ABSTRACT

Title of dissertation: ESSAYS ON MUTUAL FUNDS

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This dissertation comprises of three essays on mutual funds. In the first essay, I test whether fund investors rationally incorporate portfolio manager ownership disclosure in their portfolio allocation decisions. Using a natural experiment, regulations that mandate portfolio manager ownership disclosure, I find that investor flows respond to higher percentage ownership. The relationship between investor flows and percentage ownership is persistent well after the regulatory change in 2005, suggesting that the investor responses are permanent rather than transient and are robust to several controls as well as unobserved heterogeneity reflected in fund family and manager fixed-effects. The investor responses to ownership are rational, as investors investing in higher percentage ownership funds are rewarded back in terms of higher risk-adjusted performance. Finally, I shed light on the channels through which higher ownership translates into better investor rewards. I show that agency alleviation is one of the channels through which ownership translates into better investor rewards. These findings are consistent with a "rational investor" viewpoint in which, at least, some investors incorporate managerial ownership in their portfolio

allocation decisions.

In the second essay, I analyze the “herding” (trading together) behavior of managers, *conditional* on their ownership stakes in the funds they manage. I find that the funds with low and high managerial ownership have economically distinct patterns in their herding behavior. Each herd has its own distinct trading style and different qualitative and quantitative effect on stock prices. Low ownership funds herd more and engage in positive-feedback trading that is followed by stock price reversals. High ownership fund herding is followed by more stable price adjustments. Low ownership herding effects appear to dominate in the full sample where herding causes price reversal. These findings suggest that there is heterogeneity in the herding behavior of mutual funds, which appears to be related with ownership. It is costly for the high ownership managers to ignore their substantive information due to reputational concerns, or to engage in uninformed trading, and thus herding by such managers results in more informative prices. On the other hand, lower ownership fund herding appears to be driven by agency that generates temporary price movements that are reversed.

In the third essay, I and my co-authors, Gerard Hoberg and N. R. Prabhala, propose new techniques for identifying benchmark peers for mutual funds. We identify the location of funds in the space of stock style characteristics. All funds within a pre-specified normed distance are a fund’s peers. Our benchmark peers are customized to each fund, intransitive, and employ techniques that are readily scalable across dimensions and loss functions. We show that peers derived in this fashion are significantly different cross-sectionally from conventional peers and ex-

hibit considerable dynamic churn. The customized peers we construct outperform traditional peers in out of sample prediction tests, have lower tracking error, and our peer-excess alphas predict the future Characteristic-Selectivity and Carhart alphas of funds. We find that measures of competition derived from our peers predict performance persistency of funds for up to four quarters.

ESSAYS ON MUTUAL FUNDS

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2013

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Dedication

To my family.

Acknowledgments

I owe my gratitude to all the people who have made this thesis possible and because of whom my graduate experience has been one that I will cherish forever.

First and foremost I'd like to thank my advisor, Professor Russ Wermers, for initiating me in the field of mutual funds. I have benefited a lot from his wide knowledge of the field. It has been a pleasure to learn from an individual who is well-known in the area of mutual funds for his research. I am grateful to Prof Gerard Hoberg for the discussions I have had with him over the years, right from my first introductory finance course. He has always been available for advice and gave me patient hearing. I am grateful to Prof Pete Kyle for his insightful comments on many occasions. He has always encouraged me to look at the big picture. I learned about many fundamental issues by just listening to his lectures. Special thanks goes to Prof Georgios Skoulakis and Prof John Chao for participating in my dissertation committee. I am also grateful to Prof N. R. Prabhala for helping me out on many occasions, specially with the corporate perspective on managerial ownership. Since then we have had many fruitful discussions on mutual funds. I would also like to thank my fellow Ph.D. student Anshuman Sinha, with whom I have had numerous insightful discussions on various economic issues.

On the personal side, I am deeply grateful to my family for encouraging me to pursue my academic interests.

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Chapter 1: **Are Fund Investors Rational? Evidence from Portfolio Manager Ownership, Fund Flows, and Performance**

1.1 Introduction

Following the late trading and market timing scandals, to increase transparency, the Securities and Exchange Commission (SEC) mandated mutual funds to disclose dollar ownership levels of portfolio managers in the funds they oversee. This disclosure is required of all funds filing their disclosures after February 2005. According to the SEC, managerial ownership is a direct indication of incentive alignment between a manager and fund investors.[1] Not just the SEC, industry participants too have long been concerned about ownership of fund managers. In his testimony before the U.S. Senate Banking Committee, Managing Director of the fund rating agency, Morningstar Inc., stated:

> ".....Every week, we speak with mutual fund portfolio managers who tell us that before they buy stock in a company, they look to see how management is compensated. They want managers who eat their own cooking and whose interests are aligned with theirs.......Why, then, are fund shareholders not given the same insights into their investments?"[2]

[1]See U.S. Securities and Exchange Commission, 17 Code of Federal Regulation Parts 239, 249, 270 and 274, File No. S7-12-04, Disclosure Regarding Portfolio Managers of Registered Management Investment Companies.

[2]The full testimony can be found at http://banking.senate.gov/public/index.cfm?FuseAction=Hearings.Home. Review of current in-

Managerial ownership is disclosed in the Statement of Additional Information (SAI). Specifically, funds are required to disclose the dollar ownership in ranges of \$0, \$1-\$10,000, \$10,001-\$50,000, \$50,001-\$100,000, \$100,001-\$500,000, \$500,001-\$1,000,000 and greater than \$1,000,000. I create a new dataset on portfolio manager ownership of diversified, open-ended, actively managed U.S. equity funds covering the period from 2006 to 2009 using multiple sources. Using this dataset, I analyze whether investors value managerial ownership disclosure in directing their investments, and whether their response to ownership is rational. The basic idea is very simple. If investors react positively to managerial ownership, and if ownership also predicts superior risk-adjusted performance, then investors acted rationally. If this is the case, I then try to understand the channel through higher ownership translates into better fund performance.

There are two important reasons for studying investor behavior towards ownership disclosure. First, many studies in the past examined the rationality of fund investors in various contexts. But the evidence on investor rationality is mixed. For instance, Elton, Gruber, and Busse (2004) analyze the investor behavior in S&P 500 index funds. They show that although difference in future returns of S&P 500 index funds are predictable, yet a large amount of new cash flow goes to the poorest performing funds. The authors suggest that the relationship between cash flows and performance is weaker than would be expected by a rational investor view point. Another kind of investor irrationality is related with performance persistency and flow-performance relationship. According to Carhart (1997), after accounting for momentum, there is no significant evidence for performance persistency except for the worst performing funds, yet investors reward past winners with more flows and do not punish past losers (Sirri and Tufano (1998)). Another example is related with the "smart money" effect. According to the smart money effect, investors

vestigations and regulatory actions regarding the mutual fund industry: understanding the fund industry from the investor's perspective (February 25th, 2004).

have fund selection ability and money flows to the funds that will outperform in the future. Gruber (1996) first analyzed this effect and found supportive evidence. He concludes that investors in actively managed funds may have been more rational that previously assumed. Zheng (1999), Wermers (2004), Keswani and Stolin (2008) also find evidence to support the smart money hypothesis. But the "smart money" view is challenged by "dumb money" view by Frazzini and Lamont (2008). They find that the smart money effect is confined to the short horizons of one quarter and that by reallocating flows across different funds, retail investors reduce their wealth in the long run.[3] Thus, there appears to be no consensus on investor behavior.

Second, the question of whether investors rationally respond to managerial ownership disclosure is also important from the regulator's perspective. The call for more information disclosure is based on the premise that the new information will help investors (principal) in monitoring their portfolio managers (agents). The idea is that investors, armed with the new information, will direct their investments towards their preferred portfolio managers. This disciplining mechanism will induce managers to avoid taking actions that can harm investors' interests. Such actions can include risk-shifting associated with style changes, or convexity in flow-performance relationship (Brown, Harlow, and Starks (1996a), Chevalier and Ellison (1999a)), forgoing profitable investments and going-with-the-herd (Scharfstein and Stein (1990)), engaging in uninformed trading when no profitable trades are identified (Dow and Gorton (1997)), window dressing etc. Note that there are, at least, two types of costs associated with more disclosures as well. Fund companies have to dedicate more staff and resources towards preparing such disclosures. The increased costs will indirectly be borne by investors in the form of expenses, and thus lowering their return. Also, there are social costs associated with more disclosures.

[3] Other studies on investor behavior include Ippolito (1992), Barber and Odean (2001), Del Guercio and Tkac (2002) Barber, Odean, and Zheng (2005), Del Guercio and Tkac (2008), and Bailey, Kumar, and Ng (2011).

The regulatory authorities too have to dedicate resources and staff to discuss, debate with the interested parties that will be affected by the proposed disclosures. Unless a reasonable mass of investors value the previously undisclosed information, so that the benefits outweighs the costs, investor might be worse-off, if they do not value the new disclosures. Thus, whether investors rationally incorporate ownership disclosure in their portfolio allocations is an issue of interest for the regulatory authorities as well.[4] Note that for investors, it does not matter what the actual reason is for managers to have investment in their funds (I discuss this issue later in Section 1.2.3). Investors can interpret higher ownership as a desirable incentive alignment attribute of a fund.

I start with a natural experiment, regulations that mandate managerial ownership disclosure in 2005, to test investor responses to ownership disclosure. I find that investors respond to higher percentage ownership but not to higher dollar but low percentage stakes in larger funds, suggesting that investors possibly judge the latter type of stakes to create insufficient incentives. The investor response is economically significant. Using a cross-sectional regression of first-difference in average monthly flows between 2006 and 2004 on lagged managerial ownership and controls for fund, fund family and manager characteristics, I find that a 1% increase in percentage ownership is associated with 1.038% increase in first-difference in average monthly flows. I also measure difference in average monthly flows between 2007 and 2004 because some investors might learn about ownership disclosure with a lag. I now find that a 1% increase in percentage ownership is associated with 1.412% increase in first-difference in average monthly flows, or a one standard deviation increase in percentage ownership is associated with 0.105 standard deviation increase in difference in average monthly flows.

[4]For a more detailed and an excellent discussion, see Tkac (2004).

Thus, investors reallocated their investments taking into account the new disclosures on managerial ownership. The sharp investor reaction to percentage ownership, but not to dollar ownership is a little surprising. It suggests that (at least some) investors believe that a higher dollar ownership in the funds does not always translate into higher managerial incentives. From the investors' perspective, managers of larger funds should have larger stakes to create sufficient incentives. This is possibly based on the premise that managers of larger funds earn more and thus should have greater investment. I further examine investor reaction during the post-regulatory change period from 2007 to 2010 using a panel regression of fund flows on lagged percentage ownership and several controls as well as unobserved heterogeneity reflected in fund family fixed-effects. I continue to find robust flow-ownership relationship. To control for unobserved heterogeneities across fund managers, such as latent managerial skill, risk-preferences, etc., I consider a subsample of single manager funds in which some managers have more ownership in some funds than others and use manager fixed-effects. I find that the coefficients on percentage ownership and past return are statistically and economically significant. A one standard deviation increase in percentage ownership is associated with 0.339 standard deviation increase in subsequent average monthly flows, while a one standard deviation increase in past return is associated with 0.247 standard deviation increase in subsequent average monthly flows. Thus, both managerial ownership and past performance influence investor behavior during the post-regulatory change period.

In summary, persistency in flow-ownership relationship well after the regulatory change suggests that the investor responses are permanent rather than transient. This is also an important finding for the mutual fund industry in general, and fund management companies and managers in particular. Because management companies maximize profits by assets under management, they have an implicit incentive in voluntarily making ownership information available to investors. This can decrease search costs for investors who prefer managers who "eat their own cooking".[5]

Given that investors react positively to ownership, and if ownership also predicts fund performance, then investors' reaction to ownership can be termed as rational. I find that there is an increasing relationship between ownership and subsequent performance. A 1% increase in ownership is associated with 2.66% improvement in subsequent annual 4-factor adjusted performance after several controls as well as family fixed-effects. I also control for the time-invariant unobserved manager characteristics that could be correlated with managerial ownership through a sub-sample of single manager funds in which some managers have more ownership in some funds than others and use manager fixed-effects. I now find that a 1% increase in ownership is associated with 5.36% increase in subsequent 4-factor adjusted annual return, or a one standard deviation increase in ownership is associated with 0.177 standard deviation increase in subsequent 4-factor adjusted monthly performance. Interestingly, the coefficient on average past return is always negative and statistically significant in all regressions. In the same single manager regression as above, a one standard deviation increase in past year average monthly return is associated with 1.425 standard deviation *decrease* in future 4-factor monthly performance. There is also some weak evidence of concavity in ownership-performance relationship, suggesting managerial entrenchment at relatively higher values of percentage ownership. These are typically very small but high dollar ownership funds, and consist of just one-tenth of the sample. Overall, the ownership-performance relationship is increasing for the vast majority and more representative sample of the fund industry, and robust to unobserved heterogeneity reflected in family and

[5]Hortacsu and Syverson (2004) find that, in the case of S&P 500 index funds, which are characterized by a very high degree of portfolio homogeneity, small search costs can rationalize the price dispersion.

manager fixed-effects.

The above findings show that investors react rationally to ownership disclosure but the same cannot be said about investor response to past performance. This is consistent with the findings of Carhart (1997) and Sirri and Tufano (1998). Further, it suggests that the investor community is heterogenous. There are possibly naive investors who just irrationally chase past performance, but at the same time there are sophisticated investors who incorporate predictors of fund performance, such as managerial ownership, in their portfolio allocation decisions. These findings are also consistent with Bailey, Kumar, and Ng (2011). They find that behaviorally biased investors are more likely to chase fund performance, while sophisticated investors experience relatively good fund performance.

Khorana, Servaes, and Wedge (2007) also find positive ownership-performance relation. But this study is different in several ways. Apart from examining investor flows using a natural experiment, and flows during the post-regulatory change period, and also examining agency alleviation through decreased risk-taking, I add to their main finding of positive ownership-performance relationship in three ways. First, I use a relatively bigger sample of four years. Second, I also control for the unobserved cross-family heterogeneities that can influence managerial ownership[6] via family fixed-effects. Third, I check for non-linearities in ownership-performance relationship.

[6]For instance, in its disclosure, American Century mentions the following:

> AMERICAN CENTURY HAS ADOPTED A POLICY THAT, WITH LIMITED EXCEPTIONS, REQUIRES ITS PORTFOLIO MANAGERS TO MAINTAIN INVESTMENTS IN THE POLICY PORTFOLIOS THEY OVERSEE. HOWEVER, BECAUSE THIS PORTFOLIO MANAGER SERVES ON A TEAM THAT OVERSEES A NUMBER OF FUNDS IN THE SAME BROAD INVESTMENT STRATEGY, THE PORTFOLIO MANAGER IS NOT REQUIRED TO INVEST IN EACH SUCH FUND.

The complete disclosure can be found at http://www.sec.gov/Archives/edgar/data/100334/000010033406000048/pea118-2006.htm. Also see, “Which Fund Families Top the Manager Ownership Charts?” at http://news.morningstar.com/articlenet/article.aspx?id=251746

If ownership is influenced by the time-invariant unobserved heterogeneities across families (such as, the firm culture or policies) and managers (such as, the risk-preferences), then incentive alignment is the channel through which ownership translates into better performance. But if managers invest because they have superior information about the expected performance of their portfolio, then information is the channel through which ownership translates into better performance. It is difficult to differentiate between the incentive and information channels. However, in a sub-sample of hand-collected ownership data, I find that the dollar ownership levels of managers do not vary significantly across years. It casts a little doubt over the information channel, but it cannot be rejected, because if managers already have high investment beyond $1 million, then increase in ownership will not be reflected in the data. Thus, my limited and cautious conclusion is that *to the extent* that managerial ownership is driven by time-invariant unobserved heterogeneities, "ownership matters" for fund performance. My findings are more in line with some of the past studies in the corporate finance area which find that managerial ownership matters for firm value (Morck, Shleifer, and Vishny (1988), McConnell and Servaes (1990), McConnell, Servaes, and Lins (2008)).

While it is hard to pin down the information channel, it is possible to verify if ownership aligns managers' incentives with that of fund investors. Once a manager has ownership in the fund, for whatever reason, it imposes costs on the manager for her agency influenced actions. One particular kind of agency is associated with the increased risk-taking in the later half of a year. Since the compensation of the manager depends on the assets under management, the manager takes decisions which increase inflows to the fund, even though this may not deliver an optimal risk-adjusted performance to the investors. Thus, due to the "compensation incentives" of the manager, a fund lagging behind its peers tries to catch up by "gambling" in the later half of the year (Brown, Harlow, and Starks (1996a) and Chevalier and

Ellison (1997) and thus engages in excessive risk-taking. I examine whether higher ownership modulates the tendency to take excessive risk-taking in the later half of the year. I find that ownership indeed moderates the risk-taking behavior of managers. However, the effect is symmetric for both losers and winners. That is, there is no interaction between ownership and mid-year performance. There is also some evidence of convexity in risk-taking with respect to ownership, for very high ownership stakes. These are typically very small funds with high dollar ownership stakes.

My findings make several contributions to the literature. First, my primary contribution is to use a new economic metric, managerial ownership, to test investor rationality. I show that there exist, at least, some investors who rationally incorporate managerial ownership in their portfolio allocation decisions, but the same cannot be said about their responses to the past performance. This suggests that the investor community is heterogenous in the sense that there are there sophisticated investors who pay attention to ownership incentives. At the same time, there are naive trend chasers. These results relate to the findings in Gruber (1996), Zheng (1999), Wermers (2004), Keswani and Stolin (2008), Frazzini and Lamont (2008), Bailey, Kumar, and Ng (2011), and also provide an input to the regulators that some investors value previously undisclosed information about portfolio managers.

Second, I add to the debate in corporate finance literature on the relationship between ownership and performance. On the one hand, studies such as Demsetz and Kenneth (1985), Agrawal and Knoeber (1996), Claudio and Martin (1997), Himmelberg, Hubbard, and Palia (1999), Demsetz and Villalonga (2001), among others, suggest that ownership has little effect, perhaps because it is optimally set based on each firm's own circumstances. On the other hand, the evidence in Morck, Shleifer, and Vishny (1988), McConnell and Servaes (1990), Hermalin and Weisbach (1991), McConnell, Servaes, and Lins (2008) suggests that ownership alters the value of a firm. I add to this literature by providing evidence from the mutual fund industry. I find some support in favor of Morck, Shleifer, and Vishny (1988), McConnell and Servaes (1990), and McConnell, Servaes, and Lins (2008). A more definite conclusion can only be reached once the drivers of managerial ownership are clearly identified. The increasing ownership-performance finding is also consistent with Khorana, Servaes, and Wedge (2007), Evans (2008), and Cremers, Driessen, Maenhout, and Weinbaum (2009). Third, I find that ownership is a significant driver of risk-taking. I show that ownership moderates excessive risk-taking that managers undertake (Brown, Harlow, and Starks (1996a), Chevalier and Ellison (1997), Kempf, Ruenzi, and Thiele (2009) etc.) in the second half of the year to improve year end performance.

The rest of the paper is organized as follows. Section 1.2 describes the data and portfolio manager ownership in detail. Section 1.3 presents main results, and also discusses the seemingly puzzling co-existence of funds with varying ownership levels in the market. Section 1.4 concludes the paper.

1.2 Data

1.2.1 Sample Selection

I obtain data on diversified open-ended actively managed U.S. equity mutual funds from CRSP Survivor-Bias Free US Mutual Fund database. CRSP funds are matched with the Thomson funds by MFLINKS dataset. My sample selection procedure is similar to Kacperczyk, Sialm, and Zheng (2008). I first select funds whose Lipper Classification code is one of the following: LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, SCCE, SCGE, SCVE, EIEI, MLCE, MLGE, MLVE. If a fund's Lipper Classification code is missing, then it is selected if its Strategic Insights Objective Code (SI code) is one of the following: AGG, GMC, GRI, GRO, ING, SCG. If the fund's SI code is missing, then it is selected if its Wiesenberger code is one of the following: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, SCG. If the fund's Wiesenberger code is missing, then it is selected if its policy code is CS. If the fund's policy code is missing, then it is selected if it has an average of at least 80% but not greater than 105% of its amount invested in common stocks over its lifetime. From the above selected funds, I exclude all funds whose CRSP policy code is one of the following: C & I, Bal, Bonds, Pfd, B & P, GS, MM, TFM, or if Thomson Reuters investment code is one of the following: 1,5,6,7,8. I also exclude index funds which are identified by words such as index in their names. Finally, to focus on equity mutual funds for the sample duration, I require that fund should have at least 50% of its amount invested in common stocks at the end of the calendar year. Note that this is different requirement than the earlier requirement of an average of at least 80% investment in common stocks *over its lifetime.* But I do not exclude funds with missing values of percentage investment in common equity, because many times such funds are valid equity funds with missing values.

