadth of ownership could also be related to the number of shares available in the lending market. Asquith, Pathak, and Ritter (2005) document that short sale constraints depend not only on the demand to sell stocks short, but also on the supply of lendable shares. They suggest that the return predictability documented by Chen, Hong, and Stein (2002) could also result from institutions being willing suppliers in the short sale market. Nagel (2005) suggests that passive institutions such as insurance companies, pension funds, and bank trusts, which tend to have large and long-duration holdings, are the most active lenders and hence their ownership should have a more important impact on the constraints binding a stock. I argue that if short sale constraints are the underlying factor behind return predictability via the effect of changes in breadth on lendable shares, declines (increases) in the breadth of passive institutions will force short sale constraints to bind more (less) tightly, and therefore the return predictability for such institutions should be more pronounced than that for active institutions such as investment companies and investment advisors. The information hypothesis, in contrast, suggests that changes in breadth of investment companies and investment advisors who are supposed to possess better stock-picking skills (Almazan, Hartzell, and Starks, 2005, Bennett, Sias, and Starks, 2003, and Del Guercio, 1996) should exhibit stronger predictive power. Consistent with the information hypothesis, I find that the positive relation between changes in breadth and stock returns is significant only for investment companies and investment advisors. In the four quarters following the changes, portfolios with the largest increases in breadth significantly outperform those with the largest reductions by 3.65% for this group of institutions.

My study extends the current literature on institutional investors in several ways. Most importantly, the paper presents an answer to the debate over the reason behind the return predictability by changes in institutional ownership. My results are most consistent with the information hypothesis, that is, these changes can predict returns because institutions trade on information about the future performance of firms. In terms of the difference in performance among institutions, my paper adds evidence to confirm that institutions are not the same in their ability to predict returns. In fact, trading by active institutions appears to contain more information about future stock returns and about the firms' future operating performance than trading by passive entities. Finally, with respect to the debate over the impact of institutions on market efficiency, my paper supports the argument that institutions enhance the efficiency by trading on information.

The balance of this study is organized as follows. In section 2.2, I review the literature on the relation between changes in institutional ownership and stock returns, and discuss different hypotheses on the return predictability by changes in breadth. In section 2.3, I describe the data sources and the methodology. Section 2.4 documents abnormal performance after changes in breadth of ownership. Section 2.5 reports the regression results on return predictability and earnings growth information. Section 2.6 documents variation in performance predictability by changes in breadth across different types of institutions. Concluding remarks are presented in Section 2.7.

2.2. Literature Review on Institutional Investors

Institutions are long believed to be more sophisticated than individual investors. While the evidence for this can be found in different areas of research, such as the advantage of institutions in gathering and processing information (Lev, 1988, Kim and Verrecchia, 1994) or the performance of institutions around firm specific events (Gibson, Safieddine, and Sonti, 2004, Cohen, Gompers, and Vuolteenaho, 2002), I focus my review on the relation between general trading by institutions and stock returns.

2.2.1. Institutional trading and the contemporaneous returns

Nofsinger and Sias (1999) investigate the cross-sectional relation between aggregate trading by institutions and stock returns and find a positive relation between changes in holding and returns over the 12-month window. They attribute this relation to institutional herding. Further analysis demonstrates that this relation is not irrationally caused by intra-period herding pressure since there is no evidence of return reversals in the two years following the year of changes in institutional holdings. Moreover, stocks that institutions purchase subsequently outperform those they sell, and the difference in returns between these stocks is not fully explained by the momentum strategies. Specifically, even for the extreme past winners (losers), future returns are negative (positive) when they are sold (purchased) by institutions. Examining daily data, they document the same contemporaneous relation between daily trades and the same day returns. They conclude that 'the result is consistent with the hypothesis that institutional investors, at the margin, are better informed than other investors'. Sias (2004) further examines the rational herding behavior of institutional investors and shows that demand by institutions in a given quarter can be decomposed into portions caused by either herding in their past trades or herding in others' trades. Moreover, as trading by institutions is strongly correlated with contemporaneous returns and as future returns do not show any reversal, he suggests that institutions follow information revealed from each others' trades and that herding is primarily related to the way information diffuses. In other words, the positive relation between trading by institutions and contemporaneous returns originates from the information contained in their activities. In an attempt to clarify the source of this contemporaneous relation, Sias, Starks, and Titman (2006) decompose the quarterly correlation between returns and institutional trading into correlations in higher frequency such as monthly or weekly. They find that the positive relation observed in quarterly intervals arises from the positive contemporaneous relations in monthly and even weekly windows, suggesting that the direct effect of institutional trading is the main factor underlying the contemporaneous relation observed in the quarterly and annually windows. When using changes in number of institutions and changes in aggregate institutional holdings to proxy for information strength and price pressure, respectively, they find that the price impact of institutional trading has both temporary and permanent components. Moreover, because the contemporaneous returns are more strongly related to changes in the number of institutions, they conclude that information plays a central role in generating the widely-documented positive, contemporaneous relation.

The contemporaneous relation is also found in daily and intra-day trading. Examining NASDAQ 100 stocks from May 1, 2000 to February 28, 2001, Griffin, Harris, and Topaloglu

(2003) document that the contemporaneous relation persists in daily level and that institutional trading follows past returns. However, they find little evidence of price reversal, suggesting that information is the reason behind the documented relation. Chan, Chen, and Lakonishok (1995) examine trades executed by 37 large investment firms from July 1986 to December 1988. They find that institutions normally split their trade package into multi-day trades and that market impact and trading costs are associated with multi-factors, including firm size, relative package size, and the management firm itself. The contemporaneous price impacts are significant and different between buy and sell packages. On average, price reactions are stronger for buy packages than for sell packages. The overall evidence on the contemporaneous relation between the stock returns and changes in institution ownership is consistent with the information effect associated with institutions trading.

2.2.2. Changes in institutional ownership and future returns

While there is agreement that changes in institutional ownership can predict returns, there is no consensus on the reason behind this relation. There are three hypotheses proposed to explain this return predictability.

The information hypothesis states that changes in institutional ownership in general, and changes in institutional breadth in particular, can predict returns because institutions possess information advantage and trade on information about the fundamental value of firms. Wermers (1999) examines the herding behavior of mutual funds and find that funds are equally likely to herd when they buy and sell stocks and that funds are not homogeneous in their herding practice. More importantly, when analyzing the impact of trading by funds on long-term stock returns, he shows that stocks that mutual funds purchase significantly outperform those they sell in the quarter of trade and in the subsequent quarters, although this effect is concentrated in small-cap stocks. He argues that institutions are rational in their herd and that their trading contains information and helps to accelerate the price adjustment process. Chen, Jegadeesh, and Wermers (2000) examine the value of active mutual fund managers by evaluating the performance of stocks they hold and the performance of those they trade. They find that stocks that mutual funds actively buy significantly outperform those they actively sell over the quarter of trade and over the following four quarters. This result prevails for large as well as for small stocks, and for value as well as for growth stocks. Further analysis shows that growth-oriented and high-turnover funds possess better stock picking skills than income-oriented and low-turnover funds. The findings justify the value of actively money managers and support the hypothesis that they possess better stock picking ability.

Chen, Hong, and Stein (2002) develop and test a model for return predictability based on the Miller (1977) theory of short-sale constraint. Miller (1977) argues that when short sale constraint binds, only the optimists can register their belief in prices. As a result, prices are biased upward and returns are expected to decline in the future. Chen, Hong, and Stein (2002) use changes in breadth of mutual funds to proxy for short-sale constraint and find that this proxy can forecast returns for up to 12 months. Specifically, stocks that experience the largest increases (reductions) in breadth outperform (underperform) their benchmark portfolios by 2.3% (2.6%) in the following four quarters. They argue that the return predictability originates from the price impact of the short sale constraint on a stock, which is measure by the breadth of ownership. However, they explicitly acknowledge the possibility that the observed results can emerge from the stock-picking skills of the mutual funds.

The third hypothesis about return predictability is based on Merton (1987)'s model of capital market equilibrium under incomplete information. Merton (1987) assumes that market participants only invest in the securities that they know about and thus the variation in 'investor recognition' affects stock returns. Lehavy and Sloan (2005) use changes in institutional breadth to the proxy for investor recognition in order to test Merton (1987)'s predictions. They find that, consistent with Merton (1987), contemporaneous return is positively related to changes in breadth. Also, similar to Chen, Hong, and Stein (2002), they document a positive relation between changes in ownership in a given quarter and stock returns in the next 12 months. In the regression analysis, they show that after controlling for future trading activities of institutions, current changes in breadth are negatively related to future returns. Lehavy and Sloan (2005) argue that the return predictability by changes in institutional breadth can be attributed to the combination of the autocorrelation in changes in institutional breadth and the investor recognition effect of Merton (1987).

2.3. Data and Summary Statistics

2.3.1. Data

I obtain institutional ownership information from Thompson Financial CDA/Spectrum 13-F database. I start my institutional ownership in 1982 because data from Thompson Financial CDA/Spectrum 13-F is not completed prior to this.[3] The requirement of operating performance for two years after the changes in ownership stops my sample through the end of 2002.

[3] Four out of eight quarters in the year 1980 and 1981 do not have sufficient variation in changes in breadth within each size quintiles. For example, in the first quarter of 1980, the smallest two size quintiles have almost no changes in breadth of institution.

I measure the breadth of ownership at the end of each quarter t ($BREADTH_t$), following Chen, Hong, and Stein (2002), as the ratio of the number of institutions holding a stock to the total number of institutions at the end of the prior quarter (t–1). Because the universe of institutions increases drastically over time, only institutions that appear in both quarter (t–1) and quarter (t) are counted when computing $BREADTH_t$. This technique helps to capture the trading activities of existing institutions by excluding the impact of changes in composition of the universe. My analysis focuses on the changes in breadth of ownership from quarter t–1 to quarter t ($\Delta BREADTH_t$). This variable is expected to be associated with information about the future of firm.

I follow Chen, Hong and Stein (2002) and construct portfolios of changes in breadth conditional on capitalization. Specifically each quarter, I assign stocks into market-value-quintiles using NYSE cutoff values. Within each size quintile, stocks are assigned into deciles based on $\Delta BREADTH_t$. Finally, stocks in the same deciles of $\Delta BREADTH_t$ are combined across size quintiles to yield ten portfolios (P1 to P10). This process is necessary because $\Delta BREADTH_t$ and firm size are strongly correlated. Thus, if I formed portfolios unconditional on $\Delta BREADTH_t$, large (small) firms will dominate the high (low) $\Delta BREADTH_t$ portfolio and as a result, my tests cannot distinguish between size effect and changes in breadth effect.

I also compute the fractional holding by institutions for a stock, denoted $HOLD_t$, as the total number of shares held by all institutions at the end of a quarter (t) divided by the total share outstanding at that time. To control for the rising trend in the universe of institutions, the variable $HOLD_t$ includes only institutions that stay in the sample both in quarter t–1 and t. The changes in $HOLD_t$ from one quarter to the next, denoted $\Delta HOLD_t$, represent the aggregate buying or selling activity by all institutions, free from the changes in composition of the universe.

I examine performance for each of the ten portfolios formed above (P1 to P10) both in terms of stock returns and the underlying firms' operating earnings growth. I use data from the Center for Research in Securities Prices (CRSP) Monthly Stock file to calculate the buy-and-hold returns for one, two, three, and four quarters after the changes in breadth. I obtain all financial data from the COMPUSTAT Quarterly file. I measure book to market ratio (BTM) following Fama and French (1993). Book value is defined as the value of common equity, plus deferred taxes and investment tax credit, and minus the book value of preferred stocks. BTM for a given quarter (BTM_t) equals the book value for the fiscal year ending in calendar year t-1 divided by market value of equity at the end of year t-1. To evaluate the abnormal performance of stocks, I use characteristics-based benchmark method developed by Daniel et al. (1997). Specifically, stocks are assigned into market-cap quintiles using NYSE cutoff values every quarter. Within each size quintile, stocks are further sorted into quintiles based on book-to-market ratio (BTM), also using NYSE cutoff values, resulting in 25 portfolios. For each of the 25 size/book-to-market portfolios, stocks are finally sorted into momentum quintiles based on the previous 12-month return, yielding 125 characteristics-based benchmark portfolios. The return for each portfolio is the equally weighted average of the returns for all stocks in that portfolio. To reduce survivorship bias, if a stock is delisted during the evaluation period, I use CRSP-equally-weighted return to replace the return of that stock in calculating the benchmark average. The raw return of a given stock is then subtracted by the return of the benchmark portfolio to which that stock belongs to obtain abnormal return. For robustness purposes, I use the 25 size/book-to-market portfolios as benchmarks in some of the tests.

I use CRSP monthly file to calculate share turnover by dividing the trading volume by shares outstanding at the end of each month. I sum turnovers over every three months to obtain quarterly turnover, denoted as $TURNOVER_t$. Following Chen, Hong, and Stein (2002), I subtract the mean value of turnover for either NASDAQ firms or NYSE/AMEX firms from individual turnover data to make turnover comparable for NASDAQ and NYSE/AMEX stocks, resulting in exchange-adjusted turnover, named as $XTURNOVER_t$.

2.3.2. Summary statistics

Table 1 shows descriptive statistics on the variables used in my analysis. Panel A reports the mean, median, and standard deviation values for each variable by size quintiles. All measures of institutional ownership and changes in ownership are strongly correlated with market capitalization, which justifies my process of forming $\Delta BREADTH_t$ portfolios conditional on size. For the smallest stocks, less than 1% of institutions hold a long position compared with more than 20% for the largest ones. Institutions own about 15% of total shares outstanding in the small cap compare with more than 50% in the large cap. Changes in breadth ($\Delta BREADTH_t$) and changes in fractional holding ($\Delta HOLD_t$) are positive across size quintiles. Also, standard deviation of both $BREADTH_t$ and $\Delta BREADTH_t$ increases in market capitalization. The standard deviation of $\Delta BREADTH_t$ for the smallest stocks is only 15 percent the number for the largest stocks. Apart from the smallest stocks, all other size quintiles have similar average momentum factor, which suggests that momentum does not strongly depend on firm size. Finally and not surprisingly, turnover appears to be a function of size.

In panel B and C, I report the average of quarterly-values for $HOLD_t$ and $\Delta HOLD_t$, and $BREADTH_t$ and $\Delta BREADTH_t$ every two years from 1982 to 2002, respectively. $HOLD_t$ more than doubled during 1982-2002 period, from 18.36% in 1982 to 38.19% in 2002. The increase is more pronounced for the small and medium size quintiles, suggesting the increasing interest of institutions toward smaller capitalization stocks. This is consistent with Bennett, Sias, and Starks (2003) who find that institutions have migrated toward small stocks to exploit their information advantage. In panel C, the level of $BREADTH_t$ for the whole sample appears to be time independent. However, it stays fairly stable for small stocks but falls for large stocks. For the entire sample, average $BREADTH_t$ is about 4%-5% of the universe of institutions. That number for the smallest size quintile is less than 1% and for the largest quintiles is more than 20%. Average $\Delta BREADTH_t$ is positive in most cases, which suggests the expansion in the portfolio of institutions over time. Also, $\Delta BREADTH_t$ is more volatile for small and medium stocks than for the two large size quintiles. For example, the variation in $\Delta BREADTH_t$ for the smallest quintile is 0.19%, which is less than half the variation for the next quintile, and about one-seventh the variation for the largest quintile. Such limited variation in the smallest quintile could be an obstacle in detecting a relation between changes in breadth and future returns. Therefore, I follow the approach in Chen, Hong, and Stein (2002) and Hong, Lim, and Stein (2000) and include only stocks with market capitalization above the 20 percentile NYSE breakpoint in my analysis.

2.4. Return Predictability and the Information Content of Changes in Breadth

2.4.1. Abnormal performance following changes in breadth

Table 2 reports the relation between changes in breadth ($\Delta BREADTH_t$) and future stock returns. Panel A examines the raw returns for those portfolios. It shows that returns increase monotonically with changes in breadth. For 4-quarter window, return for portfolio 1 (P1), with the lowest $\Delta BREADTH_t$, is 12.36%, while return for portfolio 10 (P10), with the largest $\Delta BREADTH_t$, is 18.47%. The differences in raw returns for the two extreme portfolios (P10–P1) are significant for up to 3 quarters following the formation date. The magnitude of the difference is economically significant; 6.88% and 6.11% for 3-quarter and 4-quarter windows, respectively.

Panel B reports the characteristic-based abnormal returns.[4] Similar to the raw returns, the abnormal returns appear to have a positive relation with $\Delta BREADTH_t$. Further, the abnormal returns for extreme portfolios (P1 and P10) are significant across all holding periods, suggesting that changes in ownership predict returns both when there are increases or declines in breadth. The return differences (P10-P1) are economically large, at 4.98% for the three-quarter holding period and 4.82% for the four-quarter holding period, and statistically significant.

Next, I partition the sample based on market capitalization and reexamine the relation between changes in breadth and returns to see how this relation varies across size quintiles. In Table 3, I report returns of the two extreme portfolios (P1 and P10) and their differences by size quintiles. Panels A, and B report raw returns, abnormal returns adjusted for size/book-to-market/momentum benchmarks, respectively.[5] As results from the two panels are comparable, for brevity, I focus on Panel C. Across size quintiles and time windows, portfolios with the largest reductions in breadth (P1) underperform while those with the largest increases in breadth (P10) outperform their benchmark portfolios. As a result, the differences between P10 and P1 are larger for small and medium quintile than for the largest quintiles. For 4-quarter window, the differences in returns for small and medium sizes stocks are 4.23%, 6.77%, 5.25%, and those

[4] I report the abnormal returns adjusted for size/book-to-market benchmark in Appendix

[5] I report the abnormal returns adjusted for size/book-to-market benchmark by size quintiles in Appendix

numbers for the largest two quintiles are 2.21% and 3.50%. The conclusions obtained above are also applicable to the panel B which reports abnormal returns adjusted for size/book to market benchmarks.

In terms of raw return, which is reported in panel A, portfolios with the largest reductions in breadth (P1) underperform portfolios with the largest increases (P10). For example, the 4-quarter returns for P1 and P10 for the smallest quintile are 11.68% and 19.97%, respectively. The numbers for the largest quintile are 13.81% and 18.14%, respectively. Also, across windows examined, the differences in returns between P10 and P1 are larger for small and medium size portfolios than for the two largest size portfolios, suggesting that return predictability is more pronounced for small and medium stocks.

The above findings on the relation between returns and changes in breadth are not only consistent with short sale constraint model by Chen, Hong, and Stein (2002) but also consistent with information hypothesis. According to information hypothesis, this positive relation is expected as institutions enter stocks with better future and exit those with poor prospect. Also, from information angle, this effect is expected to be stronger for small and medium size stocks, which suffer from severe information asymmetry. In order to investigate whether information is the reason for the return predictability, I first look at the relation between changes in breadth and operating earnings growth of firms around the quarter of changes in breadth. Next, I examine whether the predictive power of changes in breadth persists after controlling for information about the future earnings growth of firms. Then, I examine how the predictive power varies among different types of institutions. Finally, for robustness purpose, I examine the predictive power of the two components of changes in breadth, namely the proportions of institutions that enter and exit a give stocks.

2.4.2. Changes in breadth and future operating earnings growth

In this section, I examine the relation between changes in breadth of ownership and the future operating earnings performance of firms. Because earnings are a fundamental source for stock returns, I expect that if institutions trade on information about firm values, their trading should be associated with the future earnings. The short sale constraint and investor recognition do not anticipate such a relation.