I also exclude all funds that can't be linked by MFLINKS dataset. I further require that the total net assets of a fund should be at least $5 million at the start of a calendar quarter. I then categorize funds into five investment objective categories - Aggressive Growth, Growth, Growth and Income, Equity Income, and Capital Gains[7].

Portfolio manager ownership data is obtained from Morningstar and the SAI disclosure filed by funds with the SEC. The SAIs are obtained from the SEC

[7]The fund objective categorization is done on the basis of a fund's Lipper Objective Code (Lipper Code), Strategic Insights Objective Code (SI code), Thomson Investment Objective Code (IOC) and Wiesenberger Objective Code (Wiesenberger code). I follow the following rule in investment objective categorization of a fund. If SI code is AG or IOC is 2, then objective is set to "Aggressive Growth". Otherwise if Lipper Code is GI or SI code is GRI or Wiesenberger code is GCI or IOC is 4 then objective is set to "Growth & Income". Otherwise if Lipper Code is G or SI code is GRO or SI code is SCG or Wiesenberger code is G or Wiesenberger code is SCG or IOC is 3 then objective is set to "Growth". Otherwise if Lipper Code is EI or SI code is ING then objective is set to "Equity Income". Otherwise if Lipper Code is CA or Wiesenberger code is MCG then objective is set to "Capital Gains".

Edgar. The CRSP-Thomson matched dataset is then combined with the Morningstar dataset. Thus, I create a dataset having information on fund returns, various fund, fund family and manager characteristics, such as expense ratio, turnover ratio, fund age, family size, manager tenure, and managerial ownership. The ownership data used in this study covers the period from 2006 to 2009.

1.2.2 Recorded Ownership Over Time

The data on portfolio managerial ownership was obtained from Morningstar in January 2009. Since ownership data is declared annually and most funds file this information in the later half of a year, the ownership data obtained corresponds to the year 2008. Unfortunately, Morningstar does not achieve historical data on ownership. This creates a big data challenge because the ownership disclosure is not made in any standard format in the SEC filings, and thus can't be extracted through a script.

To overcome the data challenge, I use Morningstar data for 2008, hand-collected data and ownership estimates to build a dataset consisting of managerial ownership from 2006 to 2009. I hand-collect ownership data for a sample of funds for 2006, 2007, and 2009 and compare it with the ownership of the same manager for 2008. In unreported results, I confirm that the sample selected from 2008 is unbiased as far as the ownership is concerned. I compare difference-in-mean in percentage ownership of selected sample and the remaining sample from 2008 and found it not to be statistically significant even at 10% level. In the hand-collected sample, there are 449 unique managers of 166 funds, who managed the same fund in both 2007 and 2008 (see Table 1.1). I find no change in managerial ownership for 92% of the managers. 97% of the managers show no change in ownership level or change of just one level in ownership. Thus, there is strong consistency in managerial ownership across consecutive 2007 and 2008.

When I compare ownership of same managers for 2006 and 2008, I find no change, or change of just one level in dollar ownership for 88.4% of the managers, which is still almost 9/10th of the hand-collected sample. For 2008 and 2009, the corresponding percentage is 90.2%. So, even across 2006/2008, and 2008/2009, I find strong consistency in managerial ownership. This finding is also consistent with the slow changes in top executive ownership of corporations over the years as reported by Zhou (2001). Thus, for 2006, 2007, and 2009, where the same manager manages the fund in 2008 as well, I estimate ownership from 2008. Sometimes the ownership data is not available, just because of the timing of disclosure. For instance, if a manager left the fund on July 31, 2007 and the fund filed its disclosure on October 31, 2007, then the ownership data for that particular manager is not available for 2007. In such cases, where possible, I bring forward their ownership from the previous year. This is reasonable given that ownership doesn't change much across years. Thus, I am able to build a dataset consisting of managerial ownership from 2006 to 2009.

1.2.3 Descriptive Statistics

My final sample consists of 1463 distinct funds and 4673 fund-years. The total dollar managerial ownership is calculated using mid-points of the reported ranges, except for the last range, greater than \$1 million, where I take \$1 million as ownership, and then summing ownership of all managers in case of multi-manager funds. I follow Khorana, Servaes, and Wedge (2007) and measure ownership as percentage of shares outstanding. Also, to have a precise measure of managerial ownership, I first calculate quarterly managerial ownership and then take average over the four quarters to arrive at yearly ownership. The reason is that in some funds there might be managerial turnover in the middle of the year, and when that fund discloses ownership in the last quarter, one may not have a precise measure of ownership for that fund during the first quarter. It is thus important to know which managers oversee the fund during any particular quarter. There are 44,010 fund-quarter-managers in the sample, out of which I am able to obtain ownership data on 41,203 fund-quarter-managers, which is almost 94%. Thus, for the sample considered, I have comprehensive data on managerial ownership.

Table 1.2 shows descriptive statistics on ownership. Panel A shows that, on an average, around 27% of the funds have zero ownership. Khorana, Servaes, and Wedge (2007) report a figure of 57%, but they include bond funds as well. They also find that ownership is higher in equity funds than in bond funds Thus, ownership numbers seem consistent with that of Khorana, Servaes, and Wedge (2007). The mean and median ownership in my sample is around \$500,000 and \$250,000, respectively, which translates into roughly 0.420% and 0.030% of total net assets, after taking average over the four years. Khorana, Servaes, and Wedge (2007)'s sample has 606 fund-years for domestic equity funds (their total sample consists of 1406 fund-years including bond, international, sector and balanced funds) and report a mean of \$226,000 which is half of what I find. This could be because of the differences in the sample. Given consistency in individual managerial ownership across years, I find almost no variation in mean and median total ownership (that is, total ownership of all managers overseeing a fund) across years either if it is measured in dollar terms or in percentage terms.

Panel B shows ownership by fund segment. Both mean and median dollar ownership is highest among the Capital Gains fund segment. While in percentage terms, mean and median ownership is highest for the Equity Income funds and Aggressive Growth funds, respectively. There is considerable variation in percentage ownership across fund segments. For instance, the mean percentage ownership in the Aggressive Growth segment is only 0.11%, while in the Equity Income segment it is 0.538%. Panel C shows the correlation of ownership with fund, family, and manager characteristics. To avoid multiple counting of fund-classes, expense ratio and turnover ratio are weighted by fund class total net assets. Fund total net assets is the sum of total net assets of all fund classes, and fund age is the age of the oldest class. Note that generally, percentage ownership has low correlation with other characteristics than dollar ownership. For instance, dollar ownership has high correlation of 0.464 and 0.314 with fund size and manager tenure (average tenure in case of multi-manager funds). While the corresponding correlations in the case percentage ownership are -0.070 and 0.054 only. Thus, in multivariate regressions, multi-collinearity concerns are alleviated when one works with the percentage ownership rather than with the dollar ownership.

Panel D shows variation of dollar and percentage managerial ownership within and across families. The variation is the overall variation and variation by fund segments for the year 2008. Results for other years are qualitatively similar. Overall within family variation is calculated by first taking standard deviation of ownership within each family and then taking mean of standard deviation across families. Across variation is calculated by first calculating mean ownership for each family and then taking standard deviation of means across families. Similarly, within and across family variation is also calculated for each segment. It can be seen that there is less variation within families and more variation across families. For instance, the overall average standard deviation of percentage ownership across families is 2.067, which is more than three times the standard deviation within families, 0.623. Similarly, there is more variation in ownership across families than within families for all fund segments. For the growth oriented funds, that form a major part of the sample, the ratio of across family to within family percentage ownership variation is 4.24. One arrives at a similar conclusion if dollar ownership variation is examined. It thus appears that there are significant cross-family heterogeneities that influence managerial ownership, such as the corporate culture. It is also consistent with the findings of Chen, Goldstein, and Jiang (2008). They report from an *Investment*

Company Institute document that 14% of fund complexes require fund directors to own shares in the funds they oversee, and 37% encourage it. I control for these (time-invariant) unobserved heterogeneities across families using family fixed-effects.

There could be other reasons as well for manager to own stakes in the funds they oversee. For instance, managers may invest in funds that are more aligned with their risk-preferences. I control for such (time-invariant) unobserved characteristics through manager fixed-effects. Managers may also voluntarily invest because they may have superior information about the expected performance of their portfolios. But in the hand-collected ownership data, I find that the dollar ownership levels of managers do not vary significantly across years. It casts a little doubt over the information channel, but it cannot be rejected, because if managers already have investment beyond $1 million, then increase in ownership will not be reflected in the data. Or if the managerial ownership is, say $125,000, then she will have to invest a lot to cross $500,000 for the change to be reflected in the data, assuming no big change in fund size to due to returns. So, although managers have same ownership levels across years, they may increase or decrease ownership within their current levels according to the fund's expected performance. Finally, managers may invest if they are overconfident of their abilities. But this is inconsistent with the positive ownership-performance result that I find in Section 1.3.3.

1.3 Results

1.3.1 Do Investors React to Ownership Disclosure?

I start with a natural experiment to examine whether investors channeled their flows towards higher ownership managers. I use two measures of managerial ownership, dollar ownership in millions and percentage ownership. Dollar ownership, *Own($)*, is calculated at the start of every calendar quarter, then average of quarterly ownership is taken for each fund, so that for each fund and for each year, there is one observation for managerial ownership. Similarly, percentage ownership, *Own(%)*, is calculated at the start of every calendar quarter by dividing the dollar ownership with total net assets of the fund, then average of quarterly percentage ownership is taken for each fund. The flow for a fund i, during the period t to t+*1*, is measured by

$$Flow_{i,t+1} = \frac{TNA_{i,t+1} - TNA_{i,t}(1 + R_{i,t+1})}{TNA_{i,t}} \tag{1.1}$$

where $TNA_{i,t}$ represents the total net assets of fund i at the end of period t and $R_{i,t+1}$ is the return of the fund i during the period t to t+*1*. To neutralize the affect of outliers and obtain robust results, I winsorize dollar and percentage ownership at the 90th percentile for each segment and for each year. Also, because of the high volatility of fund flow, it is winsorized at corner 5 percentile for each month. The empirical strategy to examine the investor reaction to ownership disclosure is to employ a cross-sectional regression of first-difference in fund flows on managerial ownership and first-difference in control variables.

In Panel A of Table 1.3, the dependent variable is the difference in average monthly flows between 2006 and 2004. *Own($)* and *Own(%)* represent dollar and percentage ownership at the end of 2005.[8] In Panel B, the dependent variable is the difference in average monthly flows between 2007 and 2004. I use flow difference between 2007 and 2004, because some investors may learn about ownership disclosure with a lag. In this case, *Own($)* and *Own(%)* represent dollar and percentage ownership at the end of 2006. The first-differences in controls in Panels A and B are obtained by subtracting the control value at the end of 2003 from the control value at the end of 2005 and 2006, respectively. The control variables are average monthly fund return over the past year *(Fundret)*, turnover ratio *(Turnratio)*,

[8]Actually, since the ownership data begins from the start of the first quarter of 2006, it represents ownership data at the start of 2006, which is same as ownership data at the end of 2005.

expense ratio *(Expratio)*, natural logarithm of fund size *(Log(Fundsize))*, fund age *(Log(Fundage))*, family assets *(Log(Famassets))*, and average manager tenure of all managers overseeing the fund *(Log(Mgrten))*. P-values are reported in parentheses. All regressions in Table 1.3 are performed without intercept.

Panel A, in which the dependent variable is the first-difference in flows between 2006 and 2004, shows that investors do not react to dollar ownership. The coefficient on *Own($)* in Model 1 is -0.063 (P-value 0.76). Similarly, with all controls in Model 2, the coefficient on *Own($)* is 0.145 with a P-value of 0.48. The coefficient on Δ*Fundret* is 0.660 with a P-value of 0.00. Thus, fund investors do not seem to react to dollar ownership disclosure, while they give more importance to increase in average past performance. But investors' reaction is very different to percentage ownership. Model 3 shows that the coefficient on *Own(%)* is 1.297 (P-value 0.00) and the coefficient on Δ*Fundret* is 0.661 (P-value 0.00). That is, a 1% increase in percentage ownership is associated with 1.297% increase in difference in average monthly flows, and a 1% increase in difference in average past returns is associated with 0.661% increase in difference in average monthly flows. Similarly, with all controls in Model 4, the coefficient on *Own(%)* is 1.038 (P-value 0.01) and the coefficient on Δ*Fundret* is 0.683 (P-value 0.00).

Panel B, in which the dependent variable is the first-difference in flows between 2007 and 2004, shows similar results. In Model 6, with all controls, the coefficient on *Own($)* is -0.184 ($P$-value 0.38) and the coefficient on Δ*Fundret* is 0.400 (P-value 0.00). In Model 8, with all controls, the coefficient on *Own(%)* is 1.412 (P-value 0.00) and the coefficient on Δ*Fundret* is 0.492 (P-value 0.00). That is, a 1% increase in percentage ownership is associated with 1.412% increase in difference in average monthly flows, and a 1% increase in difference in average past returns is associated with 0.492% increase in difference average monthly flows. In terms of comparable economic magnitude, a one standard deviation increase in *Own(%)* is associated with 0.105 standard deviation increase in difference in average monthly flows. And a one standard deviation increase in $\Delta Fundret$ is associated with 0.103 standard deviation increase in difference in average monthly flows. In other words, in their portfolio allocations, investors not just paid attention to increase in past returns, but also to percentage managerial ownership disclosure.

In summary, investors did not react to dollar ownership disclosure. Instead they reacted sharply to percentage ownership. This is a little surprising and suggests that, at least some, investors believe that a higher dollar ownership in funds does not automatically translates into higher managerial incentives. From the investors' perspective, fund managers of larger funds should have larger stakes to create sufficient incentives. This is possibly based on the premise that managers of larger funds earn more and thus should have greater investment. For the rest of the paper, I use percentage ownership as a measure of managerial stake in the fund.

1.3.2 Fund Flows Post-Regulatory Change

I next test whether funds with higher managerial ownership continue to attract greater flows during the post-regulatory change in 2005 or whether it was just a transient phenomenon. Table 1.4 reports coefficients from panel regression of subsequent flows (during 2007 to 2010) on lagged managerial ownership, fund, fund family and manager characteristics, with cluster-robust standard errors, where clustering is by fund. The control variables are average monthly fund return over the past year *(Fundret)*, turnover ratio *(Turnratio)*, expense ratio *(Expratio)*, natural logarithm of fund size *(Log(Fundsize))*, fund age *(Log(Fundage))*, family assets *(Log(Famassets))*, and average manager tenure of all managers overseeing the fund *(Log(Mgrten))*. All regressions include time and investment objective fixed-effects.

In Panel A, I include all funds and use family fixed-effects to control for time-invariant unobserved heterogeneities across fund families. In Model 1, the coefficient on *Own(%)* is statistically and economically significant with a magnitude of 1.215 and P-value of 0.00. The coefficient on *Fundret* is 0.408 (P-value 0.00). This is consistent with earlier studies which find that investors are return chasers. In Model 2, with all controls, I find that the coefficient on *Own(%)* slightly reduces to 0.828 with a P-value of 0.00, while the coefficient on *Fundret* is 0.438 with a P-value of 0.00. That is, a one standard deviation increase in *Own(%)* is associated with 0.118 standard deviation increase in average monthly flows. And a one standard deviation increase in *Fundret* is associated with 0.509 standard deviation increase in average monthly flows in the next year. Thus, past return seems to have a greater effect on investor flows than *Own(%)*, but investors do give importance to ownership as well in deciding their capital allocations. In Model 3, I restrict the sample to the funds for which the manager tenure is greater than 1 year because investors may avoid funds with recent manager turnover. In Model 4, I restrict the sample to the funds with turnover greater than 20% to remove closet index funds. In both Models 3 and 4, I find similar results as in Model 2.

In Panel B, I consider a sub-sample of single manager funds in which some managers have more ownership in some funds than others and use manager fixed-effects to control for time-invariant unobserved manager characteristics that happen to be correlated with managerial ownership. The variation in ownership comes only from the managers who manage multiple funds. Model 5 shows that the coefficient on *Own(%)* is 2.915 with a P-value of 0.00, while the coefficient on *Fundret* is 0.175 with a P-value of 0.11. When all controls are included in Model 6, the coefficient on *Own(%)* is 2.689 with a P-value of 0.00, while the coefficient on *Fundret* is 0.209 with a P-value of 0.07. In terms of comparative economic magnitude, a one standard deviation increase in *Own(%)* is associated with 0.339 standard deviation increase in average monthly flows, while a one standard deviation increase in *Fundret* is associated with 0.247 standard deviation increase in average monthly flows in the next year. Models 7 and 8 yield similar results.[9]

Thus, the relation between ownership and subsequent flows appears to be very strong and is robust to the inclusion of several controls as well as unobserved heterogeneity observed in family and manager fixed-effects. It suggests that the investor reaction to initial ownership disclosure was not transient, rather they continue to channel more flows into higher ownership funds well the regulatory change. This is also an important finding for the mutual fund industry in general, and fund management companies and managers in particular. Because management companies maximize profits by assets under management, they have an implicit incentive in voluntarily making ownership information available to investors. This can decrease search costs for investors who prefer managers who "eat their own cooking".

1.3.3 Are Investors Rewarded by Higher Ownership Managers?

If ownership predicts superior risk-adjusted performance, it would imply that investors rationally incorporated ownership in their portfolio allocation decisions. I use managerial ownership for the year t to predict average monthly risk-adjusted performance for the year $t+1$. As before, managerial ownership for the year t is calculated as the average of quarterly percentage ownership for each fund. The future monthly risk-adjusted one-factor alpha (Jensen (1968)), three-factor alpha (Fama and French (1993)), and four-factor alpha (Carhart (1997)) are obtained by subtracting the estimated fund return from the fund's return. The estimated return is obtained by multiplying estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. Finally, average monthly future risk-adjusted return is obtained over the next year, which is the dependent variable in all linear regressions in Table 1.5.

Motivated by the finding in the corporate finance literature that there is a

[9] I also perform regressions of flows on lagged dollar ownership and controls. I find relatively weaker results.

non-linear relationship between executive ownership and firm performance (Morck, Shleifer, and Vishny (1988), McConnell and Servaes (1990), McConnell, Servaes, and Lins (2008)), I also employ two piecewise linear specifications. For the first piecewise linear specification, I define *Own1* and *Own2* as,

Own1 = managerial ownership if managerial ownership $<$ 0.5

= 0.5 if managerial ownership $\geq$ 0.5

Own2 = 0 if managerial ownership $<$ 0.5

= managerial ownership - 0.5 if managerial ownership $\geq$ 0.5

For the second piecewise linear specification, I define *Own1* and *Own2* as,

Own1 = managerial ownership if managerial ownership $<$ 0.6

= 0.6 if managerial ownership $\geq$ 0.6

Own2 = 0 if managerial ownership $<$ 0.6

= managerial ownership - 0.6 if managerial ownership $\geq$ 0.6

There is no strong theoretical justification for the above break points. I perform non-parametric tests to check where possible infection points could be and use them as guidance for breakpoints in piecewise linear regressions. Around 86% of the sample has ownership below 0.5%. Thus, only a relatively small sample of funds has ownership greater than 0.5%. The control variables are turnover ratio *(Turnratio)*, expense ratio *(Expratio)*, natural logarithm of fund size *(Log(Fundsize))*, fund age *(Log(Fundage))*, family assets *(Log(Famassets))*, average manager tenure of all managers overseeing the fund *(Log(Mgrten))*, and average monthly fund return over the past year *(Fundret)*. All regressions include time and investment objective fixed-effects. Standard errors are clustered by fund.

In Panel A, I consider full sample and use family fixed-effects to control for time-invariant unobserved heterogeneities across fund families. In Model 1, the coefficient on *Own(%)* is 0.139 with a P-value of 0.00. This suggests that a 1% increase in managerial ownership is associated with 1.668% (0.139 multiplied by 12) CAPM-adjusted annual return in the next year. Interestingly, the coefficient on *Fundret* is negative and statistically significant. Its magnitude is -0.132 (P-value 0.00). Model 2, in which the dependent variable is the 3-factor risk-adjusted performance, shows that the coefficient on *Own(%)* is 0.066 (P-value 0.17), however when the 4-factor model is used to calculate the risk-adjusted return in the next year, the coefficient on *Own(%)* is 0.115 (P-value 0.01). This suggests that the lower ownership funds may be betting significantly on high past return stocks. Indeed, Kumar (2012) shows that the low ownership funds employ momentum trading strategies, while it is not the case with the high ownership funds.

In Models 4-6, I employ the piecewise linear specification with percentage ownership breakpoint at 0.50%. I now find that the coefficients on *Own1(%)* are higher than the corresponding coefficients in Models 1-3. For instance, in Model 5 with 3-factor adjusted average future return as the dependent variable, the coefficient *Own1(%)* is 0.174 (P-value 0.08), while in Model 2 with the linear specification it is only 0.066. Similarly, in Models 4 and 6, with CAPM and 4-factor adjusted average future return as the dependent variables, respectively, the coefficient on *Own1(%)* is double the earlier coefficient in the linear specifications in Models 1 and 3. The coefficient on *Own2(%)* is statistically insignificant, and the Wald test fails to reject the equality of coefficients on *Own1(%)* and *Own2(%)*. I find similar coefficients on *Own1(%)* in Models 7-9 that employ the piecewise linear specification with ownership breakpoint at 0.60%. In Models 8 and 9, the coefficient on *Own2(%)* is slightly negative, and the coefficients on *Own1(%)* and *Own2(%)* are marginally different from each other in Model 9. Thus, there appears to be some weak evidence of concavity in ownership-performance relationship. Beyond, 0.60% managerial stake, ownership-performance relationship is flat. The mean and median fund size of the sample above 0.60% ownership are \$72M and \$42M, and below 0.60% are \$2189M and \$492M. It suggests some managerial entrenchment in small funds with high managerial ownership. These funds could be started by wealthy managers who break away from their earlier fund companies.

In Panel B, I include only single manager funds in which some managers have more ownership in some funds than others and use manager fixed-effects to control for time-invariant unobserved manager characteristics that happen to be correlated with managerial ownership, such as latent managerial ability, risk-preference etc. The variation in ownership comes only from managers who manage multiple funds. With CAPM-adjusted future return as the dependent variable, I find that the coefficient on *Own(%)* is 0.380 (P-value 0.05). I find similar result with 3-factor and 4-factor adjusted dependent variable. In Model 3, with 4-factor adjusted future performance, the coefficient on *Own(%)* is 0.447 with a P-value of 0.04. In economic terms, it means that a 1% increase in managerial ownership is associated with 5.36% increase in subsequent Carhart-adjusted annual return, or a one standard deviation increase in *Own(%)* is associated with 0.177 standard deviation increase in future Carhart-adjusted monthly performance. Also, the coefficient on average past return, *Fundret*, is always negative and statistically significant in all regressions. In Model 3, a one standard deviation increase in *Fundret* is associated with 1.425 standard deviation *decrease* in future Carhart-adjusted monthly performance. As earlier, I also employ piecewise linear specifications. But Wald test does not reject the equality of coefficients on *Own1(%)* and *Own2(%)*. Thus, when the same manager manages multiple funds with variable ownership stakes, ownership-performance relation is linearly increasing in ownership.

The above findings show that investors rationally incorporate ownership in their portfolio allocation decisions, because the same metric, managerial ownership, also predicts future fund performance after several controls as well as family and manager fixed-effects. However, trend chasers do not realize superior future risk-adjusted performance. It suggests that the investor community is heterogeneous in the sense that there are naive investors who just irrationally chase past performance, whose money is possibly “dumb”, but at the same time there are sophisticated investors who incorporate predictors of fund performance in their portfolio allocation decisions, whose money is “smart”. These findings are consistent with the findings of Bailey, Kumar, and Ng (2011). They find that behaviorally biased investors are more likely to chase fund performance, while sophisticated investors experience relatively good fund performance.

These findings also contribute to the debate in corporate finance literature on the relationship between ownership and performance. On the one hand, studies such as Demsetz and Kenneth (1985), Agrawal and Knoeber (1996), Claudio and Martin (1997), Himmelberg, Hubbard, and Palia (1999), Demsetz and Villalonga (2001), among others, suggest that ownership has little effect, perhaps because it is optimally set based on each firm’s own circumstances. On the other hand, the evidence in Morck, Shleifer, and Vishny (1988), McConnell and Servaes (1990), Hermalin and Weisbach (1991), McConnell, Servaes, and Lins (2008) suggests that ownership alters the value of a firm. Based on the findings, one can only make a limited and cautious conclusion, because ownership may also be driven by manager’s information, that *to the extent* that managerial ownership is driven by time-invariant heterogeneities across fund families and managers, “ownership matters” for fund performance.

Before I move onto the next section, I want to mention one limitation of the above findings. It is possible that governance also plays a role in affecting fund performance. I do not have explicit data on board of directors of mutual funds. The interesting work in this area is done by Khorana, Servaes, and Wedge (2007) and Chen, Goldstein, and Jiang (2008). In their sample of one year, Khorana, Servaes, and Wedge (2007) control for governance measures and find that ownership still strongly predicts fund performance, and that there is no relation between governance and performance. Chen, Goldstein, and Jiang (2008) find weak relationship between the director ownership and future fund performance.

1.3.4 Does Ownership Moderate Risk-Taking?

I now explore the channel through which higher ownership translates into better performance. One reason for such a finding could be that higher ownership alleviates managerial agency by aligning the incentives of mangers and fund investors. The other reason could be that managers with high ownership have superior information about the expected performance of their funds, and this is reflected in better performance. While it is hard to pin down the information story fully, it is possible to verify if ownership alleviates agency problem. Past literature has examined many manger-investor conflicts. These include excessive risk-taking in the later half of the year due to convexity in flow-performance relationship, (Brown, Harlow, and Starks (1996a), Chevalier and Ellison (1999a)), forgoing profitable investments and going-with-the-herd (Scharfstein and Stein (1990)), engaging in uninformed trading when no profitable trades are identified (Dow and Gorton (1997)), window dressing, risk associated with style changes etc. A comprehensive analysis of whether ownership moderates all agencies is beyond the scope of this study. I focus only on the first agency.

Since the compensation of the manager depends on the assets under management, the manager takes the decisions which increase inflows to the fund, even though this may not deliver an optimal risk-adjusted performance to the fund investors. Thus, due to the "compensation incentives" of the manager, a fund lagging behind its peers tries to catch up by "gambling" in the later half of the year (Brown, Harlow, and Starks (1996a) and Chevalier and Ellison (1997).[10] This causes fund managers to shift risk onto investors. Huang, Sialm, and Zhang (2011a) show that

[10]Also see Busse (2001), Elton, Gruber, and Blake (2003), Kempf and Ruenzi (2008), Chen and Pennacchi (2009), Massa and Patgiri (2009), Hu, Kale, Pagani, and Subramanian (2011).

risk-shifting adversely effects the performance of a fund. To the extent that risk-shifting is harmful for the investors, higher managerial ownership in the fund could alleviate risk-shifting. Once a manager has ownership in the fund, for whatever reason, it influences her risk-taking behavior (at least to some extent). Thus, she is less likely to engage in risk-shifting after she has stakes in the fund. That is, the "ownership incentives" may balance the "compensation incentives".

1.3.4.1 Risk-Taking Measure

Risk-taking associated with the convexity in flow-performance relation in mutual funds is usually measured by the increase in volatility of fund returns in the second half of a year. I follow Kempf, Ruenzi, and Thiele (2009) and Huang, Sialm, and Zhang (2011a), and calculate intended risk change by the fund, instead of realized risk change. Intended risk change is a better metric to measure risk-shifting than realized risk change because the latter could be affected by the market volatility. The original formulation of Brown, Harlow, and Starks (1996a) is $(\sigma_{2L}/\sigma_{1L}) > (\sigma_{2W}/\sigma_{1W})$, where the subscripts L and W refer to the mid-year losers and winners, and 2 and 1 refer to the second and first half of a year (see p.89 of Brown, Harlow, and Starks (1996a)). By subtracting 1 from both sides, it translates into risk increase in the second half of a year as a fraction of risk experienced in the first half of the year. I thus calculate intended risk increase as a fraction of risk experienced in the first half of a year.

To calculate the intended risk increase, I first calculate the realized risk, σ_t^1, in the first half of the year as the standard deviation of realized daily portfolio returns. Next, I construct hypothetical returns using portfolio weights from the current quarter and stock returns from the prior quarter. Thus, for a stock held in the third quarter, I use returns from the second quarter. And for a stock held in the fourth quarter, I use returns from the third quarter. I thus construct a hypothetical daily return series of a fund for the second half of the year. The standard deviation of this hypothetical daily return series is the "intended" risk, $\sigma_t^{2,int}$, in the second half of a year. I finally define intended risk increase, *IntdRiskInc*, as:

$$Intended\ Risk\ Increase_t = (\sigma_t^{2,int} - \sigma_t^1/\sigma_t^1) * 100 \tag{1.2}$$

1.3.4.2 Multivariate Regression

I now test in a multivariate regression setting, whether the high ownership funds increase less risk than the risk increased by the low ownership funds controlling for mid-year performance and other controls. Table 1.6 reports coefficients from panel regression of intended risk increase *(IntdRiskInc)* on linear, and piece-wise linear functions of managerial ownership, mid-year objective-adjusted rank of a fund *(Rank)*, interaction of ownership and rank, for the period 2006 to 2009, with cluster-robust standard errors, where clustering is by fund. The piecewise linear regressions are performed to capture any non-linearities in risk-taking with respect to ownership. As before, managerial ownership (*Own*) is calculated at the start of every calendar quarter by dividing the dollar ownership with total net assets of the fund, then average of quarterly percentage ownership is taken for each fund. Piecewise linear regressions specifications are defined as earlier in Section 1.3.3. For each year and for each fund, *Rank* is obtained by ranking funds in the same investment objective category based on cumulative raw returns in the first half of the year. To capture any asymmetry in risk-taking with respect to ownership, that is, whether higher ownership makes mid-year losers more risk-averse than mid-year winners, I interact ownership and mid-year rank. I first demean *Own* and *Rank* and then calculate *Own*Rank*. Similarly, other interaction terms of ownership and mid-year rank are obtained by first demeaning the variables. *Turnratio* and *Expratio* are expense ratio and turnover ratio, respectively. *Log(Fundsize), Log(Fundage), Log(Famassets),* *Log(Mgrten)* are natural logarithm of total net assets of the fund, fund age, fund family assets, and average manager tenure of all managers overseeing the fund, respectively. All explanatory variables are measured at the end of the calendar year of year. In Panel A, I include all funds and control for time-invariant unobserved heterogeneities across fund families using family fixed-effects. In Panel B, I include only single manager funds and control for time-invariant unobserved heterogeneities across managers using manager fixed-effects.

In Panel A, Model 1, I find that the coefficient on managerial ownership, *Own*, is -2.36 (P-value 0.03), which is statistically and economically significant, while the coefficient on *Rank* is -3.75% (P-value 0.00). The coefficient on *Rank* suggests in moving from the highest to the lowest rank, a fund increases risk by 3.75%. But at the same time, a 1% increase in ownership is associated with 2.36% decrease in risk-taking. Thus, higher ownership mitigates tendency to take excessive risk in the later half of the year. In Model 2, I also test if ownership and rank interact ownership with each other. I do not find that to be the case. It thus appears that for both losers and winners, higher ownership is associated with lower risk-taking.

In Models 3-4, I perform piecewise linear regressions with 0.50% ownership as the break point. In Model 3, the coefficients on *Own1* and *Own2* are -5.87 (P-value 0.01) and 0.72 (P-value 0.72) and they are different from each other at 10% level. This suggests that there is some convexity in risk-taking with respect to ownership at high values of ownership. For the vast majority of the sample (86%), for which ownership is less than 0.5%, ownership mitigates managerial tendency to take excessive risk in the later half of the year, but in very small funds with high managerial stake there appears to be no relationship between ownership and risk-taking. As in Model 2, in Model 4 too, I find no interaction between ownership and *Rank*. I find similar results in Models 5-6, where the breakpoint in ownership is set at 0.60%.

In Panel B, I test the relationship between ownership and risk-taking, controlling for unobserved manager characteristics that could be correlated with managerial ownership. To control for such characteristics, I consider a sub-sample of single manager funds in which some managers have more ownership in some funds than others and use manager fixed-effects. None of the variables, including main variables of interest such as *Own*, *Own1*, *Own2*, *Rank* or the interaction variables, is statistically significant. The most likely explanation seems to be that the sample size is too small and hence the power is less to detect the ownership and risk-taking relation. Perhaps a larger sample is required to say anything about the within-manager ownership-risk-taking relation or even about the performance and risk-taking relation. In summary, from the regression on the full sample, I find that ownership moderates excessive risk-taking in the second half of a year that managers undertake to improve end-of-year reported performance, and there is weak evidence to suggest that the relationship between ownership and risk-taking is convex in nature.[11]

1.3.5 What Explains the Coexistence of the Low and High Ownership Funds?

One of the puzzling question that arises from the above results is that if the high ownership managers to better than the low ownership managers, then what explains their coexistence? Several explanations are possible based on the past literature. There may exist different clienteles (Gruber (1996)). There are sophisticated well-informed investors who gather all possible information about fund managers and then direct their investments based on their perception of manager's ability to outperform. The second category of investors are disadvantaged investors who direct their investments based on advertising (Jain and Wu (2000)) and advice from

[11] In unreported robustness results, I get qualitatively similar results if I work with the absolute intended risk change, $\sigma_t^{2,int}$ - σ_t^1, instead of the percentage intended risk change.

brokers, or tax benefits may make it inefficient to move money across funds. In the similar spirit, Tkac (2004) mentions that there are considerable heterogeneities across fund investors. She cites evidence from an *Investment Company Institute* report that while some investors hold funds on their own, others hold through their retirement plans. Some investors buy funds through broker dealers while others buy though fund companies. Some investors use sophisticated analysis and are more educated than others in finance and economics. The broader point is that investor heterogeneities may result in channeling of their investment into funds with varying ownership levels. Finally, search costs can also rationalize the coexistence of funds with varying managerial ownership. For instance, in the case of S&P 500 index funds, which are characterized by a very high degree of portfolio homogeneity, Hortacsu and Syverson (2004) find that small search costs can rationalize the fact that the index fund offering the highest utility doesn't capture the whole market.

The other related concern in the above analysis is that the greater flows into higher ownership funds may dilute managerial ownership. While this is a valid concern, I find that the relative percentage ownership ranking of funds persist. I calculate the transition probabilities of percentage managerial ownership across consecutive years. Results are reported in Table 1.7. I find about 90% of the funds in the top quartile remain in the same ownership quartile in the next year as well. I find similar results for other quartiles. Thus, while it is true that higher ownership funds attract more flows, the relative ownership ranking persists. This is consistent with the investor heterogeneity argument. If investors are homogenous in the sense that they all value managerial ownership highly, then low ownership managers will die out in the sample very soon. The eventual death of these funds is an interesting question for the future.

1.4 Conclusion

I analyze whether investors value managerial ownership disclosure in directing their investments, and whether their response to ownership is rational. There are two reasons for studying investor behavior towards ownership disclosure. First, many studies in the past examined the rationality of fund investors in various contexts. The evidence on investor rationality from these studies is mixed (Elton, Gruber, and Busse (2004), Carhart (1997), Sirri and Tufano (1998), Gruber (1996), Zheng (1999), Frazzini and Lamont (2008)). Second, the question of whether investors rationally respond to managerial ownership disclosure is also important from the regulator's perspective. The is based on the premise that investors, armed with the new information, will allocate their investments towards their preferred portfolio managers. This disciplining mechanism will induce managers to avoid taking actions that harm investors' interests.

Using a natural experiment, regulations that mandate portfolio manager ownership disclosure, I find that investor flows respond to higher percentage ownership but not to, higher dollar but low percentage stakes in larger funds, suggesting that investors possibly judge the latter type of stakes to create insufficient incentives. The relationship between investor flows and percentage ownership is persistent well after the regulatory change in 2005, which indicates that the investor responses are permanent rather than transient and are robust to several controls as well as unobserved heterogeneity reflected in fund family and manager fixed-effects. Second, the investor responses to ownership are rational, as investors investing in higher percentage ownership funds are rewarded back in terms of higher risk-adjusted performance. Finally, I shed light on the channels through which higher ownership translates into better investor rewards. I show that ownership moderates agency problems from excessive risk-taking in the second half of a year that managers undertake to improve end-of-year reported performance. These findings are consistent with a "rational investor" viewpoint in which, at least, some investors incorporate managerial ownership in their portfolio allocation decisions.

Table 1.1: **Recorded Managerial Ownership Over Time**
This table reports statistics from comparison of managerial ownership for the same manager for different years for the hand-collected sample. *Nfunds* is the number of funds compared across two years, such as for 2007 and 2008 this number is 166. *NMgrs* is the number of managers compared across two years, and *Diff(Own Range)* is the difference in managerial ownership range reported by the fund for two years. For instance, if a fund manager has disclosed dollar range of \$1-\$10,000 in 2006 and \$50,001-\$100,000 in 2007, then *Diff(Own Range)* for that fund manager is 2.

	2008-2007		2008-2006		2008-2009	
Nfunds	166		153		170	
Diff(Own Range)	NMgrs	Percent	NMgrs	Percent	NMgrs	Percent
-6	0	0.00	0	0	2	0.38
-5	0	0.00	1	0.28	2	0.38
-4	4	0.89	4	1.13	5	0.96
-3	0	0.00	0	0.00	5	0.96
-2	5	1.11	8	2.26	22	4.23
-1	10	2.23	12	3.39	32	6.15
0	415	92.43	268	75.71	397	76.35
1	10	2.23	33	9.32	40	7.69
2	1	0.22	15	4.24	8	1.54
3	3	0.67	5	1.41	1	0.19
4	1	0.22	6	1.69	5	0.96
5	0	0.00	1	0.28	1	0.19
6	0	0.00	1	0.28	0	0.00
Total	449	100.00	354	100.00	520	100.00

Table 1.2: **Descriptive Statistics**

This table reports descriptive statistics on managerial ownership in Panel A, descriptive statistics on managerial ownership by fund segment in Panel B, correlation of ownership with fund, family, and manager characteristics in Panel C, and average standard deviation ownership within and across families for the year 2008 in Panel D. In Panel A, *N* and *Zero* represents the number of funds and number of funds with zero managerial ownership, respectively. In Panel B, *N* and *Zero* represents the number of fund-years, and number of fund-years with zero managerial ownership, respectively. Mean and median of dollar ownership, and dollar ownership as percentage of total net assets is also reported. Dollar ownership is calculated by first taking the midpoint of range of managerial ownership reported by the fund in the SEC filings and then summed across all managers in case of multi-manager funds. For the last range, greater than \$1 million, \$1 million is taken as ownership. Percentage ownership is calculated at the start of every calendar quarter by dividing the dollar ownership by total net assets of the fund, then average of quarterly percentage ownership is taken for each fund, so that for each fund and for each year, there is one observation for percentage ownership. Panel C reports contemporaneous correlation of managerial ownership with average monthly fund return measured over the current year *(Fundret)*, end-year fund age *(Fundage)*, total net assets *(Fundsize)*, turnover ratio *(Turnratio)*, expense ratio *(Expratio)*, total family assets *(Familyassets)*, average manager tenure of all managers overseeing the fund *(Mgrten)*. In Panel D, within family ownership variation is obtained by first calculating standard deviation of ownership for each family and then average of the resulting series is calculated. Across family variation is obtained by first calculating average ownership for each family and then standard deviation of the resulting percentage ownership series is calculated. Similarly, within and between family variation for each fund segment is also calculated.