Barber and Lyon (1996) find that tests using changes in the firm's operating performance yield more powerful test statistics than those based on the level of the performance. Therefore, I use the earnings growth instead of earnings level. I follow Asquith, Healy, and Palepu (1989) in forming an earnings growth measure. Annual earnings are defined as the sum of earnings before extraordinary items and discontinued operation (DATA 25 in the COMPUSTAT Quarterly dataset) over the four quarters. The calculation of earnings is shown in the Figure 2.1, in which year 0 includes quarter 0, the quarter of changes in institutional ownership, and the three quarters before.

Earnings growth in a given year t (EG_t) is the change in earnings from year t-1 to year t, scaled by the market capitalization at the end of quarter 0. Specifically, earnings growth for year t is calculated as:

$$\mathbf{EG_t} = \frac{\mathbf{Earning_t - Earning_{t-1}}}{\mathbf{Quarter\ \ 0\ \ Market\ \ Value}} \tag{2.1}$$

According to the time schedule above, the earnings following year 0 are measured strictly after the quarter of changes in breadth. Therefore any relation between the changes in breadth and future earnings growth can be interpreted as a result of the information institutions possess when they trade.

Table 4 reports the relation between earnings growth and changes in breadth over the five years around year 0. Panel A exhibits an interesting pattern of raw earnings growth for ten portfolios (P1 to P10). Before changes in breadth occur, P10 underperforms P1 by 0.35% and 0.30%, for year -2 and year -1, respectively. However, in the year of changes and the year after, earnings growth monotonically increases in $\Delta BREADTH_t$. In year 0, earnings growth for portfolio with the largest reductions in breadth (P1) is -0.19% while the growth for portfolio at the other extreme (P10) is 1.29%, creating a difference of 1.48%. The difference widens in the following year (year 1) to reach 1.97%. All numbers are statistically significant. Also, there is no sign of reversal in the year after.

For abnormal earnings growth, to be consistent with the method of calculating abnormal returns, I adjust earnings growth of the individual stock for the median growth of the size/book-to-market/momentum benchmark portfolio to which the firm belongs.[6] The relation between changes in breadth and abnormal growth is presented in panel B. Before the year of changes, P1 outperforms while P10 slightly underperforms their benchmark portfolios, generating the negative and significant difference in abnormal growth between P10 and P1. However, in year 0 and year 1, abnormal growth appears to increase with changes in breadth; especially in year 1, the relation becomes monotonic. In year 0 and year 1, P1 underperforms its peers by 0.09% and 0.69%, respectively. At the same time, P10 outperforms its benchmarks by 0.13% and 0.35%. The differences between the two extreme portfolios (P10–P1) are significant. In year 2, P10 still exhibits better performance than P1 but the difference is no longer significant.

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[6] Barber and Lyon (1996) suggest that tests based on earnings growth adjusted for the industry level are powerful and well specified. In a robustness check not tabulated here, I analyze the abnormal earnings growth adjusted for the median value of the industry, which is classified according to Fama and Frech (1997). The results obtained are consistent with those presented in panel B of table 4.

Table 5 reports the relation between earnings growth and changes in breadth by size quintiles. The purpose of this table is to examine whether the variation in the information environment has any impact on the information content of changes in breadth. Panel A examines raw earnings growth differences between extreme portfolios (P10–P1). Before year 0, earnings growths of both portfolios are positive and significant (except for small size firms). Moreover, P10 appears to underperform P1. However, in the year of changes in breadth and the year after, the differences P10–P1 are positive and significant. For the largest size firms, the difference is 1.18% in year 0 and 1.54% in year 1. For the smallest size category, the numbers are 2.43% and 2.47%. Panel B examines abnormal earnings growth adjusted for the benchmark level. Similar to the raw data, before the quarter of changes in breadth, abnormal growth for P10 is lower than that for P1, in most cases. Moreover, P10 appears to underperform the benchmark in pre-change windows. However, in year 0 and the year after, portfolios with the highest increases in breadth (P10) significantly outperform their benchmark by 0.29% and 0.56% for the smallest size quintiles and by 0.12% and 0.23% for the largest quintile. At the same time, portfolios with the largest reductions in breadth (P1) underperform their benchmark by 0.05% and 1.18% for the smallest size and by 0.23% and 0.51% for the largest size quintile. Not surprisingly, the differences in abnormal earnings growth for the two extreme portfolios are all positive and significant in year 0 and year 1. Also, there is no significant difference between the two portfolios in year 2. The above findings are consistent with the notion that across size quintiles, institutions trade on information about firms. They exit stocks with poor future earnings while enter those with better prospects.

The pattern of earnings growth observed in this table is similar to the pattern of returns reported in Table 3. In fact, stocks with the largest reductions (increases) in breadth experience both negative (positive) abnormal returns and negative/positive abnormal earnings growth. Moreover, the differences in raw as well as abnormal earnings growth and returns are larger for small and medium stocks than for large stocks. This is consistent with the information argument that changes in breadth are more informative when the information asymmetry is more severe.

The results with earnings and returns suggest that institutions trade on information about the future growth of firms and their trades help to disseminate information to the market. When the information is finally revealed, the market reacts accordingly and moves stock prices in the direction predicted by institutions' trades.

2.5. Regression Analysis

In this section I use regression analysis to formally test the conclusions obtained above. First, I show that consistent with univariate results, changes in breadth ($\Delta BREADTH_t$) can be used to forecast future returns under regression framework. Second, I extend the literature on institutional investors by investigating whether this return predictability emerges from the fact that institutions trade on information about operating performance.

2.5.1. Return predictability and changes in breadth

I use $\Delta BREADTH_t$ to predict future returns through Fama-MacBeth (1973) regressions. Each quarter, I estimate a cross-sectional regression of 12-month abnormal return on changes in breadth and control variables for the whole sample. As my sample spans 21 years from Jan 1982 to Dec 2002, I have 84 quarters, and therefore 83 regressions for each specification. Thus, for a given explanatory variable, I have 83 coefficient estimates. The average and the standard error for the average are calculated from the time series of 83 estimates and corrected for serial correlation using Newey West method (with 4 lags).

Table 6 reports the results from these regressions. The most important finding is that $\Delta BREADTH_t$ appears to be the only factor that explains the variation in future returns. In the first specification, 12-month abnormal returns are regressed only on $\Delta BREADTH_t$. The coefficient of 1.73 on $\Delta BREADTH_t$ implies that a two-standard deviation difference in $\Delta BREADTH_t$ (0.79×2) generates a difference of 2.73% in 12-month abnormal returns. In the second column, the model includes changes in fractional holding ($\Delta HOLD_t$). The results show that changes in holding by institutions at quarter 0 do not have any predictive power over returns. In the third column, I control for firm characteristics at the end of quarter 0. These characteristics, including size, book-to-market, momentum, and exchange-adjusted turnover, appear unable to predict abnormal returns for the whole sample as the absolute value of the t-statistics for individual characteristics is no more than 1.30. The predictive power of $\Delta BREADTH_t$ seems to be unaffected by the inclusion of new factors. Again, the coefficient of 1.95 in the last specification suggests that a spread of two standard deviations in $\Delta BREADTH_t$ predicts a difference of 3.08% in abnormal returns. In short, Table 6 shows that $\Delta BREADTH_t$ can reliably predict abnormal performances of stocks while other firm characteristics fail to do so.

2.5.2. Return predictability and information on earnings growth

In section 4.2, I document that changes in breadth are positively correlated with both future returns and future operating performances. This finding suggests that return predictability may come from the information that institutions possess at the time they trade. In this section, I use regression analysis to formally test this prediction. I use the same method as in Table 6 and add earnings growth variables to examine how the return predictability by changes in breadth varies when past and future information about earnings are controlled for. The results are reported in Table 7.

It is possible that institutions simply trade on past operating performances or herd on public information. To investigate this possibility, I first examine whether return predictability by changes in breadth survives when past and contemporaneous earnings growths are controlled. The regression results are reported in the first two models in Table 7. The coefficients on past earnings growth (year -1) and contemporaneous growth (year 0) are positive and significant, suggesting that past and contemporaneous performances has certain implications about future stock returns. More importantly, changes in breadth still appear to be able to predict returns. When only changes in ownership and past and contemporaneous growth are used, the coefficient on $\Delta BREADTH_t$ is 0.83, statistically significant. When firm specific characteristics are controlled for, the coefficient is 0.96, again statistically significant. The results suggest that information on past and contemporaneous operating performance does not subsume the information contained in changes in breadth.

To examine whether return predictability remains after controlling for information about the future performance of firms, I include earnings growths for the two years following the changes in ownership (year +1 and +2) in my regression. The results reported in the last two columns demonstrate that with the existence of future earnings information, changes in breadth lose their predictive power; the p-value for $\Delta BREADTH_t$ rises to 74% in the last model. The findings suggest that information on future growth of firms subsumes the information contained in changes in breadth. The findings are consistent with the information hypothesis that changes in breadth can predict returns because institutions trade on information about future performance of firms. Therefore, once the original source of information is controlled for, changes in ownership do not exhibit the return predictability.

2.6. Return Predictability for Different Types of Institutions

2.6.1. Return predictability for institutions with different portfolio turnover ratios

In Chen, Hong, and Stein's (2002) model, the ability to predict future returns arises from the fact that mutual funds are constrained from taking short positions when they have unfavorable information. In the model, mutual funds are assumed to be homogeneous in terms of the short sale constraints they face, and hence there should be no difference in return predictability among them. If I relax this assumption and allow institutions to face different levels of constraints, Chen, Hong, and Stein's (2002) model will predict that changes in breadth of those institutions that are more likely to be constrained should be better able to predict stock returns. Almazan, Brown, Carlson, and Chapman (2004) find that mutual funds with higher turnover are less likely to be constrained. The short sale constraint hypothesis should therefore predict that changes in the breadth of high-turnover institutions should have less ability to predict returns. The turnover ratio also has implications about information. Chen, Jegadeesh, and Wermers (2000) and Yan and Zhang (2006) find evidence that high-turnover institutions are better informed and have better stock-picking skills. Therefore, if superior information is the source of return predictability, changes in breadth of high-turnover institutions should have better predictive power. In this section, I empirically evaluate how return predictability varies with institutions' trading frequency.

I follow Yan and Zhang (2006) in calculating my measure of trading turnover (churn rate). Specifically, every quarter I separately calculate the aggregate purchase and sale for each institution:

$$BUY_{k,t} = \sum_{\substack{i=1 \\ S_{k,i,t} > S_{k,i,t-1}}}^{N_k} \left| S_{k,i,t} P_{i,t} - S_{k,i,t-1} P_{i,t-1} - S_{k,i,t-1} \Delta P_{i,t} \right| \tag{2.2}$$

$$SELL_{k,t} = \sum_{\substack{i=1 \\ S_{k,i,t} < S_{k,i,t-1}}}^{N_k} \left| S_{k,i,t} P_{i,t} - S_{k,i,t-1} P_{i,t-1} - S_{k,i,t-1} \Delta P_{i,t} \right|, \tag{2.3}$$

where $S_{k,i,t}$ and $S_{k,i,t-1}$ are the numbers of shares of stock (i) held by institution k at the end of quarter t and quarter (t-1), respectively, and $P_{i,t}$ and $P_{i,t-1}$ are the prices of stock (i) at the end of quarter t and quarter (t-1), respectively. $\Delta P_{i,t}$ is the change in price during quarter t. Both shares and prices are adjusted for stock splits and stock dividends. The churn rate for each institution is then calculated as:

$$CR_{k,t} = \frac{\min(BUY_{k,t}, SELL_{k,t})}{\sum_{i=1}^{N_k} \frac{S_{k,i,t} P_{i,t} + S_{k,i,t-1} P_{i,t-1}}{2}}. \tag{2.4}$$

Each quarter, I calculate the average churn rate over the preceding four quarters for each institution as:

$$AVG\_CR_{k,t} = \frac{1}{4} \sum_{0}^{3} CR_{k,t-j}. \tag{2.5}$$

Following Yan and Zhang (2006), I rank institutions into low-, medium-, and high-turnover tertiles based on the average of past churn rates. I then examine how changes in breadth of institutions in each tertile predict returns and operating performance. The results are reported in Table 8. Panel A shows that the predictability by changes in breadth increases in trading turnover. For high-turnover institutions, the three-quarter and four-quarter abnormal returns increase almost monotonically in changes of breadth of ownership. Abnormal returns for the extreme portfolios are statistically significant and economically large. For medium-turnover institutions, individual returns for extreme portfolios are not as significant as those for the high-turnover panel. As a result, the differences (P10-P1) for medium-turnover institutions are less than half those for high-turnover institutions. Also, the significance of the differences is only at the 5% level compared with the 1% level for the high-turnover group. When I move to low-turnover institutions, there appears to be little relation between changes in breadth and future returns. The differences (P10-P1) are economically small (even negative) and statistically insignificant. Finally, I compare the differences in return predictability between the high- and low-turnover institutions and find that abnormal returns for the stocks in the low (high) changes in breadth deciles are significantly lower (higher) than those for the high-turnover institutions. As a result, the differences (P10-P1) are statistically significant. These findings are consistent with the information hypothesis but appear to be at odds with the short sale hypothesis.

Panel B reports the relation between abnormal earnings growth and changes in breadth for the three types of institutions. I focus on the magnitude of abnormal earnings growth, and how earnings growth varies around the year of changes in breadth. First, the information content about future earnings performance, as reflected in the earnings growth for year 1, increases in the trading frequency of institutions. For the extreme portfolios, the magnitude of year 1 abnormal earnings growth increases from the low-turnover to the high-turnover groups. As a result, the differences (P10-P1) in year 1 increase monotonically in trading turnover. The difference for the high-turnover sample is 1.05%, compared with 0.45% and 0.21% for medium- and low-turnover institutions, respectively.[7]

[7] Though not tabulated for brevity, I find that the difference of 0.75% in (P10-P1) between the high- and low-turnover institutions is statistically significant at the 1% level.

Second, the pattern of changes in abnormal earnings growth around year 0 exhibits a sharp difference among the three types of institutions. For high-turnover institutions, before year 1, there is no clear relation between changes in breadth and abnormal earnings growth; P10 even underperforms P1 in year -2 and year -1. However, in year 1, earnings growth appears to increase monotonically in changes in breadth. P1 underperforms its benchmark by 0.67% while P10 outperforms its benchmark by 0.38%, creating a significant difference of 1.05%. In contrast, such a positive relation prevails even in year -1 and year 0 for medium- and low-turnover panels. In fact, stocks that experience decreases (increases) in breadth of ownership already underperform (outperform) the benchmark during these two years. As a result, the differences in P10 and P1 are positive and significant in both year -1 and year 0. The results from these two years suggest that medium- and low-turnover institutions herd to past and contemporaneous earnings information. High-turnover institutions, on the other hand, appear to initiate and terminate positions based on their information about future earnings growth.

In Panel C, I reexamine return predictability using regression analysis. In the first model, for each type of institution I regress abnormal four-quarter returns on changes in breadth and controlled variables. The coefficient on $\Delta BREADTH_t$ measures the return predictability. Model M1 does not include any variable related to earnings information. I find that both the magnitude of coefficients on $\Delta BREADTH_t$ and the level of significance increase in institutions' turnover, consistent with the results reported in Panel A. In fact, low-turnover institutions do not exhibit any predictive power. When I include past and contemporaneous earnings growth as independent variables in the regression models (Model M2), the coefficient on $\Delta BREADTH_t$ for high-turnover institutions becomes smaller and less significant, while that for the medium-term group becomes insignificant. This is consistent with the conclusion from the univariate analysis that medium-turnover institutions tend to herd to past and contemporaneous information. Finally, when I include variables related to future earnings growth (Model M3), the coefficient on $\Delta BREADTH_t$ for the high-turnover institutions becomes insignificant, suggesting that the return-predictive power of $\Delta BREADTH_t$ originates from information about firms' future performance.

2.6.2. Return predictability for institutions as classified by the Thomson Financial

Asquith, Pathak, and Ritter (2005) suggest that short sale constraints depend not only on the demand to sell short stocks but also on the supply of lendable stocks, and hence that Chen, Hong, and Stein's (2002) return predictability could result from the role of institutions as a supplier in the lending market for shares. According to Nagel (2005) and Duffie, Garleanu, and Pedersen (2002), passive institutions such as insurance companies and pension funds are the most active stock lenders, and hence their ownership should have more of an impact on the short sale constraints that bind a stock. I reason that if short sale constraints are the source of return predictability via the effect of breadth on lendable shares, changes in breath of passive institutions will affect short sale constraints more and therefore should have a stronger effect on future returns than changes in breath of active institutions. On the other hand, if information is the reason for the return predictability, then changes in breadth for investment companies and investment advisors who are supposed to have a better information advantage and better stock-picking skills (Almazan, Hartzell, and Starks, 2005, Bennett, Sias, and Starks, 2003, and Del Guercio, 1996) should forecast future returns, while changes in breadth for passive institutions should not exhibit such ability.

Based on the classification by the Thomson Financial (TFN) 13F Holding data set, I partition the universe of institutions into (i) a passive group, which includes bank trusts and insurance companies, (ii) an active group, which includes investment companies and independent investment advisors, and (iii) all others, which include pension funds, foundations, university endowments, and ESOPs. I examine return predictability for each category and report the results in Table 9.

The reason I create passive and active groups is that there is significant variation in the size of the population of institutions across different types. Over the period examined, on average there are 55 investment companies and 68 insurance companies, compared with 202 bank trusts and 437 investment advisors. Thus, if I examine each type of institution independently, the tests for small-population institutions cannot be as powerful as those for large-population institutions. Also, for the purpose of testing the short sale constraint as well as information hypotheses, it should be more meaningful to examine institutions of similar nature together. I focus my analysis on the relative return-predictive power between passive and active groups as the nature of the "All other" group is not conclusive.

Panel A reports the relations between three-quarter and four-quarter abnormal returns and changes in breadth. Consistent with the information hypothesis, the passive management group exhibits very weak predictive power as the extreme portfolios of changes in breadth do not experience significant performance, while returns appear to increase in changes in breadth for investment companies and investment advisors and the returns for the four extreme portfolios are highly significant. As a result, differences in four-quarter returns (P10-P1) are economically large and statistically significant for the active group but not for the passive category. The differences (P10-P1) between the active institutions and passive institutions are statistically significant at the 1% level.

To further investigate the information hypothesis, I examine the relation between abnormal earnings growth and changes in breadth in Panel B. I observe a sharp difference in earnings growth around year 0 between the two groups of institutions. Before year 0, the difference (P10-P1) is much larger and significant for active institutions, active institutions are not concerned about past earnings performance. In year 0, the difference (P10-P1) for passive institutions is about two times the number for actives institutions. In year 1, the absolute growth rates for the extreme portfolios are larger for active than for passive institutions. The difference (P10-P1) for the former is about one and a half that for the latter: 0.78% for active institutions, significantly greater than 0.45% for the passive institutions. Thus, even though all stocks that experience increases in breadth (for all types of institutions) perform well both in the year of changes in breadth and in the year after, changes in breadth of active institutions appear to contain more information about future firm performance. This finding fits well with the relative return predictability across different institutions documented in Panel A.

The results from these two panels are consistent with the information hypothesis, which allows different types of institutions to have differential ability to predict future returns. In particular, active institutions exhibit stronger return predictability.

In Panel C, I reexamine the return predictability using regression analysis. Similar to my procedure in Panel C of Table 6, I regress four-quarter abnormal returns on changes in breadth, control variables, and information about abnormal earnings growth for each category of institution. Again, the coefficient on $\Delta BREADTH_t$ measures the return predictability. The results from model M1 reconfirm the conclusion obtained in Panel A that only changes in breadth of active institutions can predict returns; the t-statistics on $\Delta BREADTH_t$ for investment companies and investment advisors are 3.10 compared with 1.68 for passive institutions. In model M2, when I control for past and contemporaneous earnings information, changes in breadth for active institutions remain capable of forecasting returns, with a t-statistic of 2.61. In the last model (M3), when I include future earnings growth in my regressions, the coefficient on changes of breadth of active institutions becomes statistically insignificant. The findings in this panel support the information hypothesis' conjecture that changes in breadth predict returns because certain types of institutions succeed in taking advantage of their superior information related to future earnings growth.

2.7. Conclusions

My paper examines why changes in breadth predict return. Consistent with the existing literature, I document that changes in breadth measure, when applied to the universe of institutions, can predict returns in the following four quarters. By including future earnings growth in my analysis, I first extend the literature by documenting that changes in institutional breadth can predict earnings growth in the first year after the changes in breadth, with no reversal in the second year. Specifically, firms that experience the highest increases in breadth significantly outperform their benchmarks, while those experiencing the largest reductions in breadth significantly underperform their peers. This finding supports the hypothesis that trading by institutions is related to information on the future operating performance of firms. Second, I investigate how return predictability changes when I control for information about earnings growth. I document that while changes in breadth can predict returns even after controlling for the past and contemporaneous earnings growth, they lose the predictive power when future earnings growth is included in analysis. This finding supports the information argument that changes in institutional breadth can predict returns because institutions trade on information about the future earnings of firms. As a result, in the presence of the original source of information, changes in breadth are no longer able to forecast returns. Third, when I partition the sample into different types of institutions, I document significant variation in the predictive power across institutions. Specifically, only changes in breadth for active institutions, whose stock picking skill has been documented in the literature, are positively correlated with future returns while passive institutions such as banks, insurance companies, and pension funds do not exhibit such power. In general, the findings in this study support the information hypothesis that the documented return predictability can be attributed to the information contained in institutional entrances and exits.

2.8. Figure for Chapter Two

Q-7	Q-6	Q-5	Q-4	Q-3	Q-2	Q-1	Q0	Q1	Q2	Q3	Q4
YEAR -1				YEAR 0				YEAR 1			

Figure 2. 1. Schedule for calculating earnings growth

2.9. Tables for Chapter Two

Table 2. 1: Summary Statistics

Panel A: Summary Statistics by Size Quintiles

	Size Quintiles						
	1 (Smallest)	2	3	4	5 (Largest)	All	Quintiles 2-5
$BREADTH_t$ (%)	0.82 0.63 0.68	2.67 2.55 1.22	4.94 4.86 1.95	9.17 9.06 3.24	23.45 20.37 11.73	4.55 1.73 7.56	8.54 5.16 9.32
$\Delta BREADTH_t$ (%)	0.00 0.00 0.19	0.06 0.05 0.43	0.13 0.11 0.61	0.19 0.17 0.83	0.30 0.28 1.29	0.07 0.01 0.58	0.15 0.10 0.80
$HOLD_t$ (%)	14.54 10.04 14.46	32.39 30.88 18.75	41.41 41.76 19.71	47.66 49.33 19.11	52.34 53.79 15.98	27.93 23.57 22.13	41.74 42.42 20.14
Δ $HOLD_t$ (%)	0.09 0.03 4.23	1.23 0.55 5.83	1.80 0.77 6.42	1.85 0.74 6.55	1.71 0.53 6.52	0.86 0.17 5.45	1.61 0.63 6.34
$SIZE_t$ ($ million)	36 29 28	172 165 47	425 406 112	1,141 1,062 361	9,856 4,486 17,021	1,188 103 6,111	2,317 457 8,393
BTM_t	1.02 0.78 1.18	0.72 0.61 0.61	0.65 0.57 0.49	0.63 0.56 0.42	0.59 0.53 0.37	0.84 0.65 0.94	0.65 0.57 0.51
$PRET12_t$ (%)	7.24 -4.03 71.68	26.61 12.88 74.80	28.97 16.37 64.83	28.30 17.00 59.01	26.21 18.35 45.92	17.26 7.22 71.91	27.63 15.94 65.94
NASDAQ $TURNOVER_t$ (%)	21.86 13.46 33.52	36.60 24.32 40.63	45.08 30.95 47.21	53.43 36.86 54.24	68.30 53.52 56.92	30.01 17.42 41.54	43.76 29.06 47.65
NYSE/AMEX $TURNOVER_t$ (%)	12.41 8.25 15.87	17.98 12.56 19.17	20.79 15.46 19.75	23.41 18.52 19.12	22.55 18.43 15.79	18.82 14.21 18.67	21.43 16.74 18.75

Panel B. $HOLD_t$ (%) and $\Delta HOLD_t$ (%) over Time

	Size quintile						
Year	Quintile 1 (Smallest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Largest)	All firms	Quintiles 2-5 firms
1982	8.05 0.26	18.18 0.95	25.70 1.14	32.36 1.04	39.96 0.90	18.36 0.66	27.37 1.01
1984	10.63 0.28	23.73 0.51	30.17 0.69	37.85 0.94	43.26 0.68	20.49 0.46	31.80 0.68
1986	13.06 0.38	27.67 1.40	33.05 1.56	39.99 1.77	45.77 1.68	22.72 0.91	35.08 1.58
1988	12.73 0.15	28.74 0.50	35.50 0.71	41.89 0.32	46.49 0.38	23.01 0.30	36.64 0.50
1990	13.62 -0.52	31.03 0.03	39.08 0.49	44.69 0.44	50.06 0.60	25.41 -0.13	39.58 0.35
1992	15.33 0.04	33.68 1.13	42.32 1.77	47.92 1.95	52.44 2.10	28.69 0.83	42.64 1.66
1994	15.97 0.11	33.96 0.70	42.75 1.35	49.00 1.75	52.89 1.20	28.75 0.62	43.40 1.20
1996	16.13 0.46	34.89 1.81	43.53 2.98	51.00 3.42	54.56 3.21	30.45 1.61	44.38 2.72
1998	15.88 -0.37	35.31 0.77	46.52 1.67	52.63 2.40	57.34 2.92	31.33 0.72	46.23 1.77
2000	16.14 -0.50	35.34 0.53	47.41 1.93	56.22 3.42	60.31 3.79	33.64 1.00	48.49 2.25
2002	18.07 -0.30	45.41 1.44	58.05 2.08	61.65 1.66	63.96 1.29	38.19 0.73	55.80 1.62

Panel C. $BREADTH_t$ (%) and $\Delta BREADTH_t$ (%) over Time

	Size quintile						
Year	Quintile 1 (Smallest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Largest)	All firms	Quintiles 2-5 firms
1982	0.65 0.01	2.24 0.08	5.04 0.14	10.77 0.19	28.74 0.30	5.47 0.09	9.68 0.16
1984	0.80 0.00	2.86 0.03	5.72 0.06	11.12 0.11	27.61 0.12	4.95 0.03	9.71 0.07
1986	0.89 0.01	3.02 0.04	5.46 0.10	11.07 0.21	28.02 0.38	4.86 0.07	9.93 0.15
1988	0.94 0.02	2.94 0.07	5.48 0.16	10.95 0.23	27.35 0.36	4.76 0.09	9.82 0.18
1990	0.99 -0.04	2.91 -0.05	5.31 -0.05	10.44 -0.05	27.06 -0.08	4.90 -0.05	9.60 -0.06
1992	0.95 -0.01	2.88 0.08	5.24 0.16	9.81 0.26	24.77 0.36	5.08 0.09	9.37 0.19
1994	0.88 -0.01	2.56 0.03	4.44 0.08	7.98 0.05	21.29 0.08	4.24 0.02	8.01 0.06
1996	0.71 0.00	2.29 0.06	4.14 0.18	7.14 0.24	19.07 0.38	3.95 0.10	7.11 0.19
1998	0.66 0.00	2.26 0.05	4.15 0.13	7.01 0.22	18.60 0.59	3.92 0.11	7.05 0.22
2000	0.63 -0.04	2.17 -0.03	4.13 0.10	7.21 0.26	18.76 0.37	4.29 0.07	7.36 0.16
2002	0.76 -0.04	2.90 0.03	4.97 0.04	7.99 0.07	19.07 -0.01	4.48 0.00	7.70 0.03

The sample includes stocks from the NYSE, AMEX, and NASDAQ from 1982 to 2002. $BREADTH_t$ is the fraction of the universe of institutions that holds a given stock at the end of quarter t. $\Delta BREADTH_t$ is the changes in $BREADTH_t$ from quarter t–1 to quarter t. $HOLD_t$ is the faction of total share outstanding held by institutions at the end of quarter t. $\Delta HOLD_t$ is the change in $HOLD_t$ from quarter t–1 to quarter t. IN_t is the fraction of the universe of institution that enters a stock during quarter t. OUT_t is the fraction of the universe of institution that exits a stock during quarter t. $SIZE_t$ is the market capitalization at the end of quarter t. BTM_t is the book-to-market ratio at the end of quarter t. $PRET12_t$ is the raw return over 12-month period prior to the end of quarter t. NASDAQ $TURNOVER_t$ is the equally average turnover for stocks listed on NASDAQ during quarter t. NYSE/AMEX $TURNOVER_t$ the equally average turnover for stocks listed on either NYSE or AMEX during quarter t. Panel A reports the mean, median, and standard deviation values of variables by size quintiles. Panel B reports the mean values for quarterly fractional holding ($HOLD_t$) and change in fractional holding ($\Delta HOLD_t$) every two years, by size quintiles. The first number is $HOLD_t$, while the second is $\Delta HOLD_t$. Panel C reports the mean values for quarterly breadth ($BREADTH_t$) and quarterly changes in breadth ($\Delta BREADTH_t$) every two years, by size quintiles. The first number is $BREADTH_t$, while the second is $\Delta BREADTH_t$.

Table 2. 2: Returns for Portfolios Formed on $\Delta BREADTH_t$

Panel A. Raw Returns

$\Delta BREADTH_t$ Deciles	1-quarter	2-quarter	3-quarter	4-quarter
1	2.73%**	5.55%**	8.70%***	12.79%***
2	3.66%***	7.22%***	10.68%***	14.79%***
3	3.79%***	7.62%***	11.40%***	15.35%***
4	3.99%***	8.19%***	12.03%***	16.42%***
5	3.78%***	7.78%***	11.72%***	15.91%***
6	3.94%***	8.15%***	12.36%***	16.49%***
7	4.18%***	8.44%***	12.52%***	16.73%***
8	4.46%***	8.30%***	12.16%***	16.00%***
9	4.97%***	9.51%***	13.77%***	17.71%***
10	5.67%***	10.30%***	15.03%***	18.42%***
P10–P1	2.94%***	4.75%***	6.33%***	5.63%**

Panel B. Abnormal Returns Adjusted for Size/Book-to-Market/Momentum

$\Delta BREADTH_t$ Deciles	1-quarter	2-quarter	3-quarter	4-quarter
1	-0.83%***	-1.61%***	-2.36%***	-2.44%***
2	-0.26%	-0.64%*	-1.02%**	-1.22%***
3	-0.19%	-0.36%	-0.90%	-1.37%**
4	-0.06%	-0.01%	-0.26%	-0.07%
5	-0.26%	-0.32%	-0.51%	-0.55%
6	-0.29%*	-0.30%	-0.10%	-0.07%
7	-0.12%	-0.28%	-0.34%	-0.32%
8	0.08%	-0.07%	-0.24%	-0.45%
9	0.54%**	0.81%**	1.18%**	1.44%**
10	0.98%**	1.52%*	2.62%**	2.38%*
P10–P1	1.81%***	3.13%***	4.98%***	4.82%***

At the end of each quarter, stocks are first sorted into quintiles on market capitalization. Stocks within the same size quintile are then assigned into deciles of changes in breadth, $\Delta BREADTH_t$. Next, stocks are recombined based on $\Delta BREADTH_t$ deciles across size quintiles to form ten portfolios. Stocks with market capitalization below the 20th percentile using NYSE break points are excluded. Stocks are bought and hold for the next four quarters. For each quarter t, equally-weighted average returns are calculated for each portfolio. The numbers reported in this table are the equally-weighted average of these time series. The last row of each panel (P10-P1) reports the difference in mean returns between portfolio with the largest increases in $\Delta BREADTH_t$ (P10) and portfolio with the largest decreases in $\Delta BREADTH_t$ (P1). Panel A reports the raw returns for each portfolio. Panel B reports abnormal returns adjusted for size/book-to-market and size/book-to-market/momentum benchmarks. The significance level is adjusted for serial correlation using a Newey-West estimator with a lag of up to four quarters. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 2. 3: Returns for Portfolios formed on $\Delta BREADTH_t$ by Size Quintiles

Panel A. Raw Returns

$SIZE_t$ quintiles	$\Delta BREADTH_t$ Deciles	2-quarter	3-quarter	4-quarter
2	1	3.69%**	6.86%**	11.68%***
	10	11.43%***	16.41%***	19.97%***
	P10–P1	7.75%***	9.55%***	8.29%*
3	1	4.35%**	7.39%***	10.98%***
	10	9.76%***	14.99%***	17.84%***
	P10–P1	5.42%*	7.60%**	6.86%*
4	1	5.83%***	9.81%***	14.18%***
	10	9.06%***	13.68%***	17.47%***
	P10–P1	3.22%	3.88%	3.29%
5	1	6.28%***	9.50%***	13.81%***
	10	8.58%***	13.93%***	18.14%***
	P10–P1	2.30%	4.43%	4.33%

Panel B. Abnormal Returns Adjusted for Size/Book-to-Market/Momentum

$SIZE_t$ quintiles	$\Delta BREADTH_t$ Deciles	2-quarter	3-quarter	4-quarter
2	1	-2.58%***	-3.77%***	-3.78%***
	10	2.49%***	3.40%***	2.99%**
	P10–P1	5.07%***	7.17%***	6.77%***
3	1	-1.40%**	-1.96%**	-2.28%**
	10	1.80%*	3.17%**	2.63%
	P10–P1	3.20%***	5.13%***	4.91%**
4	1	-0.59%	-0.77%	-0.55%
	10	0.66%	1.34%	1.59%
	P10–P1	1.25%	2.11%	2.14%
5	1	-0.43%	-1.04%*	-0.96%
	10	0.59%	1.57%*	1.57%
	P10–P1	1.02%	2.61%**	2.53%**

At the end of each quarter, stocks are first sorted into quintiles on market capitalization. Stocks within the same size quintile are assigned into deciles of changes in breadth, $\Delta BREADTH_t$. For each size quintile, stocks are recombined based on $\Delta BREADTH_t$ deciles to form ten equally-weighted portfolios. Stock returns and portfolio returns are calculated in the same manner as in table 2. This table reports returns of the two extreme portfolios (P10 and P1) and the difference in returns between them (P10–P1) for each size quintile. Panel A reports the mean value of raw returns. Panel B reports the mean values of abnormal returns adjusted for size/book-to-market and size/book-to-market/momentum benchmarks, respectively. The significant level is adjusted for serial-correlation using a Newey-West estimator with lag of four quarters. ***, **, and * denote significance at 0.01, 0.05, and 0.10, respectively.

Table 2. 4: Earnings Growth for Portfolios Formed on $\Delta BREADTH_t$

Panel A. Raw Earnings Growth (%)

$\Delta BREADTH_t$ Deciles	Year -2	Year -1	Year 0	Year 1	Year 2
1	0.86***	0.92***	-0.19	-0.62***	0.65***
2	0.71***	0.76***	0.28**	0.15	0.68***
3	0.70***	0.71***	0.49***	0.43***	0.31
4	0.69***	0.68***	0.62***	0.51***	0.86***
5	0.65***	0.68***	0.65***	0.63***	0.71***
6	0.65***	0.69***	0.76***	0.72***	0.73***
7	0.61***	0.68***	0.85***	0.78***	0.71***
8	0.59***	0.71***	0.92***	0.82***	0.02
9	0.60***	0.68***	1.07***	1.03***	0.73***
10	0.51***	0.62***	1.29***	1.35***	0.65***
P10–P1	-0.35***	-0.30***	1.48***	1.97***	0.00

Panel B. Abnormal Earnings Growth Adjusted for Size/Book-to-Market/ Momentum Benchmark

$\Delta BREADTH_t$ Deciles	Year -2	Year -1	Year 0	Year 1	Year 2
1	0.07***	0.14***	-0.09***	-0.69***	-0.01
2	0.01	0.02	-0.04	-0.22***	-0.05**
3	0.00	0.00	-0.04***	-0.06***	-0.09
4	0.01	-0.03**	0.00	-0.04***	0.08
5	0.00	-0.02***	-0.03***	0.01	0.01
6	0.01	-0.01*	-0.02**	0.01	0.02
7	-0.01	0.00	0.01	0.02	0.00
8	0.00	0.01	0.03**	0.04**	-0.23
9	0.01	-0.01	0.06***	0.15***	0.03
10	-0.01	-0.02*	0.13***	0.35***	0.03
P10–P1	-0.08***	-0.16***	0.22***	1.05***	0.04

At the end of each quarter, stocks are first sorted into quintiles on market capitalization. Stocks within the same size quintile are assigned into deciles of changes in breadth, $\Delta BREADTH_t$. Stocks are recombined based on $\Delta BREADTH_t$ deciles across size quintiles to form ten equally-weighted portfolios. Stocks with market capitalization below 20th percentile using NYSE break point are excluded. Earnings growths for each portfolio are tracked for the five years (20 quarters) around the formation quarter. The time schedule is exhibited below where quarter 0 (Q0) is the portfolio formation quarter:

Q-7	Q-6	Q-5	Q-4	Q-3	Q-2	Q-1	Q0	Q1	Q2	Q3	Q4
YEAR -1				YEAR 0				YEAR 1			

Earnings growth in a given year (EG_t) is the difference in earnings before extraordinary items and discontinued operation between year (t) and the year before (t–1), scaled by market capitalization at the end of the portfolio formation quarter.

$$EG_t = \frac{Earning_t - Earning_{t-1}}{Quarter\,0\,MarketValue}$$

For each quarter, median values of annual earnings growth are calculated for each $\Delta BREADTH_t$ deciles. Numbers reported in this table are the mean values of the time series of median growth for each portfolio. The last row in each panel (P10–P1) reports the difference in earnings growths between portfolio with highest increase in $\Delta BREADTH_t$ (P10) and portfolio with largest reduction in $\Delta BREADTH_t$ (P1). Panel A reports raw earnings growth. Panel B reports abnormal earnings growth adjusted for the median earnings growth of the size/book-to-market/momentum benchmark portfolio. The significant level is adjusted for serial-correlation using a Newey-West estimator with lag of four quarters. ***, **, and * denote significance at 0.01, 0.05, and 0.10, respectively.