Panel A: Descriptive statistics by year

			Mgr Own(\$)		Mgr Own(% of TNA)	
Year	N	Zero	Mean	Median	Mean	Median
2006	1139	306	536351	250000	0.422	0.031
2007	1144	311	505013	250000	0.390	0.025
2008	1244	352	503525	250000	0.421	0.026
2009	1146	303	504921	250000	0.437	0.038
Total fund-years	4673					
Total funds	1463					

Panel B: Descriptive Statistics by Fund Segment

			Mgr Own(\$)		Mgr Own(% of TNA)	
Fund Segment	N	Zero	Mean	Median	Mean	Median
Equity Inc (EI)	237	46	431461	250000	0.538	0.025
Growth (G)	2964	822	514101	250000	0.451	0.033
Growth & Inc (GI)	1020	293	523511	250000	0.386	0.021
Capital Gains (CG)	269	71	559261	280000	0.273	0.032
Agg Growth (AG)	183	40	454590	250000	0.111	0.034

Panel C: Correlation of managerial ownership with fund, fund family, and manager characteristics

	Fundret	Fundage	Fundsize	Turnratio	Expratio	Familyassets	Mgrten
Own(\$)	0.014	0.131	0.464	-0.185	-0.092	0.129	0.314
	(0.356)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Own(%)	0.012	-0.131	-0.070	-0.028	0.135	-0.110	0.054
	(0.444)	(0.000)	(0.000)	(0.059)	(0.000)	(0.000)	(0.000)

Panel D: Managerial ownership variation within and across fund families for the year 2008

	Std Dev	Overall	AG	G	GI	CG	EI
Own(\$)	Within	341698	459627	355919	351506	483518	210512
	Across	765128	501544	723245	889486	516683	523742
Own(%)	Within	0.623	0.019	0.480	0.436	0.291	0.015
	Across	2.067	0.179	1.870	1.760	2.095	2.052

Table 1.3: **The Effect of Ownership Disclosure on Fund Flows**

This table reports coefficients from a cross-sectional regression of first-difference in fund flows on dollar or percentage ownership and first-difference in fund, family, and manager characteristics. First-difference in flows is obtained by subtracting the average monthly flows over 2004 from average monthly flows over 2006 and 2007 in Panels A and B, respectively. *Own($)* and *Own(%)* represent dollar and percentage ownership at the end of 2006. Dollar ownership, *(Own($))*, is calculated at the start of every calendar quarter, then average of quarterly ownership is taken for each fund, so that for each fund, there is one observation for managerial ownership. Similarly, percentage ownership *(Own(%))* is calculated at the start of every calendar quarter by dividing the dollar ownership with total net assets of the fund, then average of quarterly percentage ownership is taken for each fund, so that for each fund, there is one observation for managerial ownership. The first-differences in controls are obtained by subtracting the control value at the end of 2003 from the control value at the end of 2005 and 2006 in Panels A and B, respectively. The control variables are average monthly fund return over the past year *(Fundret)*, turnover ratio *(Turnratio)*, expense ratio *(Expratio)*, natural logarithm of fund size *(Log(Fundsize))*, fund age *(Log(Fundage))*, family assets *(Log(Famassets))*, and average manager tenure of all managers overseeing the fund *(Log(Mgrten))*, respectively. *P*-values are reported in parentheses.

	Panel A: 2006-2004				Panel B: 2007-2004			
ΔFlow	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own($)	-0.063	0.145			-0.645	-0.184		
	(0.769)	(0.489)			(0.005)	(0.388)		
Own(%)			1.297	1.038			0.926	1.412
			(0.001)	(0.012)			(0.034)	(0.002)
ΔFundret	0.540	0.660	0.661	0.683	0.668	0.400	0.907	0.492
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
ΔTurnratio		-0.137		-0.126		-0.140		-0.141
		(0.370)		(0.381)		(0.300)		(0.262)
ΔExpratio		-1.637		-1.880		-0.313		-0.413
		(0.105)		(0.066)		(0.639)		(0.546)
ΔLog(Fundsize)		-2.147		-2.087		-1.650		-1.623
		(0.000)		(0.000)		(0.000)		(0.000)
ΔLog(Fundage)		2.573		2.198		-0.262		-0.702
		(0.003)		(0.015)		(0.632)		(0.231)
ΔLog(Famassets)		0.459		0.429		0.239		0.193
		(0.214)		(0.238)		(0.244)		(0.333)
ΔLog(Mgrten)		0.147		0.116		0.174		0.140
		(0.111)		(0.218)		(0.136)		(0.221)
N	1033	971	1033	971	975	925	975	925
Adj-R^2	0.076	0.173	0.085	0.179	0.108	0.218	0.106	0.227

Table 1.4: **Fund Flows Post-Regulatory Change**

This table reports coefficients from panel regression of fund flows *(Flow)*, for the period 2007 to 2010, *(Flow)* on lagged managerial ownership, fund, fund family and manager characteristics, with cluster-robust standard errors, where clustering is by fund. Fund flows are measured by percentage average monthly net inflow of money over the next year *(Flow)*. Managerial ownership *(Own(%))* is calculated at the start of every calendar quarter by dividing the dollar ownership with total net assets of the fund, then average of quarterly percentage ownership is taken for each fund, so that for each fund and for each year, there is one observation for managerial ownership. *Log(Fundsize), Log(Fundage), Log(Famassets), Log(Mgrten)* are natural logarithm of total net assets of the fund, fund age, fund family assets, and average manager tenure of all managers overseeing the fund, respectively. *Expratio* and *Turnratio* are expense ratio and turnover ratio, respectively. *Fundret(t)* is average monthly fund raw return in year *t*. All regressions include intercept and explanatory variables are measured at the end of the calendar year *t*. The last two rows show number of observations used *(N)* and adjusted-R^2 *(Adj-R^2)*. *P*-values are reported in parentheses.

	Panel A: All Funds				Panel B: Single Manager Funds			
Flow(t+1)	(1)	(2)	(3) Mgrten>1	(4) Turnover>0.2	(5)	(6)	(7) Mgrten>1	(8) Turnover>0.2
Own(%)(t)	1.215	0.828	0.864	0.872	2.915	2.689	2.693	2.758
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fundret(t)	0.408	0.438	0.452	0.465	0.175	0.209	0.206	0.233
	(0.000)	(0.000)	(0.000)	(0.000)	(0.119)	(0.071)	(0.073)	(0.072)
Turnratio(t)		-0.015	-0.018	-0.033		-0.241	-0.240	-0.286
		(0.835)	(0.808)	(0.653)		(0.309)	(0.311)	(0.239)
Expratio(t)		-0.278	-0.261	-0.259		-0.475	-0.474	-0.668
		(0.126)	(0.166)	(0.185)		(0.335)	(0.336)	(0.184)
Log(Fundsize)(t)		-0.131	-0.122	-0.169		-0.233	-0.229	-0.385
		(0.001)	(0.003)	(0.000)		(0.115)	(0.119)	(0.010)
Log(Fundage)(t)		-0.142	-0.133	-0.096		-0.141	-0.143	0.072
		(0.068)	(0.101)	(0.254)		(0.621)	(0.616)	(0.799)
Log(Famassets)(t)		-0.602	-0.584	-0.629		-0.183	-0.183	-0.084
		(0.003)	(0.005)	(0.006)		(0.239)	(0.242)	(0.612)
Log(Mgrten)(t)		-0.028	-0.048	-0.009		0.048	0.038	0.132
		(0.646)	(0.490)	(0.888)		(0.800)	(0.843)	(0.525)
TimeFE	Y	Y	Y	Y	Y	Y	Y	Y
Obj FE	Y	Y	Y	Y	Y	Y	Y	Y
FamFE	Y	Y	Y	Y	N	N	N	N
MgrFE	N	N	N	N	Y	Y	Y	Y
N	4144	4115	3950	3627	1459	1447	1430	1270
Adj-R^2	0.172	0.180	0.184	0.175	0.264	0.267	0.263	0.266

Table 1.5: **Fund Performance**

This table reports coefficients from panel regression of average monthly fund performance over the next year *(FundPerf)*, for the period 2006 to 2009, on lagged managerial ownership, fund, fund family and manager characteristics, with cluster-robust standard errors, where clustering is by fund. To obtain average monthly future performance, first, risk-adjusted monthly 1-factor Jensen (1968), 3-factor Fama and French (1993) and 4-factor Carhart (1997) alpha are obtained by subtracting estimated fund return from a fund's return. The estimated return is obtained by multiplying estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. Then average risk-adjusted monthly return is obtained over the next year. Managerial ownership *(Own(%))* is calculated at the start of every calendar quarter by dividing the dollar ownership with total net assets of the fund, then average of quarterly percentage ownership is taken for each fund, so that for each fund and for each year, there is one observation for managerial ownership. For piecewise linear regressions *(Own1(%))* and *(Own2(%))* are used (see text for details). *Turnratio* and *Expratio* are expense ratio and turnover ratio, respectively. *Log(Fundsize), Log(Fundage), Log(Famassets), Log(Mgrten)* are natural logarithm of total net assets of the fund, fund age, fund family assets, and average manager tenure of all managers overseeing the fund, respectively. *Fundret(t)* is average monthly fund raw return in year *t*. All regressions include intercept and explanatory variables are measured at the end of the calendar year *t*. In Panel A, all funds are included, while in Panel B, only single-manager funds are included. The last four rows show the umber of observations *(N)*, adjusted-R^2 *(Adj-R^2)*, breakpoints used for *Own1(%)* and *Own2(%)*, *P*-values for test of equality of coefficients on *Own1* and *Own2* . *P*-values are reported in parentheses.

Panel A: All Funds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fundperf(t+1)	CAPM	Fama French	Cahart	CAPM	Fama French	Cahart	CAPM	Fama French	Cahart
Own(%)(t)	0.139	0.066	0.115						
	(0.007)	(0.171)	(0.016)						
Own1(%)(t)				0.269	0.174	0.222	0.241	0.158	0.221
				(0.013)	(0.084)	(0.023)	(0.012)	(0.075)	(0.012)
Own2(%)(t)				0.025	-0.030	0.020	0.012	-0.050	-0.018
				(0.770)	(0.714)	(0.792)	(0.901)	(0.586)	(0.835)
Turnratio(t)	0.060	0.013	0.004	0.060	0.013	0.004	0.060	0.013	0.004
	(0.010)	(0.529)	(0.844)	(0.010)	(0.528)	(0.842)	(0.010)	(0.528)	(0.843)

Expratio(t)	0.083	-0.029	-0.032	0.081	-0.031	-0.034	0.081	-0.030	-0.034
	(0.076)	(0.460)	(0.429)	(0.083)	(0.429)	(0.402)	(0.082)	(0.433)	(0.402)
Log(Fundsize)(t)	-0.019	-0.019	0.005	-0.017	-0.018	0.007	-0.018	-0.018	0.007
	(0.096)	(0.064)	(0.639)	(0.143)	(0.096)	(0.533)	(0.138)	(0.096)	(0.519)
Log(Fundage)(t)	0.128	0.060	0.061	0.128	0.061	0.061	0.128	0.061	0.061
	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)
Log(Famassets)(t)	-0.366	-0.476	-0.323	-0.367	-0.477	-0.324	-0.366	-0.476	-0.323
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Mgrten)(t)	-0.011	-0.004	-0.008	-0.014	-0.007	-0.010	-0.014	-0.007	-0.011
	(0.556)	(0.830)	(0.623)	(0.444)	(0.709)	(0.501)	(0.457)	(0.714)	(0.488)
Fundret(t)	-0.132	-0.141	-0.219	-0.133	-0.141	-0.220	-0.133	-0.141	-0.220
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TimeFE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obj FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
FamFE	Y	Y	Y	Y	Y	Y	Y	Y	Y
MgrFE	N	N	N	N	N	N	N	N	N
N	4158	4158	4158	4158	4158	4158	4158	4158	4158
Adj-R^2	0.168	0.200	0.176	0.168	0.200	0.177	0.168	0.200	0.177
Own(%) BP				0.50	0.50	0.50	0.60	0.60	0.60
PWald				0.13	0.18	0.16	0.15	0.17	0.10

Panel B: Single Manager Funds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fundperf(t+1)	CAPM	Fama French	Cahart	CAPM	Fama French	Cahart	CAPM	Fama French	Cahart
Own(%)(t)	0.380	0.339	0.447						
	(0.053)	(0.095)	(0.046)						
Own1(%)(t)				0.552	0.511	0.445	0.537	0.499	0.463
				(0.045)	(0.107)	(0.140)	(0.033)	(0.080)	(0.082)
Own2(%)(t)				0.163	0.120	0.450	0.095	0.047	0.418
				(0.652)	(0.752)	(0.330)	(0.818)	(0.915)	(0.428)
Turnratio(t)	-0.087	0.016	0.011	-0.086	0.017	0.011	-0.086	0.017	0.011
	(0.218)	(0.789)	(0.881)	(0.219)	(0.777)	(0.881)	(0.221)	(0.769)	(0.879)
Expratio(t)	-0.113	-0.058	-0.045	-0.111	-0.056	-0.045	-0.111	-0.056	-0.045
	(0.351)	(0.647)	(0.725)	(0.358)	(0.655)	(0.725)	(0.358)	(0.655)	(0.726)
Log(Fundsize)(t)	-0.064	-0.077	-0.014	-0.061	-0.074	-0.014	-0.061	-0.074	-0.014
	(0.019)	(0.017)	(0.628)	(0.027)	(0.022)	(0.635)	(0.027)	(0.022)	(0.642)
Log(Fundage)(t)	0.070	0.087	0.046	0.068	0.085	0.046	0.068	0.085	0.046
	(0.162)	(0.165)	(0.408)	(0.173)	(0.176)	(0.410)	(0.174)	(0.177)	(0.412)
Log(Famassets)(t)	-0.080	-0.075	-0.040	-0.079	-0.075	-0.040	-0.079	-0.075	-0.040
	(0.034)	(0.047)	(0.201)	(0.035)	(0.049)	(0.203)	(0.035)	(0.049)	(0.202)
Log(Mgrten)(t)	0.035	0.030	0.025	0.032	0.027	0.025	0.032	0.027	0.025
	(0.516)	(0.636)	(0.627)	(0.557)	(0.675)	(0.627)	(0.559)	(0.677)	(0.633)
Fundret(t)	-0.232	-0.242	-0.383	-0.232	-0.242	-0.383	-0.232	-0.242	-0.383

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TimeFE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obj FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
FamFE	N	N	N	N	N	N	N	N	N
MgrFE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1459	1459	1459	1459	1459	1459	1459	1459	1459
Adj-R^2	0.347	0.243	0.270	0.347	0.243	0.269	0.347	0.243	0.269
Own(%) BP				0.50	0.50	0.50	0.60	0.60	0.60
PWald				0.43	0.48	0.99	0.39	0.44	0.94

Table 1.6: **Risk-Taking**

This table reports coefficients from panel regression of intended risk increase *(IntdRiskInc)*, for the period 2006 to 2009, on linear and piece-wise linear functions of managerial ownership, mid-year objective-adjusted rank of a fund *(Rank)*, interaction of ownership and rank, fund, fund family and manager characteristics, with cluster-robust standard errors, where clustering is by fund. *IntdRiskInc* is defined as $((\sigma^{2int}\text{-}\sigma^{1})/\sigma^{1})*100$, where σ^{2int} is the intended risk taken in the second half of the year and σ^{1} is the actual risk taken in the first half of the year. See text for further details on intended risk increase. Managerial ownership (*Own*) is calculated at the start of every calendar quarter by dividing the dollar ownership with total net assets of the fund, then average of quarterly percentage ownership is taken for each fund, so that for each fund and for each year, there is one observation for managerial ownership. For piecewise linear regressions, *Own1* and *Own2* are used (see text for details). For each year and for each fund, *Rank* is obtained by ranking funds for each fund objective based on cumulative raw returns in the first half of the year. Ownership variables and *Rank* are demeaned. *Own*Rank* is the interaction of demeaned *Own* and demeaned *Rank*. Similarly, other interaction terms are obtained by first demeaning the variables. *Turnratio* and *Expratio* are expense ratio and turnover ratio, respectively. *Log(Fundsize), Log(Fundage), Log(Famassets), Log(Mgrten)* are natural logarithm of total net assets of the fund, fund age, fund family assets, and average manager tenure of all managers overseeing the fund, respectively. All regressions include intercept and explanatory variables are measured at the end of the calendar year of year *t*. In Panel A, all funds are included, while in Panel B, only single-manager funds are included. The last four rows show the umber of observations *(N)*, adjusted-R^2 *(Adj-R^2)*, breakpoints used for *Own1* and *Own2*, *P*-values for test of equality of coefficients on *Own1* and *Own2*. *P*-values are reported in parentheses.

Panel A: All Funds						
IntdRiskInc	(1)	(2)	(3)	(4)	(5)	(6)
Own	-2.360	-2.375				
	(0.031)	(0.032)				
Own1			-5.873	-5.931	-4.879	-5.034
			(0.013)	(0.012)	(0.021)	(0.017)
Own2			0.724	0.837	0.795	1.174

			(0.719)	(0.687)	(0.738)	(0.626)
Rank	-3.757	-3.754	-3.714	-3.719	-3.721	-3.731
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Own*Rank		0.257				
		(0.941)				
Own1*Rank				1.022		2.651
				(0.876)		(0.645)
Own2*Rank				-1.346		-4.243
				(0.846)		(0.567)
Turnratio	0.198	0.197	0.197	0.197	0.198	0.198
	(0.594)	(0.595)	(0.596)	(0.594)	(0.594)	(0.593)
Expratio	1.001	1.000	1.029	1.033	1.018	1.024
	(0.395)	(0.395)	(0.381)	(0.380)	(0.386)	(0.384)
Log(Fundsize)	-0.083	-0.083	-0.139	-0.140	-0.130	-0.133
	(0.743)	(0.742)	(0.591)	(0.590)	(0.615)	(0.608)
Log(Fundage)	-0.055	-0.054	-0.078	-0.078	-0.080	-0.077
	(0.917)	(0.918)	(0.881)	(0.881)	(0.879)	(0.882)
Log(Famassets)	-0.036	-0.037	-0.044	-0.044	-0.058	-0.059
	(0.977)	(0.977)	(0.973)	(0.973)	(0.964)	(0.964)
Log(Mgrten)	0.227	0.227	0.316	0.316	0.298	0.300
	(0.571)	(0.570)	(0.436)	(0.435)	(0.462)	(0.458)
TimeFE	Y	Y	Y	Y	Y	Y
ObjFE	Y	Y	Y	Y	Y	Y
FamFE	Y	Y	Y	Y	Y	Y
N	4485	4485	4485	4485	4485	4485
Adj-R^2	0.644	0.644	0.644	0.644	0.644	0.644

Own(%) BP			0.50	0.50	0.60	0.60
PWald			0.08	0.07	0.14	0.11

Panel B: Single Manager Funds

IntdRiskInc	(1)	(2)	(3)	(4)	(5)	(6)
Own	-3.267	-3.842				
	(0.366)	(0.300)				
Own1			-8.125	-7.572	-7.617	-7.315
			(0.162)	(0.198)	(0.157)	(0.178)
Own2			2.453	-0.005	4.132	1.363
			(0.742)	(1.000)	(0.641)	(0.888)
Rank	-3.550	-3.446	-3.497	-3.379	-3.490	-3.365
	(0.148)	(0.165)	(0.155)	(0.175)	(0.156)	(0.177)
Own*Rank		4.939				
		(0.590)				
Own1*Rank				-4.516		-3.089
				(0.769)		(0.823)
Own2*Rank				15.538		18.657
				(0.490)		(0.486)
Turnratio	-1.048	-1.053	-1.066	-1.093	-1.081	-1.107
	(0.606)	(0.594)	(0.597)	(0.576)	(0.591)	(0.571)
Expratio	-1.928	-1.948	-1.986	-1.985	-1.993	-1.983
	(0.543)	(0.539)	(0.532)	(0.532)	(0.530)	(0.532)
Log(Fundsize)	-0.276	-0.288	-0.354	-0.357	-0.356	-0.357
	(0.717)	(0.706)	(0.651)	(0.648)	(0.648)	(0.647)
Log(Fundage)	-0.345	-0.330	-0.265	-0.243	-0.269	-0.250

	(0.762)	(0.771)	(0.818)	(0.833)	(0.814)	(0.827)
Log(Famassets)	0.522	0.551	0.521	0.599	0.521	0.593
	(0.583)	(0.560)	(0.585)	(0.535)	(0.585)	(0.537)
Log(Mgrten)	0.747	0.752	0.861	0.876	0.865	0.879
	(0.538)	(0.535)	(0.489)	(0.483)	(0.487)	(0.482)
TimeFE	Y	Y	Y	Y	Y	Y
ObjFE	Y	Y	Y	Y	Y	Y
FamFE	Y	Y	Y	Y	Y	Y
N	1544	1544	1544	1544	1544	1544
Adj-R^2	0.667	0.666	0.666	0.666	0.666	0.666
Own(%) BP			0.50	0.50	0.60	0.60
PWald			0.34	0.52	0.33	0.50

Table 1.7: **Transition Probabilities: Managerial Ownership**

This table reports transition probabilities of managerial ownership across consecutive years. First managerial ownership is calculated at the start of every calendar quarter by dividing the dollar ownership with total net assets of the fund, then average of quarterly percentage ownership is taken for each fund, so that for each fund and for each year, there is one observation for managerial ownership. Then at the end of the calendar year, funds are ranked into quartiles based on managerial ownership. The horizontal rows report the average transition probabilities measured across consecutive years for each quartile.