Table 2. 5: Earning Growth for Portfolios formed on $\Delta BREADTH_t$ by Size Quintiles

Panel A. Raw Earnings Growth by Size Quintiles (%)

$SIZE_t$ Quintiles	$\Delta BREADTH_t$ Deciles	Year -2	Year -1	Year 0	Year 1	Year 2
	1	0.84***	0.93***	-0.78***	-1.07**	0.74**
2	10	0.50***	0.62***	1.65***	1.40***	0.57***
	P10–P1	-0.34***	-0.31**	2.43***	2.47***	-0.17
	1	0.90***	1.06***	-0.32**	-1.07***	0.72***
3	10	0.58***	0.62***	1.35***	1.46***	0.63***
	P10–P1	-0.32***	-0.44***	1.67***	2.53***	-0.09
	1	0.89***	0.95***	-0.05	-0.54**	0.68***
4	10	0.50***	0.57***	1.23***	1.35***	0.71***
	P10–P1	-0.39***	-0.38***	1.28***	1.89***	0.03
	1	0.80***	0.71***	-0.11	-0.40**	0.61***
5	10	0.48***	0.64***	1.07***	1.14***	0.64***
	P10–P1	-0.32***	-0.07	1.18***	1.54***	0.03

Panel B. Abnormal Earnings Growth Adjusted for Size/Book-to-Market/Momentum by Size Quintiles (%)

$SIZE_t$ Quintiles	$\Delta BREADTH_t$ Deciles	Year -2	Year -1	Year 0	Year 1	Year 2
	1	0.08	0.24***	-0.05	-1.18***	0.02
2	10	-0.04	-0.10***	0.29***	0.56***	-0.09
	P10–P1	-0.12	-0.34***	0.34***	1.74***	-0.11
	1	0.06	0.23***	-0.15***	-1.03***	-0.13
3	10	0.02	-0.06**	0.11***	0.47***	-0.02
	P10–P1	-0.04	-0.29***	0.26***	1.50***	0.11
	1	0.10***	0.14***	-0.10	-0.56***	-0.04
4	10	-0.04**	-0.04	0.13***	0.31***	0.11*
	P10–P1	-0.14**	-0.18	0.23**	0.87***	0.15
	1	0.06*	0.04	-0.23***	-0.51***	-0.09
5	10	-0.01	0.01	0.12***	0.23***	0.04
	P10–P1	-0.07**	-0.03	0.35***	0.74***	0.13

At the end of each quarter, stocks are first sorted into quintiles on market capitalization. Stocks within the same size quintile are assigned into deciles of changes in breadth, $\Delta BREADTH_t$. For each size quintile, stocks are recombined based on $\Delta BREADTH_t$ deciles to form ten equally-weighted portfolios. Earnings growths of the portfolio are tracked for the five years (20 quarters) around the formation quarter. Each quarter, median values of annual earnings growth are calculated for each $\Delta BREADTH_t$ deciles. This table reports the mean values of the time series of median earnings growth for the two extreme portfolios (P1 and P10) and the difference in growths between them (P10–P1) for each size quintile. Panel A reports raw earnings growth. Panel B reports abnormal earnings growth adjusted for the median earnings growth of the size/book-to-market/momentum benchmark portfolios. The significant level is adjusted for serial-correlation using a Newey-West estimator with lag of four quarters. ***, **, and * denote significance at 0.01, 0.05, and 0.10, respectively.

Table 2. 6: Predictive Power of $\Delta BREADTH_t$ by Size

Model	Model 1	Model 2	Model 3
Int	-0.44 -1.91	-0.40 -1.68	-6.87 -0.92
$LOGSIZE_t$			0.53 0.92
BTM_t			-0.17 -0.43
$PRET12_t$			0.20 0.38
$XTURNOVER_t$			-3.85 -1.27
$\Delta HOLD_t$		-0.01 -0.17	-0.01 -0.31
$\Delta BREADTH_r$	1.73 2.82	1.99 3.34	1.95 3.20
Adj. Rsqr (%)	0.24	0.38	2.0

This table reports the regression results of 12-month abnormal return adjusted for size/book-to-market/momentum benchmarks on changes in breadth ($\Delta BREADTH_t$), changes in fractional holding ($\Delta HOLD_t$) and firm specific, controlling variables. $LOGSIZE_t$ is the natural log of market capitalization of a firm at the end of quarter t. BTM_t is the book-to-market ratio of a firm at the end of quarter t. $PRET12_t$ is the raw return of a stock 12-month prior to the end of quarter t. $XTURNOVER_t$ is the turnover of a stock adjusted for its exchange's level at the end of quarter t. Every quarter, separate regressions are run for the whole sample. I obtain a time series of estimates for each coefficient. The first numbers reported on the table are the mean values of the time series of estimates, while the seconds are the t-statistic adjusted for serial-correlation with lag of four quarters.

Table 2. 7: Return Predictability and Operating Performance

Model	M1	M2	M3	M4
Int	-0.08	1.65	0.16	1.81
	-0.26	0.31	0.25	0.39
$LOGSIZE_t$		-0.09		-0.12
		-0.21		-0.38
BTM_t		-0.91		0.02
		-2.68		0.07
$PRET12_t$		-0.30		-1.65
		-0.75		-0.29
$XTURNOVER_t$		-4.14		-1.22
		-1.30		-0.32
$\Delta HOLD_t$	0.01	0.01	-0.17	0.01
	0.04	0.31	-0.62	0.37
$\Delta BREADTH_r$	0.83	0.96	-0.02	0.15
	2.22	2.29	-0.39	0.36
Ab_EG_{-1}	0.07	0.07	0.35	0.36
	1.34	1.37	7.00	7.68
Ab_EG_0	0.15	0.14	0.69	0.70
	4.60	4.47	11.59	11.64
Ab_EG_{+1}			1.16	1.17
			12.44	12.29
Ab_EG_{+2}			0.51	0.51
			9.14	9.20
R-sqr	1.21	2.41	11.55	12.95

This table reports the regression results of 12-month abnormal return adjusted for size/book-to-market/momentum benchmarks on changes in breadth ($\Delta BREADTH_t$), changes in fractional holding ($\Delta HOLD_t$), firm specific, controlling variables, and past, contemporaneous and future abnormal earnings growth (Ab_EG_i). $LOGSIZE_t$ is the natural log of market capitalization of a firm at the end of quarter t. BTM_t is the book-to-market ratio of a firm at the end of quarter t. $PRET12_t$ is the raw return of a stock 12-month prior to the end of quarter t. $XTURNOVER_t$ is the turnover of a stock adjusted for its exchange's level at the end of quarter t. Every quarter, regressions are run for the whole sample. With 84 quarters, I obtain a time series of estimates for each coefficient. The first numbers reported on the table are the mean values of the time series of estimates, while the seconds are the t-statistic adjusted for serial correlation with a lag of four quarters.

Table 2. 8: Changes in Breadth of Institutions with Different Turnover Ratios

Panel A. Changes in Breadth and Future Returns

$\Delta BREADTH_t$ Deciles	High-turnover Institutions		Medium-turnover Institutions		Low-turnover Institutions		High-turnover – Low-turnover	
	3-quarter	4-quarter	3-quarter	4-quarter	3-quarter	4-quarter	3-quarter	4-quarter
1	-1.97***	-1.94***	-0.80**	-0.82**	0.05	-0.03	-2.02***	-1.91***
2	-0.86**	-1.01***	-0.63*	-0.43	-0.10	-0.15	-0.76	-0.86
3	-0.64*	-0.71*	-0.14	0.13	0.28	0.28	-0.92**	-0.99**
4	-0.17	-0.23	-0.34	-0.51	0.01	0.29	-0.18	-0.52
5	0.02	0.04	-0.11	-0.17	-0.25	-0.06	0.27	0.10
6	-0.17	-0.07	-0.13	-0.23	0.31	0.28	-0.47	-0.35
7	0.18	0.53	0.09	-0.11	-0.11	0.26	0.29	0.27
8	0.68***	0.91***	0.54	0.62	0.44	0.70**	0.24	0.21
9	0.78**	0.79**	0.90	0.87	-0.55**	-0.95**	1.33***	1.74***
10	2.74**	2.55*	0.92	0.83	0.16	-0.18	2.58**	2.73**
P10–P1	4.70***	4.48***	1.73**	1.66**	0.11	-0.15	4.59***	4.63***

Panel B. Changes in Breadth and Operating Performance

	High-turnover Institutions					Medium-turnover Institutions					Low-turnover Institutions				
$\Delta BREADTH_t$ Deciles	Year -2	Year -1	Year 0	Year 1	Year 2	Year -2	Year -1	Year 0	Year 1	Year 2	Year -2	Year -1	Year 0	Year 1	Year 2
1	0.05***	0.22***	0.09***	-0.67***	-0.02	0.05**	0.03**	-0.15***	-0.30***	0.00	0.01	-0.06*	-0.16***	-0.13***	0.01
2	0.02*	0.08***	0.00	-0.16***	-0.02	0.01	0.02	-0.03*	-0.06***	0.01	0.00	-0.03***	-0.06***	-0.07**	-0.02
3	0.01	0.03***	0.00	-0.06***	0.00	0.02**	0.00	-0.03**	-0.06**	0.01	-0.01	-0.01	-0.02	-0.02	-0.04
4	0.00	-0.01	0.01	-0.03**	-0.02	0.01	0.00	-0.01	-0.03	-0.01	0.00	0.00	-0.04***	0.02	0.01
5	0.00	-0.02**	-0.01***	0.02	0.01	0.00	-0.02	0.00	0.00	-0.01	0.00	0.00	-0.02	0.00	0.01
6	0.00	-0.02**	-0.05**	0.02	0.01	-0.01	-0.01	0.00	-0.01	0.01	0.00	-0.02	0.02	0.00	0.01
7	0.01	0.00	-0.03	0.00	0.04	0.00	-0.01	0.01	0.03*	0.00	0.01	0.02*	0.01	0.01	-0.04**
8	0.01	-0.03***	0.02	0.06***	0.01	0.01	0.00	0.03***	0.02*	0.00	0.00	0.01	0.07***	0.02	-0.01
9	-0.01	-0.04***	0.04***	0.11***	0.04**	0.01**	0.00	0.06***	0.06***	0.01	0.02**	0.03***	0.05***	0.02**	0.00
10	-0.02	-0.07***	0.09***	0.38***	0.01	0.01	0.06***	0.12***	0.15***	0.00	0.02*	0.05***	0.10***	0.08***	0.02
P10–P1	-0.07**	-0.28***	-0.01	1.05***	0.04	-0.04*	0.03	0.27***	0.45***	0.00	0.01	0.11***	0.26***	0.21***	0.01

Panel C. Regression on Return Predictive Power for Three Types of Institutions

	High-turnover Institutions			Medium-turnover Institutions			Low-turnover Institutions		
Model	M1	M2	M3	M1	M2	M3	M1	M2	M3
Int	0.83 0.26	1.12 0.35	1.42 0.45	-0.05 -0.02	0.57 0.19	1.04 0.33	-1.40 -0.49	-0.69 -0.23	0.28 0.09
$LOGSIZE_t$	-0.05 -0.21	-0.05 -0.22	-0.09 -0.45	0.02 0.12	-0.00 -0.01	-0.05 -0.26	0.12 0.66	0.10 0.50	0.01 0.03
BTM_t	-1.02 -2.99	-0.99 -2.91	-0.02 -0.03	-0.92 -2.95	-0.97 2.94	-0.07 -0.09	-0.88 -2.74	-0.88 -2.71	-0.02 -0.03
$PRET12_t$	0.40 0.85	-0.51 -1.16	-1.87 -3.03	1.06 2.50	0.14 0.35	-1.46 -2.99	1.01 2.45	0.23 0.64	-2.43 -3.28
$XTURNOVER_t$	-5.20 -1.69	-4.00 -1.30	-1.11 -0.33	-5.26 -1.69	-4.16 -1.32	-1.14 -0.33	-5.37 -1.76	-4.39 -1.44	-1.19 -0.36
$\Delta HOLD_t$	0.08 1.61	0.09 1.83	0.07 1.54	-0.13 -2.38	-0.19 -3.55	-0.13 -2.40	-0.14 -1.93	-0.17 -2.31	-0.15 -1.74
$\Delta BREADTH_r$	0.72 2.91	0.61 2.50	0.18 0.78	0.57 1.81	0.56 1.79	0.19 0.52	-0.07 -0.37	-0.13 -0.68	-0.38 -1.38
Ab_EG_{-1}		0.08 1.43	0.36 7.76		0.07 1.30	0.36 7.51		0.08 1.41	0.36 7.58
Ab_EG_0		0.15 4.45	0.69 11.48		0.15 4.45	0.70 11.49		0.15 4.45	0.70 11.44
Ab_EG_{+1}			1.17 12.26			1.17 12.29			1.17 12.16
Ab_EG_{+2}			0.50 9.112			0.50 9.14			0.50 9.080
Adj. Rsqr (%)	1.27	2.00	12.31	1.17	1.92	12.34	1.09	1.87	12.23

Each quarter, institutions are classified into tertiles based on their past four-quarter turnover ratios. For each tertile of institutions, changes in breadth are calculated at the end of each quarter. Panel A reports the 3- and 4-quarter abnormal returns adjusted for size/book-to-market/momentum benchmarks for each $\Delta BREADTH_t$ decile. Panel B reports abnormal earnings growth for the 5-year period around the quarter of changes in institutional breadth. Panel C reports the regression results on return predictability. The methods of calculating returns, abnormal earnings growth, and coefficient estimates are detailed in Table 3, 4, and 5, respectively. In Panel C, the first number is the coefficient estimate and the second one is the t-statistic adjusted for serial correlation using a Newey-West estimator with a lag of up to four quarters. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 2. 9: Changes in Breadth by Types of Institutions

Panel A. Changes in Breadth and Future Returns

	Passive Institutions Banks and Insurance Companies		Active Institutions Investment Companies and Investment Advisors		All Others		Active – Passive	
$\Delta BREADTH_t$ Deciles	3-quarter	4-quarter	3-quarter	4-quarter	3-quarter	4-quarter	3-quarter	4-quarter
1	-0.85*	-0.90	-2.20***	-2.38***	-0.95*	-0.89*	-1.35***	-1.48**
2	-0.47	-0.82*	-1.56***	-1.62***	-0.82**	-0.53	-1.09***	-0.81**
3	-0.02	0.09	-0.36	-0.53	-0.60	-1.06	-0.34	-0.61
4	-0.60*	-0.83**	-0.50	-0.67	-0.80	-0.96	0.09	0.16
5	-0.27	-0.38	0.04	-0.14	-0.04	-0.11	0.31	0.24
6	-0.87**	-0.73	0.08	0.00	-0.36	0.01	0.95*	0.73
7	0.23	0.16	0.23	0.42	-1.43***	-1.78**	0.00	0.26
8	0.12	0.36	-0.49	-0.62	-0.07	-0.18	-0.61*	-0.98**
9	0.46	0.37	0.94***	1.30***	0.43	0.54	0.48	0.93*
10	0.69	0.21	2.13***	1.84***	0.78	0.07	1.44***	1.63***
P10–P1	1.54*	1.12	4.33***	4.22***	1.73	0.95	2.79***	3.10***

Panel B. Changes in Breadth and Operating Performance

ΔBREADTH Deciles	Passive Institutions Banks and Insurance Companies					Active Institutions Investment Companies and Investment Advisors					All Others				
	Year -2	Year -1	Year 0	Year 1	Year 2	Year -2	Year -1	Year 0	Year 1	Year 2	Year -2	Year -1	Year 0	Year 1	Year 2
1	0.04	0.07**	-0.11***	-0.30***	0.01	0.05***	0.19***	0.00	-0.48***	-0.02	0.03	-0.01	-0.09**	-0.22**	0.03
2	0.00	-0.01	-0.01	-0.12***	-0.01	0.03**	0.02***	-0.03**	-0.11***	-0.04**	0.01	-0.01	-0.01	-0.07*	0.02
3	0.02*	0.00	-0.02	-0.01	-0.02	-0.01	-0.01	-0.03	-0.04**	-0.02	0.00	0.01	-0.01	-0.04	0.00
4	0.00	-0.01	0.00	-0.01	-0.03*	0.00	-0.01	0.00	-0.02	0.01	-0.01	-0.01	-0.02	-0.01	-0.02
5	0.00	-0.01**	-0.02***	0.01	-0.01	0.00	-0.02***	-0.03*	0.02	0.00	0.01	-0.01	-0.01	0.01	0.01
6	0.00	-0.01	0.01	0.00	0.01	0.00	-0.03***	-0.02	0.02	0.02	-0.01	0.00	-0.02	0.02	0.02
7	0.00	-0.01	0.01	0.03***	0.00	-0.02	0.00	-0.02	0.02	0.04*	0.00	0.01	0.00	0.00	-0.02
8	0.00	0.00	0.02*	0.06**	0.01	0.00	-0.01**	0.01	0.04**	0.01	0.00	0.00	0.02	0.02	-0.01
9	0.01	0.02***	0.06***	0.08***	0.03**	0.00	-0.01	0.05***	0.08***	0.03	0.01	0.03**	0.05***	0.05	-0.02
10	0.00	0.04***	0.11***	0.15***	-0.01	0.00	-0.05***	0.11***	0.30***	0.00	0.01	0.03**	0.09***	0.14***	0.02
P10–P1	-0.04	-0.03	0.22***	0.45***	-0.01	-0.04	-0.24***	0.11**	0.78***	0.02	-0.02	0.04	0.17***	0.37***	-0.01

Panel C. Regression Analysis on Return Predictive Power

	Passive Institutions Banks and Insurance Companies			Active Institutions Investment Companies and Investment Advisors			All Others		
Model	M1	M2	M3	M1	M2	M3	M1	M2	M3
Int	-0.38	0.34	2.09	0.78	1.33	3.13	0.23	1.32	2.63
	-0.13	0.10	0.66	0.24	0.40	0.99	0.07	0.40	0.85
$LOGSIZE_t$	0.04	0.02	-0.10	-0.05	-0.06	-0.19	0.01	-0.05	-0.14
	0.23	0.21	-0.48	-0.23	-0.28	-0.91	0.05	-0.21	-0.72
BTM_t	-0.87	-0.94	-0.25	-0.90	-0.98	-0.27	-1.19	-1.21	-0.38
	-2.79	-2.82	-0.36	-2.80	-2.85	-0.37	-3.48	-3.30	-0.57
$PRET12_t$	0.87	0.05	-1.55	0.64	-0.33	-1.88	1.34	0.60	-1.43
	2.02	0.13	-3.66	1.42	-0.78	-4.11	3.05	1.18	-2.69
$XTURNOVER_t$	-5.17	-4.20	-0.77	-5.24	-4.02	-0.69	-4.47	-3.42	-0.26
	-1.68	-1.35	-0.23	-1.69	-1.30	-0.20	-1.51	-1.11	-0.08
$\Delta HOLD_t$	-0.09	-0.08	-0.09	0.10	0.13	0.08	-0.28	-0.23	-0.03
	-1.20	-1.48	-1.81	1.56	1.43	1.11	-2.68	-2.16	-0.26
$\Delta BREADTH_r$	0.27	0.21	-0.14	1.21	1.11	0.39	0.16	0.06	-0.34
	1.68	0.94	-0.99	3.10	2.61	0.83	0.61	0.26	-1.31
Ab_EG_{-1}		0.10	0.41		0.10	0.21		0.09	0.40
		1.38	7.81		1.43	1.84		1.26	7.64
Ab_EG_0		0.20	0.81		0.20	0.81		0.18	0.80
		4.25	13.26		4.17	13.11		3.92	12.95
Ab_EG_{+1}			1.67			1.66			1.63
			18.04			18.13			17.53
Ab_EG_{+2}			0.73			0.73			0.74
			16.17			16.11			16.55
Adj. Rsqr (%)	1.16	2.08	15.38	1.25	2.17	15.46	1.19	2.15	15.34

Based on the classification by Thomson Financial (FTN) 13F Holding data set, the universe of institutions is partitioned into (i) passive institutions, including banks and insurance companies, (ii) active institutions, including investment companies and their managers and independent investment advisors, and (ii) all others. Panel A reports the 3- and 4-quarter abnormal returns adjusted for size/book-to-market/momentum benchmarks for each $\Delta BREADTH_t$ decile. Panel B reports abnormal earnings growth for the 5-year period around the quarter of changes in institutional breadth. Panel C reports the regression results on return predictability. The methods of calculating returns, abnormal earnings growth, and coefficient estimates are detailed in Table 3, 4, and 5, respectively. In Panel C, the first number is the coefficient estimate and the second one is the t-statistic adjusted for serial correlation using a Newey-West estimator with a lag of up to four quarters. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

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CHAPTER THREE: INSTITUTIONAL HERDING AND ITS IMPACT ON STOCK PRICES

3.1. Introduction

Institutional herding refers to the tendency that institutions "*follow* each other into (or out of) the same securities *over some periods of time*" (Sias 2004). As institutions become the major players on the stock market, such behavior raises a concern that the aggregate trading by institutions could destabilize stock prices, especially when herds are not motivated by information about the value of firms. In this study, I examine herding activities by institutions using a time-dependent framework in which herds are identified on the basis of the number of quarters that institutions continuously trade on the same side. The results provide a comprehensive picture about the duration and the frequency of herds and present new evidence on the potential impact that herding exerts on stock prices.