	Own Rank (t+1)			
Own Rank (t)	1	2	3	4
1	91.22	5.43	2.23	1.12
2	3.46	83.9	12.22	0.43
3	2.68	8.03	80.88	8.41
4	2.51	0.39	6.53	90.56

Chapter 2: **Portfolio Manager Ownership, Herding and Stock Returns**

2.1 Introduction

I analyze the "herding" (trading together) behavior of managers, *conditional* on their ownership stakes in the funds they oversee. More specifically, funds are said to herd when a disproportionate number of funds end up on the same side of the market in their trades.[1] Given the large holdings and trading volume of mutual funds, they are a dominant force in influencing stock prices.[2] Because the trading decisions are under the control of managers, and if managers are agency influenced, then it is likely to be reflected in stock prices. This issue is of economic importance because informative prices in well-functioning markets affect the real economy through better investment decisions (see, Wurgler (2000) and Subrahmanyam and Titman (2001)).

Earlier studies have thrown mixed evidence on the impact of institutional herding on stock prices. For instance, studies such as Wermers (1999), Nofsinger and Sias (1999), and Sias (2004) find that herding speeds up the process of price adjustment by quickly incorporating news into prices and thus helps in making markets more informationally efficient. While more recent studies, such as Puckett

[1]Kraus and Stoll (1972) is one of the earliest papers that examine simultaneous trading, which they term as "parallel trading".

[2]Institutional funds hold more than 60% of domestic equity and account for around 70% of trading volume (Gompers and Metrick (2001), Bennett, Sias, and Starks (2003), Boehmer and Kelley (2009)). According to the *Investment Company Fact Book 2010*, the total value of the U.S. mutual fund assets at the end of 2009 is $11.1 trillion, of which approximately 33% are domestic equity funds, and a vast majority of these funds are actively managed funds.

and Yan (2008), Dasgupta, Prat, and Verado (2011a) and Brown, Wei, and Wermers (2012) find that herding leads to reversal in stock prices, and thus destabilizes stock prices.

One possibility that can explain the above findings is that there are different managers with different underlying motivations. For instance, there are reputationally concerned managers, as in Scharfstein and Stein (1990), who may not invest in profitable investments according to their substantive private information, but would rather go-with-the-herd for fear of loss of reputation from acting differently from the herd.[3] This kind of behavior is possible when managers are agency influenced and would rather "share-the-blame". In such cases, a rational manager may follow the strategies of other managers like the positive-feedback trading strategy. It is also possible that sometimes managers are not able to identify profitable investments, but yet have to trade because managers' active non-trading cannot be distinguished from the lack of stock selection skill or shirking of responsibility (Dow and Gorton (1997)). This particular kind of agency can also induce rational managers to employ positive-feedback trading. Now consider another set of managers, whose behavior is less likely to be agency influenced, such as the managers who have high ownership stakes (for whatever reason) in the funds they oversee. It is costly for the high ownership managers to ignore their substantive information and let go profitable investments, because of their ownership stakes. And precisely because of the same reason, it is again costly for them to engage in uninformed trading or engage in positive-feedback trading unless it is backed with credible investment signal.

[3]Also see Dasgupta, Prat, and Verado (2011b). In addition, herding can occur due to informational cascades (Welch (1992), Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992)). More recently, Khanna and Mathews (2011) show that under some conditions, informational cascades can result in superior aggregate information. Herding can also occur in deciding whether to investigate a piece of information that the manager believes others will also investigate, this is commonly known as investigative herding (Froot, Scharfstein, and Stein (1994), Hirshliefer, Subrahmanyam, and Titman (1994)). There is also a body of literature that argues that managers may herd because of their preferences towards securities with specific characteristics (Falkenstein (1996), Gompers and Metrick (2001), Bennett, Sias, and Starks (2003)). This list is by no means exhaustive. For literature reviews, see Graham (1999), Hirshleifer and Teoh (2003), Sias (2004).

In the former case, when managers are agency influenced, herding may result in non-informative stock prices in the sense that they do not reflect the fundamental value of the firm and may exhibit reversal subsequent to herding. While in the latter case, prices are more likely adjust in a stable manner, and improve informational efficiency of the market. Whether herding causes price reversal and increase volatility or whether it aids in informational efficiency, depends on which herd of managers dominates the other in influencing stock prices to a greater degree.

I obtain data on managerial ownership from multiple sources for the period from 2006 to 2009. Managerial ownership is disclosed in the Statement of Additional Information (SAI). Specifically, funds are required to disclose the dollar ownership of fund manager in ranges of \$0, \$1-\$10,000, \$10,001-\$50,000, \$50,001-\$100,000, \$100,001-\$500,000, \$500,001-\$1,000,000 and greater than \$1,000,000.[4] Managers may have ownership in their funds for various reasons. For instance, it can be their personal decision because their risk-preferences are better aligned with particular funds or they may have superior information about the expected performance of their fund (Khorana, Servaes, and Wedge (2007)). They may also be required by fund companies to own stakes in their funds to better align their incentives with that of fund investors or to give signal to the investors about managers' ability.[5]

[4]Following the late trading and market timing scandals, to increase transparency, the Securities and Exchange Commission (SEC) mandated mutual funds to disclose dollar ownership levels of portfolio managers in the funds they oversee. This disclosure is required of all funds filing their disclosures after February 2005. According to the SEC, managerial ownership is a direct indication of incentive alignment between the manager and fund investors. See U.S. Securities and Exchange Commission, 17 Code of Federal Regulation Parts 239, 249, 270 and 274, File No. S7-12-04, Disclosure Regarding Portfolio Managers of Registered Management Investment Companies.

[5]For instance, in its disclosure, American Century mentions the following:

> AMERICAN CENTURY HAS ADOPTED A POLICY THAT, WITH LIMITED EXCEPTIONS, REQUIRES ITS PORTFOLIO MANAGERS TO MAINTAIN INVESTMENTS IN THE POLICY PORTFOLIOS THEY OVERSEE. HOWEVER, BECAUSE THIS PORTFOLIO MANAGER SERVES ON A TEAM THAT OVERSEES A NUMBER OF FUNDS IN THE SAME BROAD INVESTMENT STRATEGY, THE PORTFOLIO MANAGER IS NOT REQUIRED TO INVEST IN EACH SUCH FUND.

The complete disclosure can be found at
http://www.sec.gov/Archives/edgar/data/100334/000010033406000048/pea118-2006.htm.

For the purpose of this study, it does not matter what the actual reason is for managers to have ownership. What is important is to realize is that once managers have ownership in their funds, for whatever reason, they also bear the cost of their agency influenced decisions. This may moderate their agency driven trading, and also impact stock prices in a more stable manner.

There are other studies which also suggest that the portfolio decisions of lower ownership managers may be agency influenced. Khorana, Servaes, and Wedge (2007) first calculate percentage ownership of the manager in a fund, and show that funds with higher managerial ownership subsequently perform better. They attribute better performance of higher ownership managers to their superior information or agency alleviation or both. Evans (2008) also finds similar evidence, and attributes it to agency alleviation.[6] Following Khorana, Servaes, and Wedge (2007), I work with the percentage ownership of managers in their funds. Also, the agency based arguments rely on percentage ownership (Jensen and Meckling (1976)).

Whether higher ownership managers exert more effort because of greater incentives to form investment signals for profitable trades or have sources of superior information, they are less likely to ignore their investment signals/information, and engage in uninformed positive-feedback trading. Further, different high ownership managers may attach different value to similar information about a stock, depending upon their subjective precision, thus lower levels of herding may be observed

Also see, "Which Fund Families Top the Manager Ownership Charts?" at http://news.morningstar.com/articlenet/article.aspx?id=251746
In the context of director ownership, Chen, Goldstein, and Jiang (2008) find that family-wide policies, such as deferred compensation plans, are important in determining director ownership. Also see Cremers, Driessen, Maenhout, and Weinbaum (2009).

[6]There is also a large corporate finance literature on the relationship between ownership and performance, however, the evidence from these studies is mixed. Some studies, such as Demsetz and Kenneth (1985), Agrawal and Knoeber (1996), Claudio and Martin (1997), Himmelberg, Hubbard, and Palia (1999), Demsetz and Villalonga (2001), among others, suggest that ownership has little effect on firm performance, perhaps because it is optimally set based on each firm's own circumstances. On the other hand, the evidence in Morck, Shleifer, and Vishny (1988), McConnell and Servaes (1990), Hermalin and Weisbach (1991), McConnell, Servaes, and Lins (2008) suggests that ownership alters the value of a firm.

among such managers. On the whole, I expect lower ownership managers - (i) to exhibit higher levels of herding, (ii) to exhibit a pronounced tendency to employ positive-feedback or momentum trading strategies, and (iii) to cause greater stock price reversal post-herding.

I test the above hypotheses using Lakonishok, Shleifer, and Vishny (1992)'s (henceforth, LSV) stock specific herding measure used in many studies (see, for example, Lakonishok, Shleifer, and Vishny (1992), Wermers (1999), Puckett and Yan (2008), Brown, Wei, and Wermers (2012)). It measures correlated trades of funds adjusted for correlated trades by chance. Using LSV's herding measure, I find that, first, the low ownership managers herd more than the high ownership managers. Second, the low ownership funds buy-herd (sell-herd) in high (low) past return stocks, confirming that the low ownership funds use positive-feedback trading strategies. I find no such evidence for the high ownership funds. In fact, the past returns of the stocks buy- and sell-herded by the high ownership funds are indistinguishable.

Third, I also conduct additional analysis of returns subsequent to herding and find return reversals in stocks herded by the low ownership funds. In contrast, there is almost no reversal in stocks herded by the high ownership funds. The above findings are consistent with the hypothesis that herding among the lower ownership funds is driven by agency. In return differential tests, I find that there is greater return reversal post-herding in stocks herded by the lower ownership funds, and the difference is statistically and economically significant for up to two quarters post-herding. The difference between the two long-short portfolios, one that is long on the intensely buy-herded stocks and short on the intensely sell-herded stocks by the low ownership managers and a similar long-short portfolio for the high ownership funds, yields a characteristic-adjusted (Daniel, Grinblatt, Titman, and Wermers (1997)) return from -4.10% to -5.94% in two quarters following herding, depending upon the degree of ownership difference between the low and high ownership managers.

Fourth, when I examine herding among all funds without conditioning on managerial ownership, as done in earlier studies, I find that the return pattern is similar to the return on the stocks herded by the low ownership funds. This can be seen very clearly in Figure 2.1. It shows the mean characteristic-adjusted cumulative returns on a long-short portfolio of stocks that is long on the buy-herded stocks and short on the sell-herded stocks by all funds (solid line), the low ownership funds (dotted line), and the high ownership funds (dashed line). The portfolio is formed during the herding quarter, and then returns are tracked on this portfolio for two quarter before and four quarter ahead of the herding quarter. From the figure, it is clear that the portfolio herded by the low ownership funds exhibit high past return, while the similar portfolio herded by the high ownership funds exhibit close to zero past return. That is, the low ownership funds strongly use positive-feedback trading strategy, while the past returns on the buy- and sell-herded stocks by the high ownership funds are indistinguishable. It also shows that the cumulative return going forward stays close to zero on the portfolio herded by the high ownership funds. But for the portfolio herded by the low ownership funds, the cumulative return continuously declines and becomes highly negative post-herding. Finally, the return pattern on the portfolio herded by all funds and the low ownership funds is very similar. On the whole, the figure shows that there are two herds in the market with different herding motivations and different consequences on stock prices, and that the low ownership herd dominates the high ownership herd in influencing stock prices.

My final tests examine how the impact on stock prices due to herding by the low and high ownership funds is related to firm size. Because smaller stocks are less liquid and if herding is motivated by agency, then it could lead to greater stock price reversal following herding. I find supportive results. I also find that the high ownership funds avoid trading in very small stocks probably because it is difficult to form precise investment signals and also the trading costs associated in such stocks are high. I obtain similar results regardless of whether I use portfolio or regression analysis.

In summary, I show that mutual funds are heterogeneous in their herding behavior. There are different herds in the market with different underlying motivations. The results help in reconciling seemingly contradictory empirical findings in the herding literature. Earlier empirical mutual fund literature on herding (Wermers (1999), Nofsinger and Sias (1999), Sias (2004)) shows that herding is primarily motivated by information and that it makes market more informationally efficient. Later papers (Puckett and Yan (2008), Dasgupta, Prat, and Verado (2011a), Brown, Wei, and Wermers (2012)) find that herding leads to reversal in stock prices, suggesting that it could be motivated by agency. I show that both herds, a "non-agency herd", primarily of high ownership funds, and an "agency herd", primarily of low ownership funds, are present in the market and that, in the earlier studies, the effect of non-agency herds could have dominated the effect of agency-herds and vice-versa, as seen in latter studies. Note that even though the high ownership managers may be acting on similar information, I call their herd, a non-agency herd, because they are less likely to ignore their investment signals/information, and engage in uninformed positive-feedback trading.

Dasgupta, Prat, and Verado (2011a) and Brown, Wei, and Wermers (2012) find that herding causes reversal only in the second half of their sample period. They argue that it is due to greater institutional holding in the later period. I add to their findings by showing that even during the later period, there are funds among which herding is non-agency driven and it causes less reversal post-herding. That is, there are multiple types of herd in the mutual fund market. Each herd has its own distinct trading style and different qualitative and quantitative effect on stock prices.

The rest of the paper is organized as follows. Section 2.2 discusses the methodology used to construct herding measures. Section 2.3 describes the data and portfolio manager ownership in detail. Section 2.4 presents main results on herding, conditional on ownership and its impact on the stock prices. Section 2.5 concludes the paper.

2.2 Herding Measures

To measure herding, I use the measure proposed by Lakonishok, Shleifer, and Vishny (1992) (henceforth, LSV), used extensively in the literature (see for example, Grinblatt, Titman, and Wermers (1995), Wermers (1999), Sharma, Easterwood, and Kumar (2006), Puckett and Yan (2008), Brown, Wei, and Wermers (2012)). It measures the correlated trading by funds in a particular stock adjusting for the correlated trading occurring by chance. For a stock i in quarter t, LSV herding measure, HM_{it}, is defined as

$$HM_{it} = |p_{it} - E(p_{it})| - E|p_{it} - E(p_{it})| \tag{2.1}$$

where p_{it} is the proportion of funds buying stock i in quarter t relative to the total number of funds trading (buying and selling) that particular stock in the same quarter. $E(p_{it})$ is the expected proportion of stock i buys in quarter t, proxied by the total number of funds buying in quarter t relative to the total number of funds trading in quarter t aggregated across all stocks. Thus, the first term, $|p_{it} - E(p_{it})|$, represents excess buying or selling in stock i in quarter t relative to the average buying or selling in the stock in the same quarter. The second term, $E|p_{it} - E(p_{it})|$, is an adjustment factor that accounts for the fact that the first term is always greater than zero. It can be easily calculated if the number of stock-buys and stock-sells in a stock-quarter are assumed to be outcomes of a binomial process (see LSV for further details). Under the null hypothesis of no herding, that is, random and independent trading by funds, one would expect that HM_{it} is not significantly different from zero. As in Wermers (1999), I require that a stock to be traded by at least five funds in a quarter to be included in the sample to have a meaningful measure of herding.

Note that HM_{it} is a directionless measure of herding, that is, it does not distinguish between the buy-side and sell-side herds. To distinguish between the buy- and sell-side herds, I use conditional herding measures, as in Wermers (1999). First, stocks are segregated into two groups, depending upon whether they have a higher or lower proportion of buyers than the average stock in the same quarter. Then herding measure is calculated as before. The adjustment factor is recalculated depending upon $p_{it} > E(p_{it})$ or $p_{it} < E(p_{it})$ for BHM_{it} or SHM_{it}, respectively.

$$\begin{aligned} BHM_{it} &= HM_{it} | p_{it} > E(p_{it}) \\ SHM_{it} &= HM_{it} | p_{it} < E(p_{it}) \end{aligned} \tag{2.2}$$

Finally, as in Brown, Wei, and Wermers (2012), I create a signed adjusted herding measure, *ADJHERD*, which combines the buy- and sell-herding measures. For each stock-quarter, I calculate the adjusted-*BHM (SHM)*, by first subtracting the minimum *BHM (SHM)* for that quarter from the stock's *BHM (SHM)*. This results in a non-negative herding measure. Then *ADJHERD* is set to adjusted-*BHM* if a stock is buy-herded during that quarter or -1 times adjusted-*SHM* if a stock is sell-herded during that quarter. Thus, a high (low) value of *ADJHERD* implies that a stock is heavily buy-herded (sell-herded) during that quarter.

The herding measures described above are simple count measures of more than expected proportion of managers trading in the same direction irrespective of the size of the trades. A large number of funds trading a particular stock may reveal more about their underlying motivation. Also, Sias, Starks, and Titman (2006) mention that contemporaneous returns are more strongly related to changes in the number of institutional investors than changes in the fraction of shares held by institutions.

2.3 Data

2.3.1 Sample Selection

I obtain data on diversified open-ended actively managed U.S. equity mutual funds from CRSP Survivor-Bias Free US Mutual Fund database. CRSP funds are matched with the Thomson funds by MFLINKS dataset (see 1.2.1 for further details). I exclude all funds that can't be linked by MFLINKS dataset. I further require that the total net assets of a fund should be at least $5 million at the start of a calendar quarter. I then categorize funds into five investment objective categories - Aggressive Growth, Growth, Growth and Income, Equity Income, and Capital Gains (see 1.2.1).

I obtain "snapshots" of quarterly holdings of funds from Thomson Reuters mutual fund holdings database. For funds which do not report quarterly, I bring forward their last quarter holdings to the current quarter. This is done for at most one quarter. Further, I move all holdings to the calendar quarter end, if a fund reports holding before the calendar quarter end. Using these quarterly holdings, I infer buy and sell trades from changes in two consecutive quarterly portfolio holdings. To make sure the changes in quarterly holdings do not capture stock splits, I first reverse split the quarterly holdings of the latter quarter and then calculate the change in holdings. While calculating trades, I also exclude all stocks that are issued in the past one year because funds may trade such stocks for reasons related with new IPO issues in the market.

Portfolio manager ownership data is obtained from Morningstar and the SAI disclosure filed by funds with the SEC. The SAIs are obtained from the SEC

Edgar. The CRSP-Thomson matched dataset is then combined with the Morningstar dataset. Thus, I create a dataset having information on fund returns, various fund, fund family and manager characteristics. The ownership data used in this study covers the period from 2006 to 2009.

2.3.2 Recorded Ownership Over Time

The data on portfolio managerial ownership was obtained from Morningstar in January 2009. Since ownership data is declared annually and most funds file this information in the later half of a year, the ownership data obtained corresponds to the year 2008. Unfortunately, Morningstar does not achieve historical data on ownership. This creates a big data challenge because the ownership disclosure is not made in any standard format in the SEC filings, and thus can't be extracted through a script.

To overcome the data challenge, I use Morningstar data for 2008, hand-collected data and ownership estimates to build a dataset consisting of managerial ownership from 2006 to 2009. I hand-collect ownership data for a sample of funds for 2006, 2007, and 2009 and compare it with the ownership of the same manager for 2008. In unreported results, I confirm that the sample selected from 2008 is unbiased as far as the ownership is concerned. I compare difference-in-mean in percentage ownership of selected sample and the remaining sample from 2008 and found it not to be statistically significant even at 10% level. In the hand-collected sample, there are 449 unique managers of 166 funds, who managed the same fund in both 2007 and 2008 (see Table 2.1). I find no change in managerial ownership for 92% of the managers. 97% of the managers show no change in ownership level or change of just one level in ownership. Thus, there is strong consistency in managerial ownership across consecutive 2007 and 2008.

When I compare ownership of same managers for 2006 and 2008, I find no change, or change of just one level in dollar ownership for 88.4% of the managers, which is still almost 9/10th of the hand-collected sample. For 2008 and 2009, the corresponding percentage is 90.2%. So, even across 2006/2008, and 2008/2009, I find strong consistency in managerial ownership. This finding is also consistent with the slow changes in top executive ownership of corporations over the years as reported by Zhou (2001). Thus, for 2006, 2007, and 2009, where the same manager manages the fund in 2008 as well, I estimate ownership from 2008. Sometimes the ownership data is not available, just because of the timing of disclosure. For instance, if a manager left the fund on July 31, 2007 and the fund filed its disclosure on October 31, 2007, then the ownership data for that particular manager is not available for 2007. In such cases, where possible, I bring forward their ownership from the previous year. This is reasonable given that ownership doesn't change much across years. Thus, I am able to build a dataset consisting of managerial ownership from 2006 to 2009.

2.3.3 Descriptive Statistics

My final sample consists of 1463 distinct funds and 4673 fund-years. The total dollar managerial ownership is calculated using mid-points of the reported ranges, except for the last range, greater than \$1 million, where I take \$1 million as ownership, and then summing ownership of all managers in case of multi-manager funds. I follow Khorana, Servaes, and Wedge (2007) and measure ownership as percentage of shares outstanding. Because I am interested in agency influenced trading, I calculate ownership for each fund at the start of each calendar quarter. It is thus important to know which managers oversee the fund during any particular quarter. There are 44,010 fund-quarter-managers in the sample, out of which I am able to obtain ownership data on 41,203 fund-quarter-managers, which is almost 94%. Thus, for the sample considered, I have comprehensive data on managerial ownership. For summary statistics in Table 2.2, I take average ownership over the four quarter in each year.

Panel A shows that, on an average, around 27% of the funds have zero ownership. Khorana, Servaes, and Wedge (2007) report a figure of 57%, but they include bond funds as well. They also find that ownership is higher in equity funds than in bond funds. Thus, ownership numbers seem consistent with that of Khorana, Servaes, and Wedge (2007). The mean and median ownership in my sample is around \$500,000 and \$250,000, respectively, which translates into roughly 0.420% and 0.030% of total net assets, after taking average over the four years. Khorana, Servaes, and Wedge (2007)'s sample has 606 fund-years for domestic equity funds (their total sample consists of 1406 fund-years including bond, international, sector and balanced funds) and report a mean of \$226,000 which is half of what I find. This could be because of the differences in the sample. Given consistency in individual managerial ownership across years, I find almost no variation in mean and median total ownership (that is, total ownership of all managers overseeing a fund) across years either if it is measured in dollar terms or in percentage terms.

Panel B shows ownership by fund segment. Both mean and median dollar ownership is highest among the Capital Gains fund segment. While in percentage terms, mean and median ownership is highest for the Equity Income funds and Aggressive Growth funds, respectively. There is considerable variation in percentage ownership across fund segments. For instance, the mean percentage ownership in the Aggressive Growth segment is only 0.11%, while in the Equity Income segment it is 0.538%.

2.4 Results

2.4.1 Overall Herding

I first examine the herding behavior of funds, *conditional* on ownership. I calculate the LSV herding measure for every stock-quarter. The LSV measure is a simple measure of the disproportionate number of funds trading in a stock on the same side of the market. After calculating the LSV measure for each stock-quarter, I take the average as done in other studies (such as Lakonishok, Shleifer, and Vishny (1992), Wermers (1999)). Table 2.3 reports results on herding in stocks by funds conditional on ownership. To contrast the effect of managerial ownership, I divide the sample into *Low* and *High* ownership funds based on the median ownership at the start of each calendar quarter for each fund segment. *All* refers to the full sample, i.e., when no distinction is made between funds by ownership. At the start of each calendar quarter, firms are allocated into one of the five size quintiles. Firm size quintile break points are calculated at the start of each calendar quarter based on the market capitalization of firms listed on NYSE, AMEX and Nasdaq. In calculating the firm size quintile break points, only stocks with sharecode of 10 or 11 are included. These quintiles are represented by S1 (small stocks) to S5 (large stocks).

First column reports the mean herding measure for the full sample and separately for the low and high ownership funds. For the overall sample, the herding measure is 4.026. That is, if 100 funds trade a stock in any quarter, then around 4 more funds trade on the same side of the market than would be expected if they were independently trading. The number in parentheses is the number of stock-quarters used to calculate the mean herding measure. It represents how widespread herding is. All mean herding levels are statistically significant at 1% significance level, except for the mean herding level for the high ownership funds in size quintile 2, which is significant at 5% level. There are no observations for the high ownership herd in stock size quintile 1.[7] It thus appears that the high ownership funds avoid trading in smaller stocks, where it is more difficult to form precise investment signals, and the associated trading are higher.

Three features stand out when I compare herding among the low and high ownership funds. First, the low ownership funds herd more than the high ownership ones. The difference-in-mean is 1.758, which is statistically and economically significant, given that the overall mean herding level is 4.026. This is consistent with the view that the low ownership funds herd on public information which tends to be more uniformly observed, while the high ownership funds could be following similar signals from their private information which tends to be more disperse or they could be analyzing public information in similar ways but distinct from the low ownership funds. Second, while herding by the low ownership funds in stocks increases as firm size decreases, there is no such pattern for the high ownership funds. This could be because the low ownership managers employ the same technical strategy of trading in smaller stocks because they are associated with better returns. On the other hand, there is no large variation in herding levels among the high ownership funds across different size quintiles. Thus, it does not appear that they are following any technical strategy that would result in their higher herding level in any particular size quintile except for size quintiles 1 and 2, which they generally seem to avoid, because of the reasons mentioned above. Third, the herding levels among the low ownership funds are very similar to the overall herding level in the full sample (first row). This implies that the herding in the full sample is greatly influenced by the low ownership funds.

[7]There are just 32 stock-quarters in size quintile 1 for the high ownership. It implies that on an average only 2 stocks are herded in size quintile 1 by high ownership funds in each quarter. This is very little information to conclude anything with confidence about their herding behavior. I thus exclude these observations from the sample because it may lead to erroneous conclusion. Including these observations does not alter the results.

Some other findings in Table 2.3 are interesting. One, herding is more widespread among the low ownership funds. The number in parentheses, stock-quarters, are much higher for the low ownership funds than that for the high ownership funds. Two, it is very unlikely that the high ownership funds are providing liquidity to the low ownership funds. If they were, one would find herding to be more widespread than what it is in smaller stocks. For instance, the number of stocks traded by the low ownership funds belonging to the size quintile S2 is 2308, while the corresponding number for the high ownership funds is only 224. These numbers would roughly be the same if the high ownership funds were providing liquidity to the low ownership funds. Third, looking at the number of stock-quarters corresponding to the low and high ownership managers, one can see that some of the stocks herded are common. This is expected because each fund typically has more than 100 stocks in its portfolio, so some of the stocks will be common between different funds. I do not discard the commonly traded stocks. The reason is that the high ownership funds may herd into a high past return stock because it may be backed by good investment information. On the other hand, the low ownership funds may herd in the same high past return because of entirely different reasons, such as the reputational concerns. Throwing away such stock-quarters means that one cannot understand the herding behavior of managers, specially of the high ownership managers. Moreover, by including commonly herded stocks, I am biasing against finding different herding behavior among the low and high ownership managers.

2.4.2 Buy- and Sell-Herding

The above results on herding do not differentiate between the buy- and sell-side herding. To investigate the differences in the buy- and sell-herding behavior of managers, conditional on ownership, I follow Wermers (1999). I calculate the buy- and sell-herding measures as described in the Section 2.2. Panels A and B of Table 2.4 report results on the buy- and sell-herding, respectively. Funds are classified into low and high ownership categories as before. Firm size quintiles are also formed as mentioned earlier in the preceding Section 2.4.1.

Because all results are very similar as in the case of direction-less herding, I only briefly discuss buy- and sell-herding results. All mean herding levels are statistically significant at 1% significance level, except for the mean herding level for the high ownership funds in size quintile 2, which is significant at 10% level on the buy-side and insignificant on the sell-side. I find that both the buy- and sell-herding measures for the low ownership funds are greater than the buy- and sell-herding measures for the high ownership funds, respectively. The difference-in-mean herding level on the buy-side between the low and high ownership funds is 2.100, while it is 1.351 on the sell-side. For both the buy- and sell-herding, the difference generally increases as firm size decreases. Further, as in the case of direction-less herding, the buy- and sell-herding levels among the low ownership managers are similar to the herding levels in the full sample. There is no clear pattern in herding among the high ownership funds, although it is slightly elevated among large sized firms. The mean buy- and sell-herding levels in size quintile S5 are 2.294 and 2.299, respectively. As before, the high ownership funds avoid trading in smaller stocks (size quintiles S1 and S2).

2.4.3 Herding and Stock Returns

2.4.3.1 Full Sample

To analyze the trading strategies and the impact of herds on stock returns, I employ the calendar-time portfolio approach. Each calendar quarter, the buy- and sell-herded stocks by all funds or of a particular ownership category, low or high, are classified into two portfolios, *Buy* and *Sell*, by buy- and sell-herding measures, respectively. The stocks in the *Buy* and *Sell* portfolios are further sorted into terciles by the buy-herding and sell-herding measures (see Section 2.2 for details on calculation of *BHM* and *SHM*). This results in classification of stocks herded into six portfolios in each quarter, *Buy1* (stocks lightly buy-herded) to *Buy3* (stocks heavily buy-herded) and *Sell1* (stocks lightly sell-herded) to *Sell3* (stocks heavily sell-herded). For each stock in each portfolio, the DGTW-adjusted return (Daniel, Grinblatt, Titman, and Wermers (1997)) is first calculated and then equal-weighted return is obtained for all portfolios for seven quarters: Q0 (herding quarter), 2 quarters prior (Q-2 and Q-1), 4 quarters ahead (Q+1, Q+2, Q+3, Q+4) of the herding quarter. Finally, the time-series mean DGTW-adjusted return is calculated for all portfolios.

Before I get into the details, I try to understand and present the big picture by plotting the long-short portfolio returns in Figure 2.1. It shows the mean DGTW-adjusted cumulative returns on the long-short portfolio of stocks, that is long on the buy-herded stocks *(Buy)* and short on the sell-herded stocks *(Sell)* by all funds, and the low and high managerial ownership funds. The figure shows the cumulative return for two quarters before the herding quarter, and up to four quarters after the herding quarter. For the herding quarter, only that quarter (Q0) return is shown. That is, for Q-2, Q0, and Q1, only the single quarter returns are shown. For Q-1, the cumulative return of Q-2 and Q-1 is shown. For Q+2, the cumulative return of Q+1 and Q+2 is shown. And similarly for the quarters Q+3 and Q+4, the cumulative returns for three and four port-herding quarter returns are shown.

Three features stand out in Figure 2.1. One, the portfolio herded by the low ownership funds exhibit high past return, while the similar portfolio herded by the high ownership funds exhibit close to zero past return. It thus appears that the low ownership funds strongly use positive-feedback trading strategy, while the past returns on the buy- and sell-herded stocks by the high ownership funds are indistinguishable. Two, the cumulative return going forward stays close to 0% on the portfolio herded by the high ownership funds. But for the portfolio herded by low ownership funds, the cumulative return continuously declines and becomes highly negative post-herding, around -4.00%. Third, the return on the portfolio herded by all funds and low ownership funds are very similar. These findings suggest that there are two herds in the market with different herding motivations and different consequences on stock prices, and that the low ownership herd dominates the high ownership herd in the full sample.

As the benchmark case, Table 2.5 shows the impact of herding on stock returns when no distinction is made between funds by ownership, as done in earlier studies. It reports the mean DGTW-adjusted returns on the *Buy* and *Sell* portfolios, and also on the zero-investment portfolio, that is long on the *Buy* portfolio and short on the *Sell* portfolio. It also reports the mean DGTW-adjusted returns on portfolios formed by herding intensities, and also on the zero-investment, portfolio that is long on the *Buy3* portfolio and short on the *Sell3* portfolio. P-values are reported in parentheses.

I find results consistent with that of earlier studies. First, funds buy- and sell-herd in stocks with high and low past return, respectively. For instance, the quarter Q-2 return for the *Buy* portfolio, call it *Buy:Q-2*, is 3.34%, and the return on *Buy:Q-1* is 4.37%. The *Sell:Q-1* return is -1.45%. All of these returns are highly statistically significant. The *Sell:Q-2* return is not statistically significant. The *Buy-Sell* portfolio return for Q-2 and Q-1 is 3.19% and 5.82%, respectively, both of which are highly statistically significant. Second, the herding portfolios experience high return during Q0. The *Buy-Sell* portfolio return for the herding quarter is 4.38% (P-value 0.00). Third, post-herding there is return reversal in Q+3 and Q+4 quarters. The *Buy-Sell* returns for quarters Q+3 and Q+4 are -0.98% (P-value 0.03) and -0.70% (P-value 0.07), respectively.

When portfolios are formed by herding intensities, I get qualitatively similar results. First, funds use positive-feedback trading strategies. Second, returns in the herding quarter are related strongly with the direction of herding in stocks. Third, there is return reversal in subsequent quarters, and it is statistically significant during Q+3. On the whole, when the past returns of herded portfolios and the impact of herding on future returns is analyzed by treating all funds as a homogenous group, I find results that are consistent with recent studies that show that the herding destabilizes stock prices (Puckett and Yan (2008), Dasgupta, Prat, and Verado (2011a), Brown, Wei, and Wermers (2012)).

2.4.3.2 Low Vs High Ownership Funds

I now analyze the past returns of buy- and sell-herded stocks and the effect of herding on future returns, *conditional* on managerial ownership. I divide the sample into *Low* and *High* ownership funds based on the median ownership at the start of each calendar quarter for each fund segment. Apart from this distinction, the portfolios are formed in exactly the same way, as before in Table 2.5. Table 2.6 reports returns on portfolios of buy- and sell-herded stocks by the low ownership funds in Panel A, high ownership funds in Panel B, and difference in returns in Panel C.

I find that the returns on stocks herded by low ownership funds in Panel A, and all funds (in Table 2.5) are very similar. This is consistent with the results on the mean herding levels in Tables 2.3 and 2.4, where it was observed that the mean herding levels among all funds and low ownership funds are similar. Here I find that, first, the low ownership funds employ positive-feedback trading strategies. For instance, *Buy:Q-2* and *Buy:Q-1* returns are 3.46% and 4.66%, respectively, and *Sell:Q-1* return is -1.78%, all of these returns are statistically significant. The *Sell:Q-2* return is not statistically significant. The *Buy-Sell* portfolio return for Q-2 and Q-1 is 3.44% and 6.44%, respectively, both of which are highly statistically significant. Second, the herding portfolios experience high return during the herding quarter. The *Buy-Sell* portfolio return for the herding quarter is 4.13% (P-value 0.00). Third, post-herding there is return reversal in all quarters, but statistically significant in Q+3 quarter. The *Buy-Sell* returns for quarter Q+3 is -0.97% (P-value 0.02). This was -0.98% (P-value 0.03) when herding by all funds was considered in Table 2.5.

When portfolios are formed by herding intensities, I find similar results. First, low ownership funds use positive-feedback trading strategies. Second, returns in the herding quarter are related strongly with the direction of herding in stocks. Third, there is return reversal in subsequent quarters, and like in the case of full sample, it is statistically significant in Q+3 quarter. The *Buy3-Sell3* portfolio returns for the quarters Q+1, Q+2, and Q+3 are -2.25% (P-value 0.18), -1.88% (P-value 0.30) and -1.92% (P-value 0.05), respectively. The corresponding returns for the quarters Q+1, Q+2, and Q+3 in Table 2.5 are -1.68% (P-value 0.39), -1.81% (P-value 0.33) and -2.00% (P-value 0.07), respectively. Thus, one can see that the return pattern in the full sample is very similar to the return pattern for the stocks herded by low ownership funds.

The empirical findings presented above are consistent with the view that the herding behavior of low ownership funds is agency influenced, as in Scharfstein and Stein (1990). In their model, managers fear loss of reputation from acting differently from the herd and thus may mimic others. Thus a rational manager may follow the strategies of other managers, like the positive-feedback trading strategy. It is also consistent with the agency identified by Dow and Gorton (1997), when managers may engage in uninformed trading because doing nothing might be seen as lack of stock selection skill or shirking of responsibility.

In contrast to the above findings on returns on the stocks herded by all and the low ownership funds, the returns on the stocks herded by the high ownership funds present a very different picture in Panel B. First, past returns are weakly related with the direction of herding. *Buy:Q-2* and *Buy:Q-1* returns are 2.19% and 2.55%, respectively. *Sell:Q-2* and *Sell:Q-1* returns are 2.87% and 1.39%, respectively. All of these returns are statistically significant. But the return difference is not statistically significant for Q-2 quarter and very low in magnitude for Q-1 quarter. The *Buy-Sell* portfolio return for Q-2 is -0.68% (P-value 0.15), and for Q-1 it is 1.16% (P-value 0.00). Thus, unlike the low ownership funds, high ownership funds do not employ short term positive-feedback strategies very strongly. Second, the herding portfolios experience high return during Q0. The *Buy-Sell* portfolio return for the herding quarter is 3.04% (P-value 0.00). Third, there is no return reversal in subsequent quarters. In unreported results, I find that even the cumulative return of four quarters post-herding is neither economically nor statistically significant. Its magnitude is only -0.05% (P-value 0.96). I find similar results, when portfolios are formed by the herding intensities.

Hence, it appears unlikely that the trades of the high ownership managers are agency driven. In contrast to the low ownership managers, the cost imposed on high ownership managers, because of their ownership stakes acts as a deterrent against ignoring their investment signals and follow the share-the-blame approach or engaging in uninformed trading. It is difficult to say whether their herding behavior conforms to any theory. It is possible that the high ownership funds may be analyzing public information in similar ways, and it is a chance phenomenon that they form a herd. Alternatively, they may be uncovering information early from analyzing the same set of stocks, as in Hirshliefer, Subrahmanyam, and Titman (1994).

Panel C shows difference in returns on the stocks herded by the low and high ownership funds. For the sake of brevity, I only report the return difference on the *Buy*, *Sell*, *Buy-Sell*, and the intensely herded portfolios. First note that there is a very clear contrast in trading strategies of the low and high ownership funds. The past returns on the stocks herded by the low ownership funds are very high, both economically and statistically, as compared to the stocks herded by the high ownership funds. The difference in the total past return on the *Buy* portfolio is 3.37% (P-value 0.00), while it is -6.03% (P-value 0.00) on the *Sell* portfolio. Similarly, the difference on *Buy-Sell* is economically and statistically very significant.

For the post-herding returns, I find that the stocks herded by the low ownership funds experience greater return reversal. On the buy-side, there is an increased return reversal, specially in Q+3 quarter. Its magnitude is -0.34% with a P-value of 0.09. There appears to be even greater reversal on the sell-side. The return difference on the *Sell* portfolio in Q+2 is 0.67% (P-value 0.00), and it is 0.64% (P-value 0.04) in Q+3. Perhaps, the low ownership funds herd out of stocks to a greater degree following consensus analyst downgrades (see Brown, Wei, and Wermers (2012)).

The difference in *Buy3-Sell3* portfolio returns for the stocks herded by the low and high ownership funds also suggests that the lower ownership funds employ positive-feedback trading strategies to a greater degree, and their herding is followed by greater return reversal. For instance, the Q-2 and Q-1 quarter return on *Buy3-Sell3* is 4.12% (P-value 0.00) and 5.28% (P-value 0.00), respectively. Post-herding, the Q+2 and Q+3 quarter return is -0.74% (P-value 0.02) and -0.99% (P-value 0.00), respectively.[8] I find similar results for the return difference when portfolios are formed by herding intensities.