The extant literature has suggested four possible theories explaining why institutions herd. First, institutions might infer information from each other's trade and hence follow the crowd while ignoring their own private information. This phenomenon is referred to as information cascades (Bikhchandani, Hirshleifer, and Welch, 1992). Second, investigative herding occurs when institutions trade in the same direction because they receive and investigate correlated signals (Froot, Scharfstein and Stein, 1992 and Hirshleifer, Subrahmanyam, and Titman, 1994). Third, herding could occur when the managers of institutions choose to trade in the same direction as others because they do not want to risk their reputation by acting differently from the herds (Scharfstein and Stein, 1990 and Trueman, 1994). Finally, institutions may herd because of their preference toward certain characteristics of securities such as size or liquidity (Falkenstein, 1996, Gompers and Metrick, 2001 and Bennett, Sias, and Starks, 2003).

Despite the strong theoretical foundation on this field, empirical studies on whether institutions "*follow* each other" (Sias, 2004) in their trades are still limited. Except for Sias (2004), who examines the trading by institutions in adjacent quarters, other studies have focused on institutional trading *within one quarter*, or intra-quarter herds. In general, the intra-quarter literature has not found much evidence for the herding tendency. For example, analyzing the quarterly trading of pension funds, Lakonishok, Shleifer, and Vishny (1992) conclude that there is virtually no herding in a typical stock-quarter. Employing a similar technique, Grinblatt, Titman, and Wermers (1995) and Wermers (1999) also find little evidence of the systematic herding by institutions within a given quarter. Explaining the weak findings, Lakonishok et al. (1992) argue that "the overall picture that emerges from this paper is one of institutional investors pursuing a broad diversity of trading styles that to a large extent offset each other".

The time-dependent approach employed in this study enables me to mitigate the offsetting effect embedded in the intra-quarter procedure. Specifically, I apply a method used by Wermers (1999) that classifies a given stock-quarter as *Buy* if the proportion of institutions that are buyers is greater than the benchmark average and as *Sell* if otherwise. Then for each stock, I identify herds on the basis of the consecutive quarters that the stock stays in the same *Buy* or *Sell* category. In fact, individual herds can last for several quarters despite the fact that across the universe of stocks, herding can appear insignificant due to the offsetting effect caused by the diverse strategies of institutions suggested by Lakonishok et al. (1992). Also, the time-dependent approach better conveys the 'following-each-other' aspect of herds because herds are structured on the consideration that the aggregate trading by institutions in one quarter is related to their activities in the previous period.

Using the institutional ownership information obtained from the Thompson Financial CDA/Spectrum 13-F database over the 1980-2005 period, I document that it is common for institutions to engage in multi-quarter herds; herds lasting for at least two quarters account for more than 40 percent of the herd sample. Moreover, institutions appear to herd as much on the buy side as on the sell side. Examining subsamples of stocks, I document an inverse relation between herding activities and stock capitalizations; the smallest capitalization quintile accounts for more than 40 percent while the largest quintile accounts for only less than 10 percent of the herd sample. According to Wermers (1999), information cascades are more likely to occur within small capitalization stocks because signals are noisier, and therefore, institutions tend to put more weight on the direction of trading by the crowd than on their own private information. Sias (2004) posits that investigative herds are more likely to occur among large capitalization securities, where information is reliable and institutions are more likely to receive and investigate correlated signals. My finding about the inverse relation between herds and stock capitalization supports the information cascades hypothesis, which is consistent with the conclusion by the intra-quarter literature. When I examine institutional trading activities in herds, I find that institutions are as active on the buy side as on the sell side.

Next, I investigate the price impact of herding. On one hand, herding could destabilize stock prices if money managers trade on concerns unrelated to the fundamental value of firms (Scharfstein and Stein, 1990, and Falkenstein, 1996). On the other hand, if herds are based on information, trading in herds could move stock prices toward, rather than away from, the equilibrium value of stocks (Froot, Scharfstein and Stein, 1992 and Hirshleifer, Subrahmanyam, and Titman, 1994). The standard approach in the intra-quarter literature to investigate the price impact caused by herds is to examine whether there are return reversals after a *herding quarter*.

Wermers (1999) and Nofsinger and Sias (1999) analyze herding by mutual funds and institutional investors, respectively, and do not find reversals following a typical quarter. Also, Sias (2004) documents a positive relation between the fraction of institutions buying a stock in a quarter and future returns. The absence of reversals leads the authors to conclude that herding by institutions is rational and that its price impact is primarily related to the way in which information becomes incorporated into stock prices.

Because trading by institutions is documented to have a strong contemporaneous impact on stock returns (Sias, Stark, and Titman, 2006, Wermers, 1999, and Nofsinger and Sias, 1999 among others), there would be a causal relation between trading in a given herding quarter and future returns, which could make conclusions on reversals by intra-quarter studies biased. Formally, as institutions in subsequent quarters follow (or herd) others' trades made in the first quarter, trading in herds will force stock prices to move in the direction of trades made in the first period. As a result, when one examines stock returns following a single herding quarter, it is less likely that he/she can detect reversals and, therefore, the conclusions drawn are biased toward an understanding that herding does not destabilize prices but rather helps to accelerate the information dissemination process. Consistent with the literature on the contemporaneous impact of institutional trading, I document a positive relation between trading during a herding period and stock returns over the same time window. This finding stresses the above concern about the way reversals in returns are examined in the intra-quarter literature.

To investigate the price impact, I employ two approaches. First, I examine reversals based on stock returns calculated from the end of the last herding quarter forward. In the absence of herding, returns over this period are free from the contemporaneous pressure caused by herds. I document that stocks that institutions buy in herds underperform those institutions sell in herds by 2.03 percent in raw returns during the first quarter after herds end. The underperformance continuously increases to reach 3.64 percent in the four-quarter window. After controlling for size, book-to-market, and momentum characteristics of stocks, I document that abnormal returns show similar reversal pattern. Moreover, over the four quarters following the end of herds, stocks on the buy side underperform their benchmarks by 1.82 percent while those on the sell side outperform their benchmarks by 1.03 percent. The reversals can be more evident if I take into account the fact that during the herding periods, stocks bought in herds consistently outperform while those sold in herds consistently underperform their benchmarks.

When I examine market capitalization subsamples, I find that the above reversal pattern concentrates in small and medium stocks. For these two samples, the difference in 4-quarter post-herd abnormal returns for buy herds and sell herds are 6.47 and 4.58 percent, respectively. For the largest size quintiles, such differences are small and insignificant. Because institutions tend to engage in positive-feedback trading (Badrinath and Wahal, 2002, Wermers, 1999, and Nofsinger and Sias, 1999), I examine herding activities and their price impact across momentum subsamples. I find that herding and return reversals prevail across the full range of momentum. Herds within each of the middle three momentum quintiles account for about 17 percent of the whole sample, while the numbers for those within each of the two extreme quintiles are around 23 percent. It suggests that positive-feedback trading is not the primary source for the herding behavior, which is consistent with Sias (2004).

The above finding on reversals in return needs careful interpretation. Because post-herd returns are calculated based on the recognition of the time the herds end, this method is subject to a looking-forward bias and, hence, the after-herd returns are biased toward finding reversals. However, I document that there is a positive relation between reversals and the duration of herds.

This relation suggests that stocks which experience more herds are subsequently associated with stronger reversals and stresses the possible price destabilizing impact associated with herding. Specifically, stocks that are purchased by institutions for only one quarter underperform their benchmark levels over the following four quarters by 1.19 percent while those that institutions keep purchasing for four quarters underperform their benchmarks by 4.53 percent. On the sell side, the abnormal returns for those two extreme herd categories are +0.42 and +2.74 percent, respectively.

Next, in an attempt to correct the above bias, I investigate whether it is possible to predict reversals in future returns based on current and past herding activities. The results obtained in the first section of the paper suggest that when the price impact of current herding is weak, it is less likely that a herd will continue. Hence, I argue that for a given quarter, if I group stocks conditional on the number of quarters herding already lasts, on the buy (sell) side, herding will tend to end if a stock belongs to the lowest (highest) return group. If trading in herds destabilizes prices, these stocks will exhibit reversals in future returns. Consistent with this expectation, I document that these two groups of stocks are more likely to experience changes in institutional trading direction. Moreover, stocks that institutions buy in herds and that belong to the lowest return group subsequently underperform those that institutions sell in herds and that belong to the top return group. Also, the former underperforms while the latter outperforms its benchmark in the following four quarters. The finding suggests that, to a certain extent, herding by institutions destabilizes stock prices.

Finally, I examine how herding behavior and its price impact vary over time. I document that herds prevail for all subperiods and that the number of herds increases from one period to the next. Examining capitalization subsamples, I find that the steady growth of herds among stocks of the smallest capitalization is responsible for the overall increase in the herd sample. Consistent with Sias (2004), I document that the number of herds among medium and large stocks is declining over time. The variation in the relative level of herding activities across market capitalizations among subperiods presents a natural experiment to examine how the intensity of herds and the reversals in future returns are related. I find that for any subperiod, the stock sample that experiences more herds will subsequently experience stronger reversals. Also, I document that for all sub-periods, stocks that are more likely to experience changes in institutional trading direction subsequently exhibit reversals in returns. These findings add evidence to the destabilizing characteristics of herding.

This is the first study that directly examines the duration and the frequency of herds. It supplements the intra-quarter herding literature and provides a better understanding about the distribution of herds across durations, capitalizations and time periods. I document that multi-quarter herds are common in practice and, hence, future research in this field should consider the time-dependent pattern in trading by institutions. Most important, by taking into account the duration of herds, I document that to a certain extent, trading by institutions in herds contains destabilizing impact. This finding is contrary to the conclusion obtained in the intra-quarter literature, which is built on the assumption that herds are completed within one quarter. In terms of the sources of herding, this paper adds new evidence supporting the hypothesis that herding by institutions is associated with information cascades.

The remainder of this paper is organized in four sections. The data and methodology are presented in Section 3.2. Section 3.3 reports the empirical analysis on herding activities. I analyze the relation between herding and stocks returns in section 3.4. I conclude the paper in Section 3.5.

3.2. Data and Methodology

I use Thompson Financial CDA/Spectrum 13-F database to obtain information on institutional ownership from January 1980 to December 2005. At the end of each quarter, I calculate the holding for each institution in each stock as a fraction of the security's total shares outstanding. Then, I calculate the changes in fractional holding for each institution in each stock-quarter. I require that there must be at least five institutions trading a stock-quarter for that observation to be included in the sample. According to Wermers (1999), this hurdle helps to better convey the concept of herding, which may not be appropriately defined if there are only one or two institutions trading in the same direction. For each qualified stock-quarter, I classify an institution as *buyer*, *seller*, or *inactive* if its fractional holding increases, decreases, or remains unchanged, respectively, compared with its position at the end of the previous quarter.[8] Then, I calculate the proportion of all active institutions that are buyers for each stock (i) in each quarter (t) as follow:

$$\text{Buy\_ratio}_{i,t} = \frac{\text{Number of institutions buying}_{i,t}}{\text{Number of institutions buying}_{i,t} + \text{Number of institutions selling}_{i,t}} \tag{3.1}$$

The intra-quarter herding literature suggests that the Buy_ratio above can be used to measure the herding activities of institutions in a given period. For each stock-quarter, I construct the Institutional Trading Direction (ITD) by identifying whether during that period, the proportion of institutions buying that stock (Buy_ratio) is larger or smaller than the benchmark levels (E[Buy_ratio]). Following Wermers (1999), the ITD is classified as follows:

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[8] Fractional holding can change due to small changes in the number of shares outstanding even though the number of shares held by an institution does not change. Hence, following Sias (2004), if the number of shares held by a given investor is the same at the end of prior quarter and at the end of current quarter, I assign the institution to the inactive group (for that stock-quarter).

Institutional Trading Direction = Buy if Buy_ratio > E[Buy_ratio]

Institutional Trading Direction = Sell if Buy_ratio < E[Buy_ratio]

Institutional Trading Direction = Neutral if Buy_ratio = E[Buy_ratio]

To control for the fact that trading by institutions varies widely across market capitalizations, I first partition the stock sample into size quintiles based on NYSE capitalization cutoff values. Following Wermers (1999), for each quintile I use the proportion of trades by institutions that are purchases as the average level (E[Buy_ratio]).[9]

To strengthen the trading direction of the sample and hence improve the reliability of the herd measure, for each quarter and size quintile I rank the Buy_ratio into quintiles for Buy and Sell, independently. I then assign the bottom quintile for Buy and the top quintile for Sell, which are least deviated from the benchmark level, to the 'Neutral' category.

Sias (2004) argues that if institutions follow each other into or out of the same securities, then the above Buy_ratio of two adjacent quarters should be positively correlated. In a time-dependent context, I argue that if institutions herd, ITDs could be the same for multiple continuous quarters. Hence, for each stock, if the ITD stays unchanged for i consecutive quarters, then I assign this stock-period to the i-quarter herd category. For example, if ITD for MICROSOFT CORP is Buy (Sell) for the first three quarters of 1990 and then becomes Sell (Buy) in the last quarter, the first 3-quarter period is classified as a 3-quarter Buy (Sell) herd. In order to examine how institutional trading and its impact on prices changes as herds proceed, I assign each quarter of a herd to a correspondent herding phase. For example, for a 3-quarter

[9] Following Wermers (1999), for a given quarter the benchmark proportion is computed by dividing the number of times that institutions purchase (observed across the universe of stocks within a given capitalization category) by the number of times that institutions either purchase or sell stocks.

herd, the first quarter is the starting phase, the second quarter is the second phase, and the last quarter is the ending phase of the herd. Figure 3.1 explains how herds are constructed.

For each herd, I calculate returns for the prior four quarters, for individual herding quarters, and for one, two, three, and four quarters following the herd, which will be referred to as past, contemporaneous, and post-herd returns, respectively. I am most interested in the post-herd returns because they can be used to evaluate the reversal associated with herding. The requirement for 4-quarter returns after the herd ends limits my sample to the end of 2004.

I use return data from the Center for Research in Securities Prices (CRSP) Monthly Stock file. For abnormal returns, I employ a method by Daniel, Grinblatt, Titman, and Wermers (1997) in which returns of stocks are adjusted by returns of a benchmark portfolio with similar size, book-to-market, and momentum characteristics. Formally, every quarter, stocks are assigned into quintiles based on market capitalization. Then, stocks within a market value quintile are assigned into book-to-market quintiles, yielding 25 portfolios; Book-to-market ratio is calculated following Fama and French (1993). Finally, stocks in each portfolio are sorted into quintiles based on the previous 4-quarter returns to yield 125 benchmark portfolios. Quintiles-cut-off values for all three dimensions are obtained from NYSE stocks. The abnormal returns for each herding phase (contemporaneous returns) are calculated based on the benchmark portfolios formed at the end of the prior quarter, while the post-herd abnormal returns are based on those formed at the end of the last herding quarter.

Table 1 provides summary statistics for the sample. Panel A reports the average number of stocks traded by the number of active institutions for three periods: 1980-1988, 1989-1996, and 1997-2004. The number of stocks traded increases over time from an average of 3,143 per quarter in the first period to 4,951 in the most recent period. Moreover, as the universe of institutions increases, institutions appear to trade the same stocks more frequently. For example, the number of stocks that are traded by at least 200 institutions in a given quarter increases from 86 to 383 over the three periods.

Panel B partitions the herd sample by the institutional trading intensity and reports the characteristics of stocks for each subsample. It is evident that the number of active institutions is positively related to the market capitalization of stocks. For stocks with less than 5 active institutions, the average market capitalization is $28.90 million. Market capitalization increases along with the intensity of trading to reach $15.18 billion for the highest bracket of at least 200 active institutions. The number of active institutions appears to be negatively related to book-to-market. These findings suggest that institutions tend to be more active on large and mature stocks. Finally, the relation between the number of active institutions and the momentum factors of stocks is not clear. Momentum starts going up with the number of active institutions and reaches a peak of around 27 percent for stocks with 30-99 traders and then begins going down in trading intensity.

3.3. Herding Activities by Institutions

In table 2, I present the overall herding activities by institutions over the 1980-2004 period. The sample includes 133,335 herds, of which those lasting for at least two quarters account for more than 40 percent. There is a negative relation between the number of herds and their duration; on both the buy side and the sell side, sample size declines by more than half as I move from one herding category to the next. As herds of up to four quarters compose more than 95 percent of the sample, I combine those of five quarters or more into one group, named ‘more than 4’. For the investigation of the price impact of herds, I limit my analysis to those that last for at most four quarters because the scarcity of longer herds makes analysis on this sample lack statistical power as well as economic significance.[10]

In panel A, institutions appear to engage in herding both when they buy and when they sell stocks. Neither buy herds nor sell herds dominate the sample, even though institutions herd slightly more on the buy side. For the whole sample, buy herds account for 51.16 percent, while for herds that last for at least two quarters (hereafter referred to as the long-herd sample), the buy-to-sell ratio is about 53/47. Also, for the long-herd sample, the number of buy herds is consistently larger than the correspondent number of sell herds. It is interesting to note that while the intra-quarter literature documents slightly more herds on the sell side (Wermers, 1999 and Grinblatt, Titman, and Wermers, 1995), when adding the time dimension to the analysis, I document the contrary.

In panel B, I present herding activities segregated by market capitalization prior to herds. Again, size quintile break values are based only on NYSE stocks. There is an inverse relation between herding activities and stock capitalizations. The smallest stocks account for more than 40 percent of the herd sample, and this number declines all the way to about 10 percent for the largest stocks. The same pattern can be observed if I focus on the long-herd sample. According to Wermers (1999) and Sias (2004), herding associated with information cascades should be more likely to occur in small-capitalization stocks where information is scarce and signals are noisy and, therefore, money managers tend to disregard their own information to follow the consensus. On the other hand, investigative herding should be strongest in large-capitalization stocks where information asymmetry is less severe and, hence, institutions tend to receive and

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[10] For example, the 10 or 11-quarter herd categories only has less than 100 observations for the whole 25-year period.

investigate the same signals. The finding in this panel is consistent with Wermers (1999) and Sias (2004) who both find higher level of intra-quarter herds for small-capitalization stocks than other size categories and supports the information cascades hypothesis. As in panel A, institutions herd more frequently on the buy side than on the sell side for all size quintiles. Also, across size categories, the number of herds declines in the duration of herds.

In table 3, I examine the trading activities by institutions for each herding category. For each herd, I calculate the number of institutions that increase their fractional holding in that stock (or the number of buyers) for each herding phase. For each quarter and herd category, I calculate the mean value of the number of institutional buyers by herding phase. I apply the same procedure in calculating the number of active institutions. Panel A reports the mean values of the two time series obtained, namely, the number of institutional buyers and the number of active institutions for each herding phase. It is evident that the numbers of active institutions on the buy side and on the sell side are comparable. Also, on both sides of herds, the differences in institutional trading activities from one herding phase to the next are marginal. As expected, the number of institutions that are buyers is smaller for the sell side than for the buy side. The general picture emerging from this panel is that institutions are as active on the sell side as on the buy side, and there is not much difference in their trading intensity across herding phases.

In panel B, I examine institutional trading by market capitalization. Trading activities by institutions appear to monotonically increase in size of firms, which is consistent with Gompers and Metrick (2001), who document that institutions prefer large and liquid stocks. On average, the number of active institutions almost doubles from one capitalization quintile to the next; starting with less than 20 for the smallest stocks, this number reaches over 240 for the largest quintiles. A similar trend can be seen on the number of institutional buyers. These findings justify the need for using a size benchmark, E[buy_ratio], in assigning institutional trading direction (ITD) to an individual stock-quarter. Also, the number of buyers on the buy side is significantly larger than those on the sell side. In summary, trading activities by institutions increase in market capitalization and within each capitalization quintile there are no significant changes in the intensity of trading from one herding phase to the next.

3.4. Institutional Herding and Stock Returns

As discussed earlier, herding by institutions can either stabilize or destabilize stock prices. The rich theoretical works in this area suggest that if herds are motivated by information, then trades in herds will help to accelerate the price adjustment process and there will be no reversal in future returns. Otherwise, if herds are associated with non-information sources, such as reputational concerns of managers or preference over certain characteristics of stocks, trading in herds will tend to destabilize stock prices and subsequent returns will be inversely related to current institutional demand; in other words, there will be reversals in returns following herds. Recent works in this field (Sias, 2004, Wermers, 1999, Nofsinger and Sias, 1999) document a weak positive relation between intra-quarter herds by institutions and subsequent returns and, therefore, suggest that institutional herding is rational and helps to enhance the price discovery process.

I revisit this issue by examining returns of stocks after herding by institutions ends. The key difference in my approach and the intra-quarter studies by Sias (2004), Wermers (1999), and Nofsinger and Sias (1999) is the assumption of when herds end. The underlying assumption in the intra-quarter herd literature is that herds could only last for one quarter. However, there are no theoretical works suggesting such duration and, more important, as exhibited in the first section, there is a significant proportion of herds that last for at least two quarters. Hence, the intra-quarter herds approach, in fact, includes the late herding phases in the analysis of post-herds reversals. Because demand by institutions has strong influence on stock prices over the same period (Sias, Stark, and Titman, 2006, Wermers, 1999, and Nofsinger and Sias, 1999 among others), trading in the late herding phases will force stock prices to move in the direction of trade made in the first period. Hence, it is less likely that intra-quarter studies can detect reversal in future returns. I employ two approaches in investigating the price impact of herding. First, I examine stock returns following the end of the last herding quarter. This method allows me to exclude the contemporaneous impact of trade in herds in calculating post-herd returns. The limitation of this approach is that it requires the recognition of the time herds end and hence it is subject to a looking-forward bias. Also by construction, after herds end institutions will either stay neutral or trade in the opposite direction. As a result, post-herd returns will be biased toward reversals. In the second approach, I predict return reversals based on the current herding activities and their impact on stock prices.

3.4.1. Institutional herding and past, contemporaneous and post-herd returns

In table 4, I report four-quarter stock returns prior to herds, quarterly returns during herding period, and cumulative one, two, three and four-quarter returns following the end of herds. Every quarter, for each herd category, I first calculate the equally-weighted averages of returns for each window of interest. The number reported is the mean value of the 99 averages obtained from the first step over the 25-year period. In the buy and sell sections, the bottom lines exhibit the mean returns for the long-herd and for the full sample, respectively. The last two lines in each panel report the differences in mean returns between buy and sell herd samples; the number in each cell is the average of the quarterly pair differences in returns between the two samples. For post-herding periods, these two lines represent the overall reversals or continuations in returns following the end of herds.

In panel A and B, I examine raw returns, and abnormal returns adjusted for size/book-to-market/momentum benchmarks, respectively. In the first panel, several interesting points emerge. First, consistent with Badrinath and Wahal (2002) and Nofsinger and Sias (1999), institutions appear to follow a positive-feedback strategy, buying stocks with higher and selling those with lower past returns. On average, the 4-quarter momentum for the buy sample is 25.57 percent, nearly 4 percent higher than the number for the sell herds. Second, the relation between the duration of the herd and past returns is positive on the buy side while it appears negative on the sell side. In other words, the higher (lower) the past returns, the longer the period that institutions will buy (sell) stocks; the absolute differences in 4-quarter momentum between 1-quarter and 4-quarter herds on either the buy side or the sell side are about 13 percent. Third, consistent with the contemporaneous literature, demand by institutions appears to exert significant impact on returns over the same period. The contemporaneous returns are larger for buy herds than for sell herds. Moreover, across herding phases, individual returns on the buy side are larger than the correspondent returns on the sell side. Fourth, there is a positive relation between the magnitude of contemporaneous returns and the duration of herds. For example, in the second phase of buy herds, the contemporaneous return for 2-quarter herds is 5.30 percent while the returns for 3 and 4-quarter herds are 5.92 and 8.40 percent, respectively. The findings on contemporaneous returns confirm the need to control the late herding-phase impact in calculating post-herd returns and hence justify the time-dependent approach employed in this study.

Perhaps the most interesting issue is associated with the returns observed after herds end. On average, future 4-quarter returns following buy herds is 14.83 percent; 3.64 percent lower than those for sell herds. Across other post herding windows, the differences in returns are all economically large and statistically significant. When I compare individual returns of any given window, surprisingly, none of the post-herding returns on the buy side are larger than those on the sell side. It should be noted that during herds, contemporaneous returns on the buy side are all larger than the correspondent returns on the sell side. The reversal can also be seen through the monotonic relation between the duration of herds and future returns. For the buy side, future returns decline steadily in the duration of herds, while for sell side, the longer the period institutions sell stocks, the larger the post-herding stock returns. This trend prevails for every windows examined.

Panel B reports abnormal returns adjusted for size/book-to-market/momentum benchmarks. Most strikingly, post-herd abnormal returns are all negative on the buy side and all positive on the sell side. On average, buy herds underperform their peers by 1.30 percent in 1-quarter window and the underperformance extends to reach 1.82 percent after four quarters. On the other side, sell herds consistently outperform benchmarks; the average abnormal returns are 0.54 and 1.03 percent for the 1 and 4-quarter windows, respectively. It should be noted that during the herding periods, stocks bought by institutions outperform while those sold by institutions underperform their benchmarks. Again, the results need to be analyzed with caution because by construction, post herd returns tend to be biased toward reversals. However, similar to panel A, there is a monotonic relation between the duration of herd and return reversals; longer herds on the buy side are associated with stronger underperformance while longer herds on sell side are followed by higher abnormal returns. Such a relation supports the argument that stocks that experience more herds subsequently experience stronger reversals.

The findings in table 2 suggest that herds are primarily associated with information cascades. Hence, I expect that the price impact of herding and, as a result, the reversals documented in panel A and B should be stronger for small-capitalization stocks. I start by sorting the herd sample into quintiles based on the market capitalization of stocks at the end of the quarter prior to herds; the quintile cut-off values are based on NYSE stock rankings. I redo the analysis on abnormal returns for each size category and report the average abnormal returns for the buy side and the sell side, and the differences between them in panel C.

In panel C, the general reversals, which are represented by the differences in returns reported in the bottom two lines of any size panel, appear to be economically larger and statistically more significant for small and medium stocks than for large stocks. Also, the reversals are significant on both sides of herds. Formally, stocks bought in herds subsequently underperform their benchmark while those sold in herds subsequently outperforms their peers. The inclusion of the benchmark enables me to have a better view on the contemporaneous impact and reversals for buy and sell herds individually. For the first three quintiles, stocks that institutions buy (sell) in herds significantly outperform (underperform) benchmark average during the herding period and, then, significantly underperform (outperform) the same benchmark after herds end. It should be noted that, reversals are stronger for the long-herd sample than for the full sample, which again adds evidence to the price impact of herding.

3.4.2. Current herding activities by institutions and return reversals

The above approach of identifying the herds and then calculating post-herd returns suffers a looking-forward bias and, hence, post-herd returns are biased toward reversals. In this section, I use information on current herding activities to anticipate whether herds will continue and, hence, whether I can predict reversals in returns. Formally, based on the finding in table 4 that the ex-post duration of herds monotonically increases in current contemporaneous returns, for a given quarter I create subsamples of stocks based on the number of quarters that herds already occur on a given stocks. Then, within each subsample, I rank stocks into tertiles based on this quarter's abnormal returns. Again, abnormal returns are based on the benchmark portfolio formed at the end of the prior quarter. I expect that on the buy side, institutions will tend to stop buying or start selling stocks that experience the lowest returns. Similarly, on sell side, institutions will more likely to either stop selling or even start buying stocks that experience the highest abnormal returns. I argue that if herding contains a destabilizing impact, stocks that institutions tend to change their trading behavior will be more likely to experience return reversals.

In panel A of table 6, I track trading activities by institutions in the four quarters after stocks are assigned into portfolios according to the above procedure. The purpose is to examine whether institutions are more likely to reverse their trading behavior for these two extreme types of stocks discussed above. The first two columns in this panel exhibit herding information in current quarter crossing with the contemporaneous abnormal returns of stocks. The last four columns report the proportion of trading by institutions that belong to different trading categories: Sell, Neutral, and Buy. I am most interested in the sample of current buy herds with the lowest abnormal returns and current sell herds with the highest abnormal returns. Consistent with this expectation, on the sell section, the proportion of 'Sell' following herds with the highest returns is the smallest compared with other correspondent numbers. In the first quarter, the proportion of sell for the bottom returns tertile is 44.25 percent, compared to 45.82 and 48.60 for the other two categories. In the second quarter, the difference widens; 41.36 percent versus 44.91 and 47.41, respectively. The result suggests that for sell herds, institutions tend to change their trading direction if stocks experience higher abnormal returns than their peers. Similarly, on the buy section, for stocks that experience lowest returns, the proportion of the sample that institutions remain the net buyers in the following four quarters is the smallest. In the first quarter, the proportion of buy is 46.31 percent for the 'Buy with the lowest returns', compared to 47.43 and 50.17 percent for the other two samples. Such difference widens in the next quarters. This suggests that for buy herds, institutions are more likely to change their trading direction on stocks that experience low contemporaneous returns.

Next, I examine future returns for those two types of stocks namely 'sell herds with the highest returns' and 'buy herds with the lowest returns' and report raw returns and abnormal returns results in panel B and C, respectively. In panel B, the first two lines in each size section reports quarterly abnormal returns for those two portfolios and the last line reports their differences in returns. The bottom section summarizes returns for the whole sample. It is evident that stocks sold in herds by institutions subsequently outperform those institutions bought in herds. The differences in returns over the last three quarters are well above one percent and all significant. When examining individual size quintiles, I can see the same pattern of reversal in returns; especially for the first two quintiles where quarterly differences in returns are about two percent. For other size categories, the differences in returns are positive but lack consistency in statistical power.

Panel C summarizes the results on abnormal returns. Consistent with panel B, reversals in returns are significant during the last three quarters and concentrate on the first two size quintiles. Moreover, with the adjustment of benchmark returns, reversals for individual herd sample become clearer. From the second quarter forward, stocks sold in herds by institutions subsequently outperform their benchmarks while those bought in herds underperform their peer. This pattern prevails for all size quintiles but again concentrates in the first two size groups. The findings on reversal in this table suggest that to a certain extent, herding by institutions may destabilize stock prices.

3.4.3. Institutional herding and momentum

Institutions are documented to engage in positive-feedback trading, buying stocks with high and selling stocks with low past returns (Badrinath and Wahal, 2002, Wermers, 1999, and Nofsinger and Sias, 1999). In table 3, I observe a positive relation between the duration of herds and past returns, hence, it is important to examine whether this common trading strategy is the source of herding by institutions. If that is the case, I expect that sell herds should be concentrated in low momentum stocks while buy herds should be formed mainly in high momentum samples. Otherwise, I expect that herding as well as its impact on prices prevails for the full range of momentum.

To evaluate the role of positive-feedback trading, each quarter I assign herds to NYSE-based momentum quintiles. Panel A of table 5 exhibits the frequency of herds across momentum categories. Most importantly, I document that institutional herding prevails for all momentum quintiles with comparable magnitude. Consistent with Wermers (1999) who document that intra-quarter herds are largest for the two extreme momentum quintiles, I find that institutions engage in herding more frequently among stocks of the top and bottom samples. These two extreme momentum groups compose about 48 percent of the herd sample. When I examine how herds of a given duration vary across momentum quintiles, I find that on the sell side, the proportion of institutional herding appears to monotonically decline in past returns, while on the buy side, the higher momentum is associated with the larger proportion of herds. This finding is consistent with the positive-feedback behavior of institutions.

Panel B reports abnormal returns around herding periods. After the herds end, the differences in returns between stocks bought and those sold in herds are all negative and significant, suggesting that price impact prevails for all momentum samples. Moreover, for buy herds, contemporaneous abnormal returns in most cases are positive and significant, especially for the first two herding phases. However, these stocks subsequently perform worse than the benchmark averages and the underperformance is significant for at least three momentum quintiles. On the other side, stocks sold in herds significantly underperform contemporaneous benchmark portfolios while they appear to outperform the post-herd benchmarks in most cases. Again, across momentum quintiles, the reversals for the long-herd sample are more pronounced than the average level of the whole sample.

In summary, the results in the panel suggest that while institutions follow momentum trading, such a common strategy is not the primary source for their herds and that herding shows destabilizing impacts across momentum samples.

3.4.4. Institutional herding over time

In this section, I examine how herding by institutions and its price impact changes over time. I split the sample into three periods of approximately equal length: 1980-1988, 1989-1996, and 1997-2004. Panel A reports the herding frequency. As the number of institutions as well as the number of stocks listed increases, it is not surprising to see that the herds sample is getting larger in the later period. It is evident that multi-quarter herds by institutions are not limited to any period. Across three subperiods, the numbers of herds that last for two quarters or more consistently account for around 40 percent of the samples. Also, for those long herds, the number of buy herds is slightly larger than the number of sell herds for all herding categories, consistent with the findings in table 2.

In panel B, I decompose herds by stock capitalization. Because herds concentrate in small stocks, which makes other capitalization samples relatively small, I combine two middle size quintiles and two top quintiles and name them medium and large size samples, respectively. I find that the proportion of herds on small stocks increases over time while those on medium and large stocks steadily decline. Herds on medium stocks in the first nine years account for more than 40 percent of the sample but this ratio declines to less than 35 percent in the most recent period. Similarly, herds on the largest sample lose more than 6 percent over time and account for about only 20 percent of the sample in recent years. Starting with around 30 percent, the proportion of herds for small stocks eventually reaches more than 45 percent of the sample. Over time, long herds for small stock increase by 185 percent while medium and large stocks increase by 27 and 17 percent, respectively. This analysis suggests that the increases in herding activities over time exhibited in panel A are primarily caused by the huge escalation in herding within small capitalization stocks.

The above findings on the changes in distribution of herds among three periods have several implications on the price impact of herding. As herding becomes more intense over time, I expect that the price impact be stronger in recent periods. Also, as the relative intensity of herds among market capitalization categories changes from one period to the next, it presents a natural experiment to examine whether the relative magnitudes of price impact change in the same direction. I expect that stronger herds are associated with stronger reversals.

In panel C, I examine the differences in abnormal returns for buy and sell herds for each market capitalization group as well as for the whole sample by three periods. First, for all periods examined, the overall reversals in returns after herds end, which are represented by the difference in returns between stocks bought in herds and those sold in herds and are exhibited in the last two lines in each section, prevail and appear significant for all periods examined. Moreover, the magnitude of reversals increases over the three periods, which is consistent with the above argument about the destabilizing impact. Second, when I relate the reversals and the magnitude of herds within a given period, an interesting pattern emerges: more herds, larger reversals. For example, for the first period, the ranking by number of herds among market capitalizations, observed in panel B, is: Medium, small and large, and the correspondent ranking in reversals is the same. When I look at the long herd sample, as large and small size samples switch their positions in ranking for herds, their positions in ranking for reversals are switched as well.

Panel D reports the differences in contemporaneous and quarterly future returns for stocks that belong to extreme herding samples namely ‘sell herds with the highest returns’ and ‘buy herds with the lowest returns’. The panel is structured in the same manner as panel C of table 6. It is evident that the differences in future returns are positive and significant in at least two quarters for any period examined. This suggests that, to a certain extent, it is possible to predict reversals in returns based on the information about current herding activities and confirms the earlier conclusion that the aggregate herding by institutions may destabilize stock prices. Examining individual capitalization categories, I find that the reversals occur mainly within the small size sample, which is consistent with the finding that herding is concentrated in this segment of the market.

3.5. Conclusions

In this paper, I examine the tendency of institutions to herd in their trades from 1980 to 2004. I document that it is common for herds by institutions to last for more than one quarter. Over the 25 years examined, herds that last for at least two quarters account for more than 40 percent of the herd sample. This finding has important implication for evaluating the price impact of herding. It suggests that the appropriate window to examine post-herd returns is from the end of the last herding quarter forward instead of from the end of any herding quarter. This recognition distinguishes my study from the intra-quarter herd literature.

Contrary to the conclusions of the intra-quarter literature, I document that there are reversals in stock returns following the end of herds. First, I find that stocks bought in herds subsequently underperform those sold in herds. The reversals are economically large and statistically significant for up to four quarters. Second, I show that stocks bought in herds subsequently underperform while those sold in herds subsequently outperform their benchmarks. It should be noted that during herding periods, stocks bought in herds outperform while those sold in herds underperform their benchmark portfolios. Finally, I document that it is possible to predict reversals based on current herding activities and their contemporaneous impact on stocks prices.

In terms of the cause of herds, consistent with the intra-quarter literature, I find that herds form disproportionately more frequently on small and medium size stocks, which supports the information cascades hypothesis. I also document that the common positive-feedback trading by institutions is not responsible for their herding behavior.

3.6. Figure for Chapter Three

Time	Quarter1	Quarter2	Quarter3	Quarter4	Quarter5	Quarter6	Quarter7
ITD	Buy	Sell	Buy	Buy	Buy	Sell	Inactive
Herding category	.	1-period sell herd	3-period buy herd	3-period buy herd	3-period buy herd	1-period sell herd	.
Herding phase	.	1st Sell	1st Buy (Starting)	2nd Buy	3rd Buy (Ending)	1st Sell	.

Figure 3. 1. Identify Institutional Herds

3.7. Tables for Chapter Three

Table 3. 1: Summary Statistics

Panel A. Average Number of Securities and Trading Intensive

	Sample Average	1980-1988	1989-1996	1997-2004
≥ 1 trader	4,072	3,143	4,238	4,951
≥ 5 traders	3,013	2,048	3,143	3,969
≥ 10 traders	2,408	1,534	2,482	3,317
≥ 20 traders	1,817	1,050	1,772	2,724
≥ 30 traders	1,490	805	1,385	2,366
≥ 50 traders	1,089	546	956	1,834
≥ 100 traders	580	263	492	1,025
≥ 150 traders	339	148	292	600
≥ 200 traders	211	86	181	383

Panel B. Stocks Characteristics and Trading Intensive

	Size (Million $)	Book-to-Market	Momentum
1-5 traders	28.90	1.04	13.34%
5-9 traders	68.84	0.95	17.43%
10-19 traders	134.09	0.85	20.49%
20-29 traders	242.58	0.75	23.58%
30-49 traders	410.53	0.70	26.87%
50-99 traders	867.67	0.68	27.43%
100-149 traders	1,855.86	0.65	25.90%
150-199 traders	3,342.10	0.63	25.03%
≥ 200 traders	15,177.24	0.58	22.05%

Every quarter during the 1980-2004 period, I calculate the number of securities traded by at least 1, 5, 10, 20, 30, 50, 100, 150 and 200 institutional investors. Panel A reports the average of the time-series of these figures for three periods: 1980-1988, 1989-1996, and 1997-2004. Panel B reports the relation between the intensive of trading by institutions and the characteristics of stocks. Every quarter, stocks are partitioned on the basis of the number of institutions trading. Then, the average size, book-to-market, and momentum factors are calculated for each subsample. The numbers reported are the average of the time-series obtained.