To bring a more clear contrast in the herding strategies and their impact on stock prices, I separate low and high ownership funds based on terciles at the start of each quarter and each fund segment. That is, at the start of each calendar quarter for each fund segment, I sort funds into terciles based on managerial ownership. The funds in the lowest and highest terciles are now termed as the low and high

[8] I also checked if the greater return reversal in stocks herded by lower ownership funds is also reflected in the post-herding cumulative returns. I find supportive results.

ownership funds. Table 2.7 reports results corresponding to the results in Table 2.6. I focus only on the key differences in Tables 2.7 and 2.6. First, it is more clear now that the past returns on stocks buy- and sell-herded by high ownership are indistinguishable. For instance, the past returns on *Buy-Sell* and *Buy3-Sell3* are statistically insignificant. There is now even greater evidence of increased return reversal due to herding by the lower ownership funds. This can be seen in post-herding returns on *Buy-Sell* and *Buy3-Sell3* in Panel C. For instance, the Q+1 quarter return on *Buy3-Sell3* is -3.65 (P-value 0.04), and it is -2.28 (P-value 0.02) for Q+2 quarter. That is, the stocks herded by the low ownership funds exhibit about 6.00% greater return reversal than the stocks herded by the high ownership funds. Overall, I find that the results are robust to separation of funds into low and high categories based on terciles of ownership, and in fact brings out a more clear contrast in herding strategies and post-herding return impact.

The above results show that the post-herding return reversal observed in the full sample appears to be driven mainly due to the agency influenced herding by the low ownership funds. That is, the low ownership herd dominates the high ownership herd in its impact on stock prices in the full sample. The big picture that emerges from the above results is that there are multiple herds in the market. There is an "agency herd", primarily of low ownership funds, and there is a "non-agency herd", primarily of high ownership funds. Note that even though the high ownership managers may be trading on similar fundamental information, I call their herd, a non-agency herd, because they do not ignore their investment signals/information, or engage in uninformed positive-feedback trading. Each of these agency and non-agency herds has its own distinct trading style and different qualitative and quantitative effect on stock prices.

The above findings also offer an explanation and reconcile seemingly contradictory empirical findings in the literature. The earlier studies use data only until

1997 and find that the herding speeds up the process of price adjustment by quickly incorporating news into prices and thus make markets more informationally efficient. For instance, Wermers (1999) uses quarterly mutual fund holdings from December 1974 to December 1994, and finds that funds use positive-feedback trading and that prices adjust permanently post-herding. Nofsinger and Sias (1999) use yearly data from 1977 to 1995 and find that institutional herding appears to be related with momentum trading. They also find no evidence of return reversal in the year following herding. Sias (2004) uses quarterly ownership data of institutions from 1983 to 1997 and find weak positive correlation between herding in the current quarter and returns over the next year. But the later studies, which use more recent data, such as, Puckett and Yan (2008), Dasgupta, Prat, and Verado (2011a) and Brown, Wei, and Wermers (2012) find that the herding leads to reversal in stock prices, and thus destabilizes stock prices. According to the *Investment Company Fact Book 2010*, there were only 4468 funds at the end of 1997, but this number has grown to around 12,000 by 2007. It could be the case that a higher proportion of all managers are agency influenced in the later years. Thus, one possible explanation for the seemingly contradictory findings is that the agency herd dominates the non-agency herd in the overall market in the later years, while the reverse could be true in the earlier years.

Note that this explanation is different from that of Dasgupta, Prat, and Verado (2011a) and Brown, Wei, and Wermers (2012). They argue greater reversal in later years is because of greater institutional holding in the later years, and thus greater trading in an average stock. Therefore, institutional herding may have a larger impact in the later years. The primary difference between their explanation and my explanation is that I treat fund managers as a heterogenous group. Using managerial ownership, I am able to separate out the managers who are more likely to be agency influenced, and it is primarily these managers who cause reversal in stock prices post-herding.

2.4.3.3 Small Vs Large Stocks

Because smaller stocks are less liquid and if herding is motivated by agency, then it could lead to greater stock price reversal following herding. I test this hypothesis in Table 2.8. As earlier, I form the *Buy* and *Sell* portfolios, depending upon whether a stock is buy- or sell-herded. This is done for the full sample of funds, and also for the stocks herded by the low and high ownership funds. I then further divide the stocks in the *Buy* and *Sell* portfolios into three groups by firm size at the start of each quarter. Thus, there are six portfolios each at the start of each quarter. For each stock in each portfolio, I calculate the DGTW-adjusted abnormal return and then I obtain equal-weighted return for all portfolios for seven quarters: Q0 (herding quarter), 2 quarters prior (Q-2 and Q-1), 4 quarters ahead (Q+1, Q+2, Q+3, Q+4) of the herding quarter. From the six portfolios above, three zero-investment *Buy-Sell* portfolios are constructed for each firm size group: small, medium and big. Firm size tercile break points are calculated at the start of each calendar quarter based on the market capitalization of firms listed on NYSE, AMEX and Nasdaq. In calculating the firm size tercile break points, only stocks with sharecode of 10 or 11 are included. Table 2.8 reports the mean DGTW-adjusted quarterly returns on these three *Buy-Sell* portfolios by firm size for all, low and high ownership funds in Panels A, B and C, respectively. Panel D shows the return difference between the Panels B and C. The funds are classified into low and high ownership categories based on median ownership for each segment at the start of each calendar quarter.

I again find that the results are very similar for the stocks herded by all and the low ownership funds. On the other hand, the results on the stocks herded by high ownership funds present a very different picture. In Panel A, first, as the firm size decreases, for the stocks herded by all funds, the total past return for the quarters

Q-2 and Q-1 increases from 4.93% for big stocks to 21.38% for small stocks, both of which are highly statistically significant. Second, the contemporaneous return decreases from 4.38% to statistically insignificant 0.40%. Third, there is greater return reversal in smaller stocks. For instance, Q+3 and Q+4 quarter return for big stocks is -0.65% (*P*-value 0.07) and statistically insignificant -0.40% (*P*-value 0.23), respectively, while it is -4.99% (*P*-value 0.05) and -5.12% (*P*-value 0.01), respectively, for the small stocks. In Panel B, where I analyze the return on the stocks herded by the low ownership funds, the return pattern is very similar to the return pattern in Panel A. Overall, I find that there is greater return reversal in smaller stocks herded by all funds and also by the low ownership funds.

Panel C provides a very different picture. First, as firm size decreases from low to medium (the high ownership funds avoid trading in small stocks), I find that for the stocks herded by the high ownership funds, the past return for Q-2 is statistically insignificant 0.08% for big stocks, and for Q-1 is 3.03% (*P*-value 0.00) for medium sized stocks. These past returns are very low as compared to the past returns on stocks herded by the low ownership funds. Second, contemporaneous return increases from 2.63% for big stocks to 4.37% for medium sized stocks. Third, there is no return reversal post-herding. Note that the high ownership funds avoid trading in small stocks. As explained earlier, possible reasons could be that the small stocks are thinly traded and have higher associated trading costs, and it is more difficult to form precise investment signals in such stocks.

Panel D shows the return difference on stocks herded by the low and high ownership funds for medium and large stocks. I find that the low ownership funds have a greater tendency to employ short-term positive-feedback trading strategy, and this tendency increases as firm size decreases. There is evidence of greater return reversal post-herding in all quarters, although it is statistically significant only for Q+2 for big stocks. However, when I use the tercile separation for the low and high ownership funds, and compare the return difference in Panel E, I find more clear evidence of return reversal. The difference in *Buy-Sell* return for the Q+2 quarter for the big firms is -1.06% (P-value 0.04), and it is -3.08% (P-value 0.05) for the Q+1 quarter for medium sized firms. In summary, the above results show that as firm size decreases, there is greater return reversal post-herding in the overall market, which is primarily driven by agency influenced low ownership funds.

2.4.4 Multivariate Regression Analysis

To test robustness of the results, I now examine the impact of herding on future stock returns using multivariate regression analysis. Specifically, I want to confirm that the herding by the lower ownership funds leads to greater price reversal post-herding, controlling for stock characteristics that may influence future return. I follow the tercile ownership separation because it brings out more clear contrast in the return patterns of stocks herded by the low and high ownership funds. Table 2.9 reports the mean coefficients from cross-sectional regressions of DGTW-adjusted quarterly return on *ADJHERD*, *DLow*, *ADJHERD*DLow* and stock characteristics. See Section 2.2 for calculation of *ADJHERD*. It is a signed herding measure, where a low (high) value of *ADJHERD* indicates that a stock is heavily sell-herded (buy-herded). *DLow* is a dummy variable for the stocks herded by the low ownership funds. *ADJHERD*DLow* is the interaction of *ADJHERD* and *DLow*. It captures the incremental effect of herding due to the low ownership funds on stock returns in addition to the effect of herding due to the high ownership funds. It is the main variable of interest in regressions. The stock characteristics included are *DivYield*, which is calculated as cash dividends for the fiscal year ended before the end of the herding quarter divided by the size of the stock at the end of the herding quarter. *Log(Vol)* is the natural logarithm of standard deviation of daily returns of the stock during the herding quarter, *Turnover* is the volume divided by the shares outstanding at the end of herding quarter, *Log(Size)* is the natural logarithm of firm size in \$millions at the end of the herding quarter, *Log(BM)* is the natural logarithm of book-to-market ratio[9], and *Qret* is the raw quarterly return during the herding quarter.

Panel A shows results for all herded stocks. Consistent with the portfolio analysis, I find that there is greater stock return reversal post-herding due to the low ownership funds. The coefficients on *ADJHERD*Dlow* for Q+1 and Q+2 quarters are -5.85 (P-value 0.06) and -3.93 (P-value 0.00), respectively. It shows that on an average, a 10% increase in the same side trading by the low ownership funds that trade the stock during that quarter results in 0.585% increased reversal in Q+1, as compared to the similar 10% increase in trading by the high ownership funds. Similarly for the quarter Q+2, a 10% increase in the same side trading by the low ownership funds that trade the stock during that quarter results in 0.393% increased reversal, as compared to the similar 10% increase in trading by the high ownership funds.

Panels B and C show results for the buy- and sell-herded stocks, respectively. In Panel B, the coefficients on *ADJHERD*Dlow* for the quarters Q+1 and Q+2 are -6.91 (P-value 0.05) and 0.35 (P-value 0.86), respectively. It suggests that a 10% increase in buy-side trading by the low ownership funds that buy the stock during that quarter results in a 0.691% increased reversal in Q+1, as compared to the similar 10% increase in trading by the high ownership funds. For the sell-side herding in Panel C, the coefficients on *ADJHERD*Dlow* for the quarters Q+1 and Q+2 are -4.55 (P-value 0.42) and -7.65 (P-value 0.05), respectively. Thus, herding by the low ownership funds results in greater return reversal on both buy- and sell-side. Overall, I find that the results from the multivariate analysis are consistent

[9]Book-to-market ratio is based on the market value of equity in December of year *t-1*, and book value of equity is calculated as in Daniel and Titman (2006). The book-to-market ratio thus obtained is applied from July of year *t* through June of year *t+1*.

with that from the portfolio analysis. In further unreported robustness tests, I also run panel regression and find similar results.

2.5 Conclusion

Using a new dataset on portfolio manager ownership, I analyze the herding behavior of managers, *conditional* on their ownership stakes in the funds they manage. The herding behavior of the low and high ownership funds is very different. Each herd has its own distinct trading style and different qualitative and quantitative effect on stock prices. Low ownership funds herd more and employ positive-feedback trading strategy, while the past returns of the buy- and sell-herded stocks by high ownership funds are indistinguishable. In other words, there is no evidence to suggest that high ownership funds use positive-feedback trading strategy. Low ownership funds herding is followed by stock price reversal, while high ownership funds herding is followed by more stable price adjustments.

The empirical findings are consistent with the view that herding among the low ownership funds is more likely to be agency driven, as in Scharfstein and Stein (1990). These managers may ignore their information and mimic other managers for fear of loss of reputation. It is also possible that when the low ownership managers are not able to identify profitable investments, they may yet have to trade because active non-trading cannot be distinguished from lack of stock selection skill or shirking of responsibility (Dow and Gorton (1997)). This can also induce the low ownership managers to employ positive-feedback trading. On the other hand, there is a cost associated for the high ownership managers for ignoring their investment signals/information, or engaging in uninformed positive-feedback trading because of their ownership in the funds.

The results also show that the post-herding return reversal observed in the full sample appears to be driven mainly due to the herding among the low ownership funds. Overall, I find that there are multiple herds with different underlying motivations. There is an "agency herd", primarily of low ownership funds, and there is a "non-agency herd", primarily of high ownership funds. In the full sample, the agency herd dominates the non-agency herd in impacting stock prices.

The above findings also offer an explanation and reconcile seemingly contradictory empirical findings in the literature. The earlier empirical studies, such as Wermers (1999), Nofsinger and Sias (1999), Sias (2004), find that herding is followed by permanent price adjustment and that it makes market more informationally efficient. However, the later studies, such as Puckett and Yan (2008), Dasgupta, Prat, and Verado (2011a), Brown, Wei, and Wermers (2012), find that herding leads to reversal in stock prices. Based on the empirical findings in this study, one explanation is that just as the agency herd dominates the non-agency herd in the overall market in the later years, while the reverse could be true in earlier years.

Figure 2.1: **Managerial Ownership, Herding and Stock Returns**
This figure shows mean DGTW-adjusted cumulative returns on a long-short portfolio of stocks that is long on buy-herded stocks *(Buy)* and short on sell-herded stocks *(Sell)* by all, low and high managerial ownership funds. Funds are classified into low and high ownership categories based on median ownership at the start of each calendar quarter for each fund segment. See text for more details. Cumulative return is shown for two quarters before the herding quarter, and up to four quarters after the herding quarter. For the herding quarter, only that quarter return is shown.

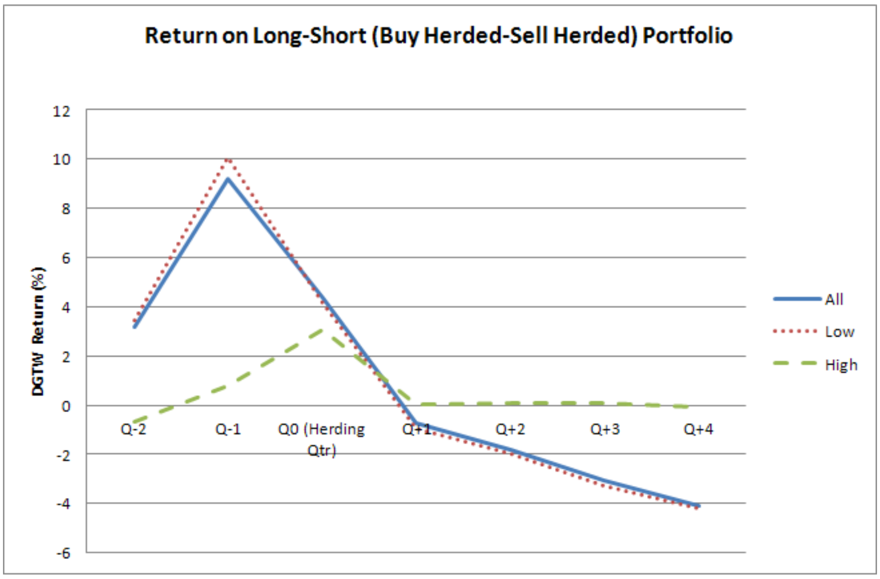


Table 2.1: **Recorded Managerial Ownership Over Time**

This table reports statistics from comparison of managerial ownership for the same manager for different years for the hand-collected sample. *Nfunds* is the number of funds compared across two years, such as for 2007 and 2008 this number is 166. *NMgrs* is the number of managers compared across two years, and *Diff(Own Range)* is the difference in managerial ownership range reported by the fund for two years. For instance, if a fund manager has disclosed dollar range of $1-$10,000 in 2006 and $50,001-$100,000 in 2007, then *Diff(Own Range)* for that fund manager is 2.

	2008-2007		2008-2006		2008-2009	
Nfunds	166		153		170	
Diff(Own Range)	NMgrs	Percent	NMgrs	Percent	NMgrs	Percent
-6	0	0.00	0	0	2	0.38
-5	0	0.00	1	0.28	2	0.38
-4	4	0.89	4	1.13	5	0.96
-3	0	0.00	0	0.00	5	0.96
-2	5	1.11	8	2.26	22	4.23
-1	10	2.23	12	3.39	32	6.15
0	415	92.43	268	75.71	397	76.35
1	10	2.23	33	9.32	40	7.69
2	1	0.22	15	4.24	8	1.54
3	3	0.67	5	1.41	1	0.19
4	1	0.22	6	1.69	5	0.96
5	0	0.00	1	0.28	1	0.19
6	0	0.00	1	0.28	0	0.00
Total	449	100.00	354	100.00	520	100.00

Table 2.2: **Descriptive Statistics**
This table reports descriptive statistics on managerial ownership by year in Panel A, and by fund segment in Panel B. In Panel A, *N* and *Zero* represents the number of funds, and number of funds with zero managerial ownership, respectively. In Panel B, *N* and *Zero* represents the number of fund-years, and number of fund-years with zero managerial ownership, respectively. Mean and median of dollar ownership, and dollar ownership as percentage of total net assets is also reported. Dollar ownership is calculated by first taking the midpoint of range of managerial ownership reported by the fund in the SEC filings and then summed across all managers in case of multi-manager funds. For the last range, greater than $1 million, $1 million is taken as ownership. Percentage ownership is calculated at the start of every calendar quarter by dividing the dollar ownership by total net assets of the fund, then average of quarterly percentage ownership over an year is taken for each fund, so that for each fund and for each year, there is one observation for percentage ownership.

Panel A: Descriptive statistics by year

			Mgr Own($)		Mgr Own(% of TNA)	
Year	N	Zero	Mean	Median	Mean	Median
2006	1139	306	536351	250000	0.422	0.031
2007	1144	311	505013	250000	0.390	0.025
2008	1244	352	503525	250000	0.421	0.026
2009	1146	303	504921	250000	0.437	0.038
Total fund-years	4673					
Total funds	1463					

Panel B: Descriptive Statistics by Fund Segment

			Mgr Own($)		Mgr Own(% of TNA)	
Fund Segment	N	Zero	Mean	Median	Mean	Median
Equity Inc (EI)	237	46	431461	250000	0.538	0.025
Growth (G)	2964	822	514101	250000	0.451	0.033
Growth & Inc (GI)	1020	293	523511	250000	0.386	0.021
Capital Gains (CG)	269	71	559261	280000	0.273	0.032
Agg Growth (AG)	183	40	454590	250000	0.111	0.034

Table 2.3: **Herding Measures by Managerial Ownership**

This table reports the overall mean herding level of funds and mean herding level of funds by firm size. See Section 2.2 for details on calculation of herding measure. *Low* and *High* refers to the sample of funds belonging to the low and high managerial ownership categories. These categories are determined based on the median ownership at the start of each calendar quarter for each fund segment. Managerial ownership is calculated at the start of every calendar quarter by dividing the dollar ownership (summed across all managers) with total net assets of the fund. Dollar ownership is calculated by first taking the midpoint of range of managerial ownership reported by the fund in the SEC filings and then summed across all managers in case of multi-manager funds. For the last range, greater than \$1 million, \$1 million is taken as ownership. *All* refers to the full sample, i.e., when no distinction is made among funds by ownership. At the start of every calendar quarter, firms are allocated into one of the five size quintiles. Firm size quintile break points are calculated at the start of every calendar quarter based on market capitalization of firms listed on NYSE, AMEX and Nasdaq. In calculating firm size quintile break points, only stocks with sharecode of 10 or 11 are included. These quintiles are represented by S1 (small stocks) to S5 (large stocks). All P-Values for mean herding levels are less than 0.01, except for high ownership funds in S2 quintile where it is 0.014. There are no observations for high ownership funds herding in size quintile S1. Numbers in parentheses are the number of stock-quarters used to calculate mean herding level. Last row shows difference-in-mean herding level between low and high ownership funds and the associated P-values.