Table 3. 2: Herding Activities

Panel A. Distribution of Herds by Herding Duration

	Sell Side					Buy Side						
Herding duration	1- quarter	2- quarter	3- quarter	4- quarter	>4 quarter	1- quarter	2- quarter	3- quarter	4- quarter	>4 quarter	Total	Excl. 1- quarter herds
Number of herds	39,794 29.85	13,867 10.40	5,779 4.33	2,668 2.00	3,012 2.26	39,735 29.80	14,869 11.15	6,761 5.07	3,318 2.49	3,532 2.65	133,335 100.00	53,806 40.35
Cumulative for Sell	65,120 29.85	25,326 40.25	11,459 44.58	5,680 46.58	3,012 48.84						65,120 48.84	25,326 18.99
Cumulative for Buy						68,125 29.80	28,480 40.95	13,611 46.02	6,850 48.51	3,532 51.16	68,215 51.16	28,480 21.36

Panel B. Distribution of Herds across Market Size Quintiles

	Sell side					Buy side						
Size	1-quarter	2-quarter	3-quarter	4-quarter	>4 quarter	1-quarter	2-quarter	3-quarter	4-quarter	>4 quarter	Total	Excl.1-quarter herds
1 (Smallest)	17,189 30.85	5,433 9.75	2,307 4.14	1,016 1.82	1,027 1.84	17,999 32.30	5,862 10.52	2,599 4.66	1,179 2.12	1,110 1.99	55,721 41.79	20,533 38.16
2	8,595 29.49	3,117 10.69	1,337 4.59	646 2.22	654 2.24	8,326 28.56	3,289 11.28	1,548 5.31	800 2.74	836 2.87	29,148 21.86	12,227 22.72
3	5,758 28.99	2,236 11.26	915 4.61	428 2.16	488 2.46	5,447 27.43	2,337 11.77	1,115 5.61	544 2.74	592 2.98	19,860 14.89	8,655 16.09
4	4,533 28.97	1,731 11.06	666 4.26	339 2.17	418 2.67	4,387 28.04	1,895 12.11	796 5.09	418 2.67	465 2.97	15,648 11.74	6,728 12.50
5 (Largest)	3,719 28.70	1,350 10.42	554 4.28	239 1.84	425 3.28	3,576 27.60	1,486 11.47	703 5.43	377 2.91	529 4.08	12,958 9.72	5,663 10.52

This table reports the number of herds for different duration. In panel A, the first two numbers are the number of herds and its percentage of the whole sample, respectively. The last two sets of number are the cumulative number for Sell herds and Buy herds, respectively. Panel B reports herding activities by market capitalization of stocks. The first number is the number of herds and the second is the percentage within each capitalization subsample.

Table 3. 3: Institutional Trading by Herding Phases

Panel A. Trading in Herds by Herding Phases

	Sell herding phases				Buy herding phase			
Herding duration	1st quarter	2nd quarter	3rd quarter	4th quarter	1st quarter	2nd quarter	3rd quarter	4th quarter
1	26.21 55.99				34.11 54.20			
2	28.37 60.77	28.66 61.03			35.39 56.27	36.86 58.51		
3	28.76 61.96	28.78 61.43	29.00 61.69		34.59 54.45	36.22 57.18	37.58 59.12	
4	29.29 62.66	28.81 61.71	28.73 61.26	28.78 62.03	33.63 53.22	35.75 56.56	37.20 58.84	38.69 61.19

Panel B. Trading in Herds by Phases across Size Quintiles

		Herding phases for Buy				Herding phases for Sell			
Size	Herding duration	1st quarter	2nd quarter	3rd quarter	4th quarter	1st quarter	2nd quarter	3rd quarter	4th quarter
1 (Smallest)	1	5.74 11.96				9.16 12.00			
	2	6.15 12.89	5.94 12.50			9.43 12.21	9.90 12.97		
	3	6.70 14.06	6.23 13.34	6.19 13.14		9.56 12.24	10.47 13.61	11.32 14.85	
	4	7.03 14.74	6.46 14.10	6.30 13.33	6.03 12.90	8.85 11.19	10.29 13.17	11.54 15.04	12.31 16.30
2	1	16.82 33.10				23.25 33.22			
	2	17.34 34.20	17.33 34.33			21.77 20.77	22.98 32.75		
	3	17.68 35.26	17.49 34.70	17.70 35.13		20.50 28.60	21.66 30.42	22.78 32.14	
	4	17.57 34.86	17.10 34.15	17.15 34.12	17.64 34.92	18.85 25.75	20.40 28.26	21.66 30.40	22.69 32.17
3	1	28.81 58.60				38.54 58.76			
	2	29.37 60.41	29.83 60.73			36.36 55.17	38.26 58.03		
	3	30.75 62.76	31.07 63.04	31.16 63.22		34.41 51.59	36.12 54.43	37.15 56.03	
	4	31.55 64.91	31.62 64.42	31.31 64.70	31.62 63.22	31.21 46.33	33.32 49.84	34.66 51.78	35.79 53.83
4	1	48.64 103.44				63.35 103.47			
	2	49.07 104.98	50.41 106.51			60.03 97.73	62.38 101.21		
	3	51.38 109.29	51.51 108.36	51.49 108.65		57.11 92.39	60.11 97.26	62.04 100.51	
	4	53.81 115.71	54.09 115.00	53.26 113.34	53.96 115.76	53.56 86.11	57.07 91.67	58.76 95.00	61.76 98.99
5 (Largest)	1	113.04 253.41				145.55 252.11			
	2	116.41 260.75	118.16 261.56			138.30 240.05	142.61 246.06		
	3	122.01 274.99	123.82 274.42	125.70 276.57		135.12 232.84	137.89 237.64	142.42 243.47	
	4	122.18 271.41	121.45 270.00	123.05 269.30	121.31 273.10	134.26 233.38	137.85 239.50	140.09 242.04	143.44 248.85

This table reports institutional trading over different herding phases. Each herding phase, I report the mean values of the number of institutional buyers and of the number of active institutions that either buy or sell stock. Panel A summarizes institutional trading for the whole sample while panel B disaggregates trading by market capitalization of stocks.

Table 3. 4: Post-herding Stock Returns

Panel A. Raw Returns

Herding duration	Pre-herd period	Herding periods (quarterly returns)				Post herding periods (cumulative returns)			
	4 quarters	1st quarter	2nd quarter	3rd quarter	4th quarter	1 quarter	2 quarters	3 quarters	4 quarters
Buy 1	22.12***	6.73***				3.03***	6.99***	11.49***	15.85***
Buy 2	29.27***	7.92***	5.30***			2.88**	6.53***	10.41***	14.16***
Buy 3	33.00***	9.84***	5.92***	4.30***		2.20**	4.93***	8.64***	12.27***
Buy 4	35.09***	11.32***	8.40***	5.21***	4.24***	1.58	4.58***	7.82***	11.42***
Excl. 1	31.23***	8.88***	5.90***	4.67***	4.24***	2.42***	5.72***	9.39***	13.01***
All	25.57***	7.61***	5.90***	4.67***	4.24***	2.84***	6.57***	10.77***	14.83***
Sell 1	24.44***	4.12***				4.54***	8.70***	12.77***	17.44***
Sell 2	19.12***	3.57***	3.40***			4.87***	9.47***	14.30***	19.21***
Sell 3	13.85***	1.45	2.53**	3.99***		5.48***	9.93***	14.42***	20.45***
Sell 4	11.73***	1.47	1.28	2.73**	3.73***	6.92***	11.53***	16.92***	22.57***
Excl. 1	16.98***	2.67***	2.94***	3.58***	3.73***	5.26***	9.90***	14.68***	19.95***
All	21.69***	3.63***	2.94***	3.58***	3.73***	4.88***	9.24***	13.58***	18.47***
Excl. 1	14.25***	6.21***	2.96***	1.09*	0.51	-2.85***	-4.18***	-5.29***	-6.94***
All	3.88***	3.98***	2.96***	1.09*	0.51	-2.03***	-2.66***	-2.82***	-3.64***

Panel B. Abnormal Returns Adjusted for Size/Book-to-Market/Momentum

Herding duration	Pre-herd period	Herding periods (quarterly returns)				Post herding periods (cumulative returns)			
	4 quarters	1st quarter	2nd quarter	3rd quarter	4th quarter	1 quarter	2 quarters	3 quarters	4 quarters
Buy 1	-1.37***	2.14***				-1.20***	-1.34***	-1.17***	-1.19***
Buy 2	0.08	3.53***	0.99***			-1.08***	-1.33***	-1.51***	-1.90***
Buy 3	1.46*	5.19***	1.88***	0.18		-1.49***	-2.57***	-2.80***	-3.51***
Buy 4	3.40**	6.57***	4.07***	1.40***	0.21	-2.15***	-2.86***	-3.86***	-4.53***
Excl. 1	0.96***	4.42***	1.63***	0.59*	0.21	-1.44***	-1.98***	-2.31***	-2.81***
All	-0.51***	3.02***	1.63***	0.59*	0.21	-1.30***	-1.59***	-1.61***	-1.82***
Sell 1	-0.35	-0.31**				0.29*	0.37*	0.13	0.42
Sell 2	-1.92***	-0.66***	-0.73***			0.66**	1.09***	1.49***	1.75***
Sell 3	-2.44***	-2.70***	-1.36***	-0.25		1.02**	1.22*	1.13	2.19**
Sell 4	-1.93***	-2.85***	-2.78***	-1.20***	-0.83*	2.32***	2.52***	2.63**	2.74**
Excl. 1	-2.08***	-1.50***	-1.16***	-0.57*	-0.83*	0.93***	1.30***	1.52***	2.01***
All	-0.98***	-0.75***	-1.16***	-0.57*	-0.83*	0.54***	0.73***	0.66***	1.03***
Excl. 1	3.04***	5.92***	2.79***	1.16***	1.04	-2.37***	-3.28***	-3.83***	-4.82***
All	0.48	3.77***	2.79***	1.16***	1.04	-1.85***	-2.32***	-2.27***	-2.85***

Panel C. Size/BTM/Momentum Adjusted Abnormal Returns by Size

	Pre-herd period	Herding periods (quarterly returns)				Post herding periods (cumulative returns)			
	4 quarters	1st quarter	2nd quarter	3rd quarter	4th quarter	1 quarter	2 quarters	3 quarters	4 quarters
Size 1 (Smallest)									
Buy	1.59*	5.98***	2.52***	1.66**	-0.75	-2.21***	-2.23***	-2.62***	-3.64***
	-0.38	2.42***	2.52***	1.66**	-0.75	-2.12***	-2.34***	-2.27***	-2.78***
Sell	-2.88***	-5.81***	-1.81***	-1.26*	-1.82	1.42***	1.38*	2.15**	2.83***
	-1.68***	-4.20***	-1.81***	-1.26*	-1.82	0.66**	0.71	0.58	1.27*
Buy-Sell	4.47***	11.79***	4.33***	2.92***	1.07	-3.63***	-3.61***	-4.77***	-6.47***
	1.30**	6.62***	4.33***	2.92***	1.07	-2.78***	-3.05***	-2.85***	-4.05***
Size 2									
Buy	1.16	5.34***	1.53***	0.26	-0.19	-1.06***	-1.85***	-2.10***	-2.55***
	-0.54	4.64***	1.53***	0.26	-0.19	-1.05***	-1.40***	-1.35***	-1.60***
Sell	-1.52***	0.17	-1.03***	-1.07*	-0.43	0.64*	1.22**	1.45**	2.03*
	-0.69	0.88***	-1.03***	-1.07*	-0.43	0.71***	1.02***	1.13***	1.43***
Buy-Sell	2.67**	5.17***	2.56***	1.33*	0.24	-1.69***	-3.07***	-3.55***	-4.58***
	0.15	3.77***	2.56***	1.33*	0.24	-1.76***	-2.42***	-2.48***	-3.04***
Size 3									
Buy	1.44	5.19***	0.98***	0.09	0.80	-0.97***	-1.21**	-1.84***	-2.09***
	-0.37	4.34***	0.98***	0.09	0.80	-0.62***	-0.77***	-1.07***	-1.02**
Sell	-2.41***	0.57*	-0.80**	0.36	-0.04	1.02***	1.37***	1.27**	1.15
	-0.89	1.42***	-0.80**	0.36	-0.04	0.70***	0.92***	0.89***	0.99**
Buy-Sell	3.85**	4.62***	1.78***	-0.27	0.84	-1.99***	-2.58***	-3.12***	-3.24***
	0.52	2.92***	1.78***	-0.27	0.84	-1.32***	-1.70***	-1.96***	-2.01***

Table 3.4: Post-herding Stock Returns

				Size 4					
Buy	-0.08	2.26***	0.85***	0.23	0.59	-0.20	-0.77*	-0.96*	-0.15
	-0.86*	2.34***	0.85***	0.23	0.59	-0.13	-0.22	-0.34	-0.05
Sell	-2.05**	2.10***	0.41	0.48	0.24	0.42	0.28	0.16	0.31
	-0.36	2.12***	0.41	0.48	0.24	-0.03	0.08	0.03	0.03
Buy-Sell	1.97	0.16	0.44	-0.25	0.35	-0.62	-1.05*	-1.12	-0.46
	-0.50	0.22	0.44	-0.25	0.35	-0.10	-0.30	-0.37	-0.08
				Size 5 (Largest)					
Buy	1.26	0.57*	-0.39	0.11	0.49	-0.28	-0.44	-0.64	-0.85
	0.43	1.23***	-0.39	0.11	0.49	0.27	0.15	0.21	0.28
Sell	-0.70	3.20***	0.37	-0.84*	0.96	0.18	0.56	1.03*	1.26*
	-0.09	2.83***	0.37	-0.84*	0.96	-0.22	-0.07	-0.15	-0.34
Buy-Sell	1.95	-2.62***	-0.76*	0.95	-0.47	-0.46	-0.99	-1.67*	-2.11*
	0.52	-1.60***	-0.76*	0.95	-0.47	0.50	0.22	0.36	0.62

This table reports four-quarter returns prior to herds, quarterly returns during herding period, and cumulative one, two, three and four-quarter returns following the end of herds. Panel A and B report raw returns and abnormal returns adjusted for size/book-to-market/momentum benchmark level, respectively. Every quarter, for each herd category, I calculate the equally-weighted averages of returns for each windows of interest. The number reported is the mean value of the 99 quarterly averages obtained from the first step over the 25-year period. The last two lines for each section, "Excl. 1" and "All", report returns for the sample of long herds, which last for at least two periods, and for the full sample, respectively. The last two lines in each panel report the differences in the average returns for buy and sell herds; number in each cell is the average of the quarterly pair differences in returns between buy and sell sample. Panel C disaggregates abnormal returns results on market capitalization. It reports the average abnormal returns for buy herds, sell herds and the differences between them. The two numbers for each cell are associated with the "Excl. 1" sample and "All" sample, respectively. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 3. 5: Institutional Herding and Future Returns

Panel A. Contemporaneous Returns and Future Trading by Institutions

Herd Categories	Contemporaneous Abnormal Returns	Future Trading Direction	Quarter 1	Quarter 2	Quarter 3	Quarter 4
Sell Herds	Low	Sell	48.60	47.41	46.01	45.33
		Neutral	21.75	22.81	24.19	24.40
		Buy	29.66	29.78	29.81	30.27
	Medium	Sell	45.82	44.91	44.10	44.32
		Neutral	21.62	22.77	23.83	23.81
		Buy	32.56	32.32	32.07	31.87
	High	**Sell**	**44.25**	**41.36**	**40.97**	**41.50**
		Neutral	21.38	23.17	23.89	24.29
		Buy	34.37	35.46	35.14	34.22
Buy Herds	Low	Sell	32.72	36.18	37.61	37.62
		Neutral	20.96	21.99	23.33	23.73
		Buy	**46.31**	**41.83**	**39.06**	**38.65**
	Medium	Sell	32.05	34.14	35.19	35.51
		Neutral	20.52	22.06	23.00	23.09
		Buy	47.43	43.81	41.82	41.40
	High	Sell	30.02	30.59	32.39	33.90
		Neutral	19.82	21.64	22.71	23.61
		Buy	50.17	47.77	44.90	42.49

Panel B. Quarterly Raw Returns of Stocks that Institutions Tend to Change Their Herding Behavior

Size	Past Herds	Quarter 0	Quarter 1	Quarter 2	Quarter 3	Quarter 4
1	Sell with high returns	28.76***	4.85***	5.22***	4.96***	5.27***
1	Buy with low returns	-15.80***	3.26**	2.84*	2.76*	2.78*
(Smallest)	Difference	44.56***	1.59***	2.38***	2.20***	2.49***
2	Sell with high returns	23.59***	3.75***	4.71***	4.53***	4.27***
2	Buy with low returns	-13.65***	3.39**	2.55*	2.45**	2.70**
	Difference	37.23***	0.36	2.16***	2.08***	1.58***
3	Sell with high returns	21.43***	3.52***	4.21***	4.08***	3.81***
3	Buy with low returns	-12.48***	3.86***	3.16**	2.55**	3.17***
	Difference	33.90***	-0.34	1.05	1.53***	0.64
4	Sell with high returns	20.02***	3.57***	4.17***	4.11***	3.98***
4	Buy with low returns	-11.16***	4.13***	2.48**	2.94**	3.95***
	Difference	31.18***	-0.56	1.69***	1.17*	0.03
5	Sell with high returns	17.98***	2.93***	3.80***	4.42***	3.82***
5	Buy with low returns	-9.78***	3.75***	2.52**	2.38**	3.18***
(Largest)	Difference	27.76***	-0.82	1.28*	2.05***	0.65
All	Sell with high returns	24.01***	3.92***	4.52***	4.54***	4.34***
	Buy with low returns	-13.71***	3.47***	2.61**	2.68**	3.07**
	Difference	37.72***	0.45	1.91***	1.86***	1.27**

Panel C. Quarterly Abnormal Returns of Stocks that Institutions Tend to Change Their Herding Behavior

Size	Past Herds	Quarter 0	Quarter 1	Quarter 2	Quarter 3	Quarter 4
1	Sell with high returns	24.32***	-0.17	0.48	0.52	1.10**
1	Buy with low returns	-21.01***	-1.05**	-1.25***	-1.51***	-1.53***
(Smallest)	Difference	45.33***	0.88*	1.73***	2.03***	2.63***
2	Sell with high returns	19.91***	-0.48	0.60**	0.70***	0.56*
2	Buy with low returns	-18.48***	-0.24	-0.98***	-1.08***	-0.91***
	Difference	38.39***	-0.24	1.58***	1.78***	1.47***
3	Sell with high returns	17.59***	-0.64***	0.22**	0.32	0.20
3	Buy with low returns	-17.14***	0.45	-0.12	-0.83**	-0.42
	Difference	34.74***	-1.09**	0.34	1.15**	0.63
4	Sell with high returns	16.16***	-0.44*	0.20	0.30	0.31
4	Buy with low returns	-15.84***	0.76**	-1.04***	-0.72**	0.09
	Difference	32.00***	-1.20**	1.25***	1.03**	0.22
5	Sell with high returns	14.11***	-0.61**	-0.17	0.62***	0.18
5	Buy with low returns	-14.34***	0.33	-0.70**	-0.81**	-0.34
(Largest)	Difference	28.45***	-0.94*	0.53	1.43***	0.52
All	Sell with high returns	20.04***	-0.49***	0.27	0.48***	0.57***
	Buy with low returns	-18.78***	-0.33	-1.03***	-1.16***	-0.90***
	Difference	38.82***	-0.16	1.30***	1.64***	1.46***

Herds sample is partitioned based on current herding duration and contemporaneous returns of stocks. Every quarter, stocks are sorted (independently for buy and sell) on the number of quarters institutions already herds. Within each category of herds, stocks are assigned into tertiles based on the contemporaneous abnormal returns. Panel A reports the trading direction for the following four quarters. Panel B reports raw returns by market capitalization for two samples: (i) stocks that are sold in herds and that experience the highest contemporaneous abnormal returns and (ii) stocks that are bought in herds and that experience the lowest contemporaneous abnormal returns. They are stocks that institutions tend to change their herding behavior. Panel C reports abnormal returns. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 3. 6: Herding by Institutions and Momentum

Panel A. Distribution of Herds by Herding Duration and Momentum Factor

Momentum	Avg. Size rank	1-quarter	2-quarter	3-quarter	4-quarter	>4 quarters	1-quarter	2-quarter	3-quarter	4-quarter	>4 quarters	Total	Excl.1- period herd
1	0.89	9,141	3,400	1,592	803	902	9,142	2,887	1,275	617	567	30,326	12,043
(Lowest)		30.14	11.21	5.25	2.65	2.97	30.15	9.52	4.20	2.03	1.87	23.19	22.66
2	1.46	6,714	2,507	1,094	523	645	6,889	2,413	1,045	521	534	22,885	9,282
		29.34	10.95	4.78	2.29	2.82	30.10	10.54	4.57	2.28	2.33	17.50	17.47
3	1.67	6,460	2,376	999	408	567	6,667	2,542	1,068	545	569	22,201	9,074
		29.10	10.70	4.50	1.84	2.55	30.03	11.45	4.81	2.45	2.56	16.98	17.08
4	1.73	6,822	2,412	979	452	483	6,729	2,654	1,261	584	666	23,042	9,491
		29.61	10.47	4.25	1.96	2.10	29.20	11.52	5.47	2.53	2.89	17.62	17.86
5	1.48	9,801	3,061	1,097	480	415	9,269	3,980	1,969	1,049	1,196	32,317	13,247
(Highest)		30.33	9.47	3.39	1.49	1.28	28.68	12.32	6.09	3.25	3.70	24.71	24.93

Panel B. Size/BTM/Momentum Adjusted Abnormal Returns by Momentum

	Pre-herd period	Herding periods (quarterly)				Post herding periods (cumulative)			
	4 quarters	1st quarter	2nd quarter	3rd quarter	4th quarter	1 quarter	2 quarters	3 quarters	4 quarters
Momentum 1 (Lowest Past Returns)									
Buy	-0.56***	8.60***	2.51***	1.17	2.57*	-2.65***	-3.12***	-3.20***	-4.54***
	-0.62***	4.80***	2.51***	1.17	2.57*	-2.57***	-2.93***	-2.55***	-3.14***
Sell	-1.41***	-3.84***	-2.84***	-0.69	-2.26*	1.44**	2.03**	2.09*	3.11**
	-1.20***	-2.36***	-2.84***	-0.69	-2.26*	0.72*	0.96	0.94	1.57
Buy-Sell	0.58***	7.16***	5.35***	1.86**	4.83**	-3.29***	-3.89***	-3.50***	-4.70***
	0.85***	12.44***	5.35***	1.86**	4.83**	-4.09***	-5.15***	-5.28***	-7.65***
Momentum 2									
Buy	0.50***	4.47***	1.66***	0.21	0.06	-1.14***	-1.53***	-1.95***	-2.56***
	0.56***	2.77***	1.66***	0.21	0.06	-1.18***	-1.25***	-1.35***	-1.36***
Sell	0.59***	-1.49***	-0.99**	-0.97*	-1.30	1.50***	2.84***	3.31***	3.74***
	0.59***	-0.66***	-0.99**	-0.97*	-1.30	0.64***	1.47***	1.59***	1.87***
Buy-Sell	-0.08	5.96***	2.65***	1.18	1.36	-2.64***	-4.37***	-5.25***	-6.30***
	-0.03	3.43***	2.65***	1.18	1.36	-1.82***	-2.72***	-2.94***	-3.23***
Momentum 3									
Buy	-1.28***	2.90***	1.85***	2.21***	0.25	-0.42	-0.80	-0.88	-1.26
	-1.30***	2.07***	1.85***	2.21***	0.25	-0.47**	-0.77**	-0.59	-0.58
Sell	-0.99***	-0.73**	-0.72*	-1.41**	-1.01	1.24***	1.65***	1.90***	1.89**
	-1.21***	-0.37**	-0.72*	-1.41**	-1.01	0.79***	1.06***	1.10**	0.85
Buy-Sell	-0.29	3.63***	2.57***	3.62***	1.26	-1.66***	-2.45***	-2.79***	-3.15***
	-0.08	2.44***	2.57***	3.62***	1.26	-1.27***	-1.83***	-1.69***	-1.43**

Momentum 4									
Buy	-7.64***	2.45***	1.14***	0.55	-1.15	-0.74**	-0.80	-0.87	-1.13
	-7.51***	1.87***	1.14***	0.55	-1.15	-0.77***	-1.03**	-1.13**	-1.19*
Sell	-7.04***	-0.97***	-0.09	-0.69	0.50	-0.16	0.15	0.64	0.70
	-7.16***	-0.39*	-0.09	-0.69	0.50	0.29	0.35	0.26	0.16
Buy-Sell	-0.60	3.42***	1.23**	1.24	-1.65	-0.58	-0.95*	-1.51*	-1.83*
	-0.35	2.26***	1.23**	1.24	-1.65	-1.06***	-1.38***	-1.39***	-1.35**
Momentum 5 (Highest Past Returns)									
Buy	9.38***	3.67***	1.01***	-0.33	-0.41	-1.46***	-2.09***	-2.83***	-3.03***
	4.35***	2.98***	1.01***	-0.33	-0.41	-0.91***	-1.27***	-1.65***	-1.93***
Sell	-1.81***	0.52	-0.59**	0.13	-0.54	0.08	-0.81	-1.05	-1.09
	2.72***	0.35	-0.59**	0.13	-0.54	0.06	-0.24	-0.68	-0.13
Buy-Sell	11.20***	3.15***	1.59***	-0.46	0.13	-1.54***	-1.28**	-1.79**	-1.94**
	1.64	2.64***	1.59***	-0.46	0.13	-0.97***	-1.03**	-0.98*	-1.80***

Panel A reports the relation between herding activities and the 4-quarter returns of stocks prior to herds. The first number is the number of herds, and the second is its percentage of the sample. Panel B reports abnormal returns adjusted for size/book-to-market/momentum benchmark level by momentum quintiles. For each cell, the first number is the mean returns for the sample of long herds which excludes 1-quarter herds while the second number is for whole sample. The 'Buy-Sell' section reports the differences in the average returns for buy and sell herds; number in each cell is the average of the quarterly pair differences in returns between buy and sell sample. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 3. 7: Herding by Institutions over time

Panel A. Distribution of Herds by Herding Duration

Period	Sell Herds					Buy Herds						
	1-quarter	2-quarter	3-quarter	4-quarter	>4 quarters	1-quarter	2-quarter	3-quarter	4-quarter	>4 quarters	Total	Excl.1-period herd
1980-1988	9,799	3,381	1,423	672	727	9,961	3,727	1,721	802	933	33,146	13,386
	29.56	10.20	4.29	2.03	2.19	30.05	11.24	5.19	2.42	2.81	24.86	24.88
1989-1996	13,311	4,650	1,949	868	1,116	13,132	5,067	2,295	1,115	1,197	44,700	18,257
	29.78	10.40	4.36	1.94	2.50	29.38	11.34	5.13	2.49	2.68	33.52	33.93
1997-2004	16,684	5,836	2,407	1,128	1,169	16,642	6,075	2,745	1,401	1,402	55,489	22,163
	30.07	10.52	4.34	2.03	2.11	29.99	10.95	4.95	2.52	2.53	41.62	41.19

Panel B. Distribution of Herds across Market Capitalization Subsamples

	Sell Herds					Buy Herds						
Size	1-quarters	2-quarter	3-quarter	4-quarter	>4 quarter	1-quarter	2-quarter	3-quarter	4-quarter	>4 quarters	Total	Excl.1-period herd
1980-1988												
Small	3,210	965	366	142	133	3,509	1,090	472	185	158	10,230	3,511
	31.38	9.43	3.58	1.39	1.30	34.30	10.65	4.61	1.81	1.54	30.86	26.23
Medium	4,105	1,482	656	342	315	4,078	1,601	800	371	442	14,192	6,009
	28.92	10.44	4.62	2.41	2.22	28.73	11.28	5.64	2.61	3.11	42.82	44.89
Large	2,484	934	401	188	279	2,374	1,036	449	246	333	8,724	3,866
	28.47	10.71	4.60	2.15	3.20	27.21	11.88	5.15	2.82	3.82	26.32	28.88
1989-1996												
Small	5,928	1,841	785	324	375	6,090	2,045	895	397	347	19,027	7,009
	31.16	9.68	4.13	1.70	1.97	32.01	10.75	4.70	2.09	1.82	42.57	38.39
Medium	4,823	1,824	773	353	445	4,605	1,949	913	475	527	16,687	7,259
	28.90	10.93	4.63	2.12	2.67	27.60	11.68	5.47	2.85	3.16	37.33	39.76
Large	2,560	985	391	191	296	2,437	1,073	487	243	323	8,986	3,989
	28.49	10.96	4.35	2.13	3.29	27.12	11.94	5.42	2.70	3.59	20.10	21.85
1997-2004												
Small	8,051	2,627	1,156	550	519	8,400	2,727	1,232	597	605	26,464	10,013
	30.42	9.93	4.37	2.08	1.96	31.74	10.30	4.66	2.26	2.29	47.69	45.18
Medium	5,425	2,047	823	379	382	5,090	2,076	950	498	459	18,129	7,614
	29.92	11.29	4.54	2.09	2.11	28.08	11.45	5.24	2.75	2.53	32.67	34.35
Large	3,208	1,162	428	199	268	3,152	1,272	563	306	338	10,896	4,536
	29.44	10.66	3.93	1.83	2.46	28.93	11.67	5.17	2.81	3.10	19.64	20.47

Panel C. Abnormal Returns around Herding Period

Size	Pre-herd period	Herding periods				Post herding periods			
	4 quarters	1 quarter	2 quarters	3 quarters	4 quarters	1 quarter	2 quarters	3 quarters	4 quarters
1980-1988									
Small	4.88**	10.35***	1.38	3.60**	-1.28	-1.52	1.88	-0.74	-0.56
	1.91	6.09***	1.38	3.60**	-1.28	-1.54**	-0.70	-1.32	-1.52
Medium	1.28	4.67***	2.31***	1.80***	1.89	-1.18**	-2.33***	-2.53**	-3.10**
	-0.17	3.69***	2.31***	1.80***	1.89	-1.49***	-2.18***	-2.16***	-1.98***
Large	0.67	0.61	0.94	1.30	-0.65	-1.11**	-1.37*	-1.63*	-2.46**
	-0.10	0.49	0.94	1.30	-0.65	-0.63*	-0.44	-0.35	-0.79
All	1.82***	4.47***	2.00***	1.81***	0.91	-1.43***	-1.54**	-2.21**	-2.74***
	0.40	3.31***	2.00***	1.81***	0.91	-1.37***	-1.43***	-1.59***	-1.70***
1989-1996									
Small	4.04***	10.43***	4.60***	3.88***	2.90	-3.74***	-5.06***	-6.08***	-6.99***
	1.34*	5.67***	4.60***	3.88***	2.90	-2.02***	-2.03**	-2.51**	-3.15**
Medium	2.03	2.71***	2.58***	0.27	1.97	-1.89***	-1.66**	-1.50	-2.38*
	0.02	2.56***	2.58***	0.27	1.97	-1.67***	-1.66***	-1.32**	-1.83**
Large	2.92***	-2.60***	-0.83**	-0.67	2.91*	0.01	0.17	-0.46	0.25
	0.13	-1.31***	-0.83**	-0.67	2.91*	0.06	-0.05	-0.67	-0.06
All	2.84***	4.52***	2.61***	1.40**	2.40**	-2.13***	-2.49***	-2.89***	-3.31***
	0.49	3.09***	2.61***	1.40**	2.40**	-1.56***	-1.57***	-1.74***	-1.95***
1997-2004									
Small	4.43***	14.82***	7.36***	0.94	2.25	-5.89***	-8.03***	-8.62***	-12.74***
	0.59	8.16***	7.36***	0.94	2.25	-5.06***	-6.20***	-5.51***	-7.99***
Medium	6.52**	7.40***	1.77	-0.33	-2.03	-2.74***	-4.76***	-6.47***	-6.88***
	1.22	4.04***	1.77	-0.33	-2.03	-1.69***	-2.68***	-3.48***	-4.11***
Large	2.47	-1.56	-0.36	-0.07	-0.40	-0.97	-2.15*	-2.55*	-1.86
	-0.15	-1.05**	-0.36	-0.07	-0.40	0.37	-0.20	0.01	0.34
All	4.61***	9.02***	3.87***	0.15	-0.32	-3.87***	-5.95***	-6.89***	-8.80***
	0.55	4.97***	3.87***	0.15	-0.32	-2.86***	-3.89***	-3.76***	-5.12***

Panel D. Abnormal Returns of Stocks that Institutions Tend to Change Their Herding Behavior

Period	Size rank	Quarter0	Quarter1	Quarter2	Quarter3	Quarter4
1980-1988	Small	35.96***	1.53*	-0.47	2.57**	3.79***
	Medium	29.25***	-1.52**	0.27	1.73***	0.83
	Large	24.61***	-1.19**	-0.50	0.24	1.30***
	All	29.83***	-0.46	-0.01	1.37***	1.91***
1989-1996	Small	43.77***	1.18	1.23**	4.08***	3.47***
	Medium	36.05***	-1.40**	0.61	1.77***	1.36**
	Large	28.12***	0.43	-1.58	3.47**	-1.31
	All	37.57***	-0.01	0.92*	2.54***	1.90***
1997-2004	Small	56.17***	0.20	2.55**	1.78**	1.47
	Medium	45.74***	-0.95	2.21**	1.57**	0.97
	Large	38.53***	-1.30	2.44***	1.60	0.17
	All	50.23***	-0.37	2.53***	1.61***	0.81

This table reports herding activities and their price impacts over three periods: 1980-1988, 1989-1996, and 1997-2004. Panel A reports the number of herds for different herding durations, their percentage of the sample, and the cumulative percentage. Panel B reports herding activities by market capitalization. Panel C reports past, contemporaneous, and post-herd abnormal returns by capitalizations. Because herds concentrate in small size stocks, which makes other samples relatively small, I combine two middle size quintiles and two top quintiles and name them medium and large size samples, respectively. Panel D reports future abnormal returns adjusted for size/book-to-market/momentum benchmark level by capitalization for: (i) stocks that are sold in herds and that experience the highest contemporaneous returns and (ii) stocks that are bought in herds and that experience the lowest contemporaneous returns. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

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CHAPTER FOUR: GENERAL CONCLUSIONS

The dissertation examines the trading by institutions and its impact on the stock market. In the first essay, I document that changes in breadth of ownership are not only associated with future stock returns but also associated with future firm operating performances. Moreover, changes in breadth appear unable to predict returns once I control for the information about performance of firms. This suggests that changes in breadth can predict returns because institutions trade on information. Consistent with this argument, I document that only active institutions could predict returns while passive entities are unable to do so. These findings add new evidence to the debate over the return predictability in favor of the information hypothesis.

In the second part of the essay, I document that it is common for herding by institutions to last for more than one quarter. By taking into account the duration of herds, I document that there are reversals in returns following the end of herds and that it is possible to predict such reversals based on the current and past herding activities. In terms of the sources of herding, this paper supports the hypothesis that herding by institutions is associated with information cascades.

In general, the dissertation suggests that institutions are not the same in terms of the information advantage they possess. It explains why in general institutions are smart investors whose trading helps to accelerate the price discovery process but in some specific situations, their trading could destabilize stock prices.

APPENDIX A:
ABNORMAL RETURNS ADJUSTED FOR SIZE/BOOK-TO-MARKET

$BREADTH_t$ Deciles	1-quarter	2-quarter	3-quarter	4-quarter
1	-1.39%***	-2.56%***	-3.25%***	-3.11%***
2	-0.58%**	-1.10%**	-1.41%***	-1.42%***
3	-0.38%	-0.59%	-1.07%**	-1.39%**
4	-0.11%	-0.07%	-0.35%	-0.15%
5	-0.32%	-0.33%	-0.52%	-0.55%
6	-0.26%	-0.23%	-0.06%	-0.12%
7	0.07%	0.04%	0.04%	-0.04%
8	0.32%	0.29%	0.08%	-0.33%
9	0.92%***	1.33%**	1.69%**	1.78%**
10	1.61%***	2.45%**	3.47%**	2.92%*
P10–P1	3.00%***	5.01%***	6.72%***	6.03%***

At the end of each quarter, stocks are first sorted into quintiles on market capitalization. Stocks within the same size quintile are then assigned into deciles of changes in breadth, ΔBREADTHt. Next, stocks are recombined based on ΔBREADTHt deciles across size quintiles to form ten portfolios. Stocks with market capitalization below the 20th percentile using NYSE break points are excluded. Stocks are bought and hold for the next four quarters. For each quarter t, equally-weighted average returns are calculated for each portfolio. The numbers reported in this table are the abnormal returns adjusted for size/book-to-market benchmark. The significance level is adjusted for serial correlation using a Newey-West estimator with a lag of up to four quarters. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

APPENDIX B:
ABNORMAL RETURNS ADJUSTED FOR SIZE/BOOK-TO-MARKET BY SIZE

$SIZE_t$ quintiles	$\Delta BREADTH_t$ Deciles	2-quarter	3-quarter	4-quarter
2	1	-3.78%***	-4.86%***	-4.54%***
	10	3.66%***	4.37%***	3.44%**
	P10–P1	7.44%***	9.23%***	7.98%***
3	1	-2.75%***	-3.44%***	-3.73%***
	10	2.56%	3.95%**	3.07%
	P10–P1	5.31%***	7.39%***	6.80%***
4	1	-1.51%**	-1.50%*	-1.21%
	10	1.65%	2.26%	1.96%
	P10–P1	3.15%***	3.76%***	3.17%*
5	1	-1.16%	-1.88%**	-1.65%
	10	1.13%	2.51%	2.79%
	P10–P1	2.29%**	4.39%***	4.44%***

At the end of each quarter, stocks are first sorted into quintiles on market capitalization. Stocks within the same size quintile are assigned into deciles of changes in breadth, $\Delta BREADTH_t$. For each size quintile, stocks are recombined based on $\Delta BREADTH_t$ deciles to form ten equally-weighted portfolios. Stock returns and portfolio returns are calculated in the same manner as in table 2. This table reports mean values of abnormal returns adjusted for size/book-to-market benchmark. The significant level is adjusted for serial-correlation using a Newey-West estimator with lag of four quarters. ***, **, and * denote significance at 0.01, 0.05, and 0.10, respectively.

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