	Overall	S1	S2	S3	S4	S5
All	4.026	17.656	7.860	4.152	3.079	3.396
	(48912)	(710)	(3801)	(11379)	(15330)	(17692)
Low	3.972	21.404	10.096	4.481	2.883	3.351
	(43723)	(432)	(2308)	(9356)	(14490)	(17137)
High	2.214	-	2.207	2.122	2.085	2.310
	(28209)		(224)	(2796)	(9661)	(15528)
Low-High	1.758	-	7.889	2.359	0.798	1.041
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)

Table 2.4: **Buy- and Sell- Herding Measures by Managerial Ownership**
This table reports mean buy- and sell-herding levels in Panels A and B, respectively. See Section 2.2 for details on calculation of buy- and sell-herding measures. *Low* and *High* refers to the sample of funds belonging to the low and high managerial ownership categories. These categories are determined based on the median ownership at the start of each calendar quarter for each fund segment. Managerial ownership is calculated at the start of every calendar quarter by dividing the dollar ownership (summed across all managers) with total net assets of the fund. Dollar ownership is calculated by first taking the midpoint of range of managerial ownership reported by the fund in the SEC filings and then summed across all managers in case of multi-manager funds. For the last range, greater than \$1 million, \$1 million is taken as ownership. *All* refers to the full sample, i.e., when no distinction is made among funds by ownership. At the start of every calendar quarter, firms are allocated into one of the five size quintiles. Firm size quintile break points are calculated at the start of every calendar quarter based on market capitalization of firms listed on NYSE, AMEX and Nasdaq. In calculating firm size quintile break points, only stocks with sharecode of 10 or 11 are included. These quintiles are represented by S1 (small stocks) to S5 (large stocks). All P-Values for mean herding levels are less than 0.01, except for high ownership funds in S2, where it is 0.067 for buy-herding, and 0.136 for sell-herding. There are no observations for high ownership funds buy- and sell-herding in size quintile S1. Numbers in parentheses are the number of stock-quarters used to calculate mean buy- and sell-herding levels. Last row shows difference-in-mean herding level between low and high ownership funds and the associated P-values.

Panel A: Buy-Herding

	Overall	S1	S2	S3	S4	S5
All	4.357	15.776	9.710	5.046	3.209	3.141
	(26618)	(311)	(2310)	(6659)	(8520)	(8818)
Low	4.317	18.962	12.250	5.574	3.161	2.898
	(23717)	(176)	(1448)	(5656)	(8186)	(8251)
High	2.217	-	2.314	2.162	2.108	2.294
	(14967)		(113)	(1470)	(5127)	(8257)
Low-High	2.100	-	9.936	3.412	1.053	0.604
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)

Panel B: Sell-Herding

	Overall	S1	S2	S3	S4	S5
All	3.604	18.262	5.076	2.941	2.890	3.597
	(22294)	(399)	(1491)	(4720)	(6810)	(8874)
Low	3.555	22.224	6.409	2.892	2.547	3.733
	(20006)	(256)	(860)	(3700)	(6304)	(8886)
High	2.204	-	1.812	2.177	2.070	2.299
	(13242)		(111)	(1326)	(4534)	(7271)
Low-High	1.351	-	4.596	0.714	0.477	1.433
	(0.000)		(0.002)	(0.075)	(0.030)	(0.000)

Table 2.5: **Herding and Stock Returns: All Funds**
This table reports mean DGTW-adjusted (Daniel, Grinblatt, Titman, and Wermers (1997)) quarterly return in percent on stocks buy- and sell-herded by all funds. Each calendar quarter stocks buy- and sell-herded by funds are classified into two portfolios, *Buy* and *Sell*. Stocks in *Buy* and *Sell* portfolios are further sorted by buy-herding measure *(BHM)* and sell-herding measure *(SHM)* (See Section 2.2 for details on calculation of *BHM* and *SHM*). This results in classification of stocks herded into six portfolios in each quarter. *Buy1* (stocks lightly buy-herded) to *Buy3* (stocks heavily buy-herded) and *Sell1* (stocks lightly sell-herded) to *Sell3* (stocks heavily sell-herded), in addition to *Buy* and *Sell* portfolios. For each stock in each portfolio DGTW-adjusted return is first calculated and then equal-weighted return is obtained for all portfolios for seven quarters: Q0 (herding quarter), 2 quarters prior (Q-2 and Q-1), 4 quarters ahead (Q+1, Q+2, Q+3, Q+4) of herding quarter. Time-series DGTW-adjusted return on portfolios is reported. Returns are also reported on two long-short portfolios, *Buy-Sell*, which is long on *Buy* and short on *Sell*, and *Buy3-Sell3*, which is long on *Buy3* and short on *Sell3*. Heteroscedasticity-consistent *P*-values are reported in parentheses.

Portfolio	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Buy	3.340	4.376	2.705	0.312	0.311	0.128	0.622
	(0.012)	(0.002)	(0.002)	(0.449)	(0.463)	(0.854)	(0.309)
Sell	0.143	-1.451	-1.684	1.058	1.064	1.118	1.325
	(0.703)	(0.003)	(0.024)	(0.320)	(0.309)	(0.155)	(0.114)
Buy-Sell	3.197	5.827	4.389	-0.746	-0.752	-0.989	-0.703
	(0.004)	(0.000)	(0.000)	(0.375)	(0.293)	(0.030)	(0.070)
Buy3	5.172	7.638	4.952	-0.039	-0.123	0.242	0.049
	(0.015)	(0.002)	(0.001)	(0.917)	(0.670)	(0.758)	(0.934)
Buy2	3.005	3.802	2.571	0.064	0.146	-0.025	0.837
	(0.006)	(0.001)	(0.003)	(0.819)	(0.719)	(0.969)	(0.221)
Buy1	1.979	1.977	0.743	0.924	0.906	0.184	0.933
	(0.033)	(0.025)	(0.115)	(0.235)	(0.251)	(0.806)	(0.188)
Sell1	0.731	0.438	-0.229	0.755	1.153	0.327	1.360
	(0.175)	(0.461)	(0.646)	(0.412)	(0.088)	(0.627)	(0.079)
Sell2	0.983	-0.794	-1.167	0.833	0.527	1.052	1.509
	(0.009)	(0.023)	(0.120)	(0.213)	(0.557)	(0.092)	(0.125)
Sell3	-1.747	-4.773	-4.290	1.648	1.694	2.251	0.955
	(0.009)	(0.000)	(0.001)	(0.403)	(0.381)	(0.089)	(0.285)
Buy3-Sell3	6.919	12.410	9.241	-1.688	-1.818	-2.009	-0.907
	(0.002)	(0.000)	(0.000)	(0.397)	(0.335)	(0.071)	(0.192)

Table 2.6: **Herding and Stock Returns: Low Vs High Ownership Funds (Median Separation)**

This table reports mean DGTW-adjusted (Daniel, Grinblatt, Titman, and Wermers (1997)) quarterly return in percent on stocks buy- and sell-herded by low and high ownership funds. Funds are classified into low or high ownership categories at the start of each calendar quarter based on the median ownership for each fund segment. Managerial ownership is calculated at the start of each calendar quarter by dividing the dollar ownership (summed across all managers) with total net assets of the fund. Dollar ownership is calculated by first taking the midpoint of range of managerial ownership reported by the fund in the SEC filings and then summed across all managers in case of multi-manager funds. For the last range, greater than \$1 million, \$1 million is taken as ownership. Each calendar quarter stocks buy- and sell-herded by low ownership funds are classified into two portfolios, *Buy* and *Sell*. Stocks in *Buy* and *Sell* portfolios are further sorted by buy-herding measure *(BHM)* and sell-herding measure *(SHM)* (See Section 2.2 for details on calculation of *BHM* and *SHM*). This results in classification of stocks herded into six portfolios in each quarter. *Buy1* (stocks lightly buy-herded) to *Buy3* (stocks heavily buy-herded) and *Sell1* (stocks lightly sell-herded) to *Sell3* (stocks heavily sell-herded), in addition to *Buy* and *Sell* portfolios. For each stock in each portfolio DGTW-adjusted return is first calculated and then equal-weighted return is obtained for all portfolios for seven quarters: Q0 (herding quarter), 2 quarters prior (Q-2 and Q-1), 4 quarters ahead (Q+1, Q+2, Q+3, Q+4) of herding quarter. Time-series DGTW-adjusted return on portfolios is reported. Returns are also reported on two long-short portfolios, *Buy-Sell*, which is long on *Buy* and short on *Sell*, and *Buy3-Sell3*, which is long on *Buy3* and short on *Sell3*. Panel A reports returns on stocks herded by low ownership funds, while Panel B reports returns on stocks herded by high ownership funds. Panel C compared returns in Panels A and B. Heteroscedasticity-consistent P-values are reported in parentheses.

Panel A: Low Ownership Funds

Portfolio	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Buy	3.465	4.660	2.542	0.121	0.260	0.140	0.644
	(0.013)	(0.002)	(0.004)	(0.718)	(0.539)	(0.839)	(0.262)
Sell	0.020	-1.788	-1.591	1.060	1.048	1.112	1.247
	(0.951)	(0.001)	(0.020)	(0.314)	(0.316)	(0.172)	(0.160)

Buy-Sell	3.445	6.448	4.133	-0.940	-0.788	-0.972	-0.603
	(0.004)	(0.000)	(0.000)	(0.294)	(0.262)	(0.024)	(0.222)
Buy3	5.468	7.823	4.502	-0.214	0.001	-0.037	0.207
	(0.010)	(0.002)	(0.000)	(0.531)	(0.998)	(0.963)	(0.737)
Buy2	3.255	4.343	2.674	0.081	0.152	0.182	0.562
	(0.004)	(0.003)	(0.009)	(0.844)	(0.730)	(0.779)	(0.375)
Buy1	1.806	2.111	0.580	0.483	0.602	0.249	1.132
	(0.089)	(0.002)	(0.261)	(0.370)	(0.328)	(0.749)	(0.072)
Sell1	0.682	0.027	-0.487	0.776	0.558	0.893	1.794
	(0.206)	(0.968)	(0.276)	(0.397)	(0.452)	(0.327)	(0.078)
Sell2	1.120	-1.118	-1.600	0.596	0.854	0.748	1.040
	(0.001)	(0.013)	(0.005)	(0.533)	(0.245)	(0.202)	(0.246)
Sell3	-2.255	-4.887	-2.983	2.040	1.881	1.886	0.821
	(0.001)	(0.000)	(0.023)	(0.201)	(0.331)	(0.114)	(0.327)
Buy3-Sell3	7.723	12.709	7.486	-2.254	-1.880	-1.923	-0.614
	(0.001)	(0.000)	(0.000)	(0.188)	(0.305)	(0.056)	(0.296)

Panel B: High Ownership Funds

Portfolio	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Buy	2.196	2.558	2.309	0.323	0.334	0.486	0.885
	(0.008)	(0.002)	(0.003)	(0.421)	(0.394)	(0.466)	(0.240)

Sell	2.877	1.394	-0.734	0.293	0.376	0.469	0.849
	(0.000)	(0.018)	(0.184)	(0.615)	(0.690)	(0.508)	(0.227)
Buy-Sell	-0.681	1.164	3.043	0.030	-0.041	0.018	0.036
	(0.151)	(0.007)	(0.000)	(0.926)	(0.954)	(0.960)	(0.869)
Buy3	2.216	3.340	3.532	0.537	0.230	-0.162	0.297
	(0.025)	(0.018)	(0.003)	(0.332)	(0.636)	(0.814)	(0.750)
Buy2	2.937	2.217	1.838	0.175	0.110	0.744	0.864
	(0.010)	(0.000)	(0.005)	(0.635)	(0.753)	(0.259)	(0.170)
Buy1	1.342	2.200	1.654	0.236	0.683	0.880	1.503
	(0.014)	(0.004)	(0.008)	(0.624)	(0.250)	(0.259)	(0.081)
Sell1	2.456	2.045	0.956	0.465	0.877	0.340	0.908
	(0.000)	(0.038)	(0.163)	(0.525)	(0.375)	(0.619)	(0.299)
Sell2	3.010	1.969	-0.855	0.070	-0.100	0.212	0.627
	(0.000)	(0.000)	(0.062)	(0.885)	(0.878)	(0.752)	(0.378)
Sell3	3.206	-0.016	-2.512	0.344	0.453	0.910	1.094
	(0.001)	(0.977)	(0.009)	(0.677)	(0.750)	(0.368)	(0.088)
Buy3-Sell3	-0.990	3.356	6.044	0.193	-0.222	-1.072	-0.797
	(0.203)	(0.010)	(0.000)	(0.723)	(0.865)	(0.237)	(0.169)

Panel C: Low Minus High

Portfolio	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Buy	1.269	2.101	0.233	-0.202	-0.074	-0.346	-0.242
	(0.055)	(0.006)	(0.442)	(0.503)	(0.717)	(0.092)	(0.485)

Sell	-2.857	-3.182	-0.857	0.767	0.672	0.644	0.398
	(0.000)	(0.000)	(0.085)	(0.169)	(0.008)	(0.044)	(0.167)
Buy-Sell	4.126	5.283	1.089	-0.969	-0.746	-0.990	-0.639
	(0.000)	(0.000)	(0.090)	(0.218)	(0.026)	(0.037)	(0.284)
Buy3	3.252	4.482	0.970	-0.750	-0.229	0.125	-0.090
	(0.014)	(0.001)	(0.151)	(0.205)	(0.564)	(0.790)	(0.892)
Sell3	-5.461	-4.871	-0.471	1.697	1.428	0.976	-0.273
	(0.000)	(0.000)	(0.597)	(0.083)	(0.063)	(0.095)	(0.500)
Buy3-Sell3	8.713	9.353	1.442	-2.447	-1.657	-0.850	0.183
	(0.000)	(0.000)	(0.281)	(0.094)	(0.067)	(0.320)	(0.834)

Table 2.7: **Herding and Stock Returns: Low Vs High Ownership Funds (Tercile Separation)**

This table reports mean DGTW-adjusted (Daniel, Grinblatt, Titman, and Wermers (1997)) quarterly return in percent on stocks buy- and sell-herded by low and high ownership funds. Funds are classified into low or high ownership categories at the start of each calendar quarter based on the lowest and highest tercile ownership for each fund segment. Managerial ownership is calculated at the start of each calendar quarter by dividing the dollar ownership (summed across all managers) with total net assets of the fund. Dollar ownership is calculated by first taking the midpoint of range of managerial ownership reported by the fund in the SEC filings and then summed across all managers in case of multi-manager funds. For the last range, greater than \$1 million, \$1 million is taken as ownership. Each calendar quarter stocks buy- and sell-herded by low ownership funds are classified into two portfolios, *Buy* and *Sell*. Stocks in *Buy* and *Sell* portfolios are further sorted by buy-herding measure *(BHM)* and sell-herding measure *(SHM)* (See Section 2.2 for details on calculation of *BHM* and *SHM*). This results in classification of stocks herded into six portfolios in each quarter. *Buy1* (stocks lightly buy-herded) to *Buy3* (stocks heavily buy-herded) and *Sell1* (stocks lightly sell-herded) to *Sell3* (stocks heavily sell-herded), in addition to *Buy* and *Sell* portfolios. For each stock in each portfolio DGTW-adjusted return is first calculated and then equal-weighted return is obtained for all portfolios for seven quarters: Q0 (herding quarter), 2 quarters prior (Q-2 and Q-1), 4 quarters ahead (Q+1, Q+2, Q+3, Q+4) of herding quarter. Time-series DGTW-adjusted return on portfolios is reported. Returns are also reported on two long-short portfolios, *Buy-Sell*, which is long on *Buy* and short on *Sell*, and *Buy3-Sell3*, which is long on *Buy3* and short on *Sell3*. Panel A reports returns on stocks herded by low ownership funds, while Panel B reports returns on stocks herded by high ownership funds. Panel C compared returns in Panels A and B. Heteroscedasticity-consistent P-values are reported in parentheses.

Panel A: Low Ownership Funds

Portfolio	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Buy	3.793	4.890	2.588	0.005	0.141	0.175	0.738
	(0.009)	(0.002)	(0.003)	(0.986)	(0.728)	(0.816)	(0.237)
Sell	0.237	-1.620	-1.399	1.054	0.948	0.939	1.191
	(0.533)	(0.000)	(0.042)	(0.310)	(0.309)	(0.240)	(0.177)

Buy-Sell	3.556	6.510	3.988	-1.049	-0.808	-0.764	-0.453
	(0.002)	(0.000)	(0.000)	(0.250)	(0.209)	(0.033)	(0.257)
Buy3	5.560	7.962	4.610	-0.489	-0.258	-0.180	0.240
	(0.005)	(0.005)	(0.001)	(0.209)	(0.489)	(0.825)	(0.712)
Buy2	3.497	4.327	2.844	0.546	0.033	0.422	0.714
	(0.013)	(0.000)	(0.003)	(0.248)	(0.945)	(0.558)	(0.179)
Buy1	2.431	2.614	0.448	-0.108	0.589	0.268	1.247
	(0.020)	(0.003)	(0.361)	(0.784)	(0.394)	(0.769)	(0.178)
Sell1	0.740	-0.051	-0.428	0.901	0.848	0.528	1.745
	(0.149)	(0.888)	(0.419)	(0.263)	(0.308)	(0.455)	(0.069)
Sell2	1.174	-0.412	-0.935	0.338	0.606	0.793	0.873
	(0.024)	(0.215)	(0.092)	(0.710)	(0.358)	(0.316)	(0.357)
Sell3	-1.536	-4.965	-3.158	2.126	1.450	1.628	0.950
	(0.006)	(0.000)	(0.008)	(0.208)	(0.333)	(0.112)	(0.287)
Buy3-Sell3	7.097	12.928	7.767	-2.615	-1.708	-1.808	-0.710
	(0.001)	(0.000)	(0.000)	(0.153)	(0.296)	(0.028)	(0.250)

Panel B: High Ownership Funds

Portfolio	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Buy	2.541	2.047	2.549	0.389	0.455	0.321	0.727
	(0.001)	(0.001)	(0.000)	(0.361)	(0.431)	(0.607)	(0.377)

Sell	3.184	1.807	-0.957	-0.035	0.195	0.515	1.091
	(0.000)	(0.000)	(0.111)	(0.949)	(0.779)	(0.540)	(0.125)
Buy-Sell	-0.643	0.240	3.506	0.423	0.260	-0.194	-0.364
	(0.252)	(0.421)	(0.000)	(0.186)	(0.453)	(0.698)	(0.292)
Buy3	2.308	2.083	4.108	0.896	0.516	0.073	-0.205
	(0.004)	(0.000)	(0.001)	(0.150)	(0.221)	(0.916)	(0.812)
Buy2	2.403	2.163	1.737	-0.089	-0.273	0.545	0.622
	(0.000)	(0.001)	(0.000)	(0.780)	(0.679)	(0.404)	(0.337)
Buy1	2.987	1.925	1.791	0.371	1.104	0.273	1.758
	(0.014)	(0.048)	(0.011)	(0.480)	(0.175)	(0.729)	(0.116)
Sell1	2.758	2.222	0.090	-0.167	1.192	0.548	1.579
	(0.002)	(0.001)	(0.868)	(0.798)	(0.160)	(0.533)	(0.082)
Sell2	3.128	2.044	-0.746	0.212	-0.542	0.270	0.450
	(0.000)	(0.000)	(0.213)	(0.740)	(0.266)	(0.744)	(0.360)
Sell3	3.693	1.041	-2.383	-0.146	-0.056	0.794	1.311
	(0.000)	(0.108)	(0.014)	(0.809)	(0.959)	(0.458)	(0.149)
Buy3-Sell3	-1.385	1.043	6.491	1.043	0.572	-0.721	-1.515
	(0.146)	(0.196)	(0.000)	(0.058)	(0.566)	(0.510)	(0.005)

Panel C: Low Minus High

Portfolio	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Buy	1.252	2.843	0.039	-0.384	-0.315	-0.146	0.012
	(0.090)	(0.007)	(0.927)	(0.161)	(0.336)	(0.581)	(0.976)

Sell	-2.947	-3.427	-0.442	1.089	0.753	0.424	0.100
	(0.000)	(0.000)	(0.396)	(0.093)	(0.046)	(0.207)	(0.756)
Buy-Sell	4.199	6.270	0.481	-1.473	-1.068	-0.570	-0.089
	(0.000)	(0.000)	(0.478)	(0.068)	(0.072)	(0.252)	(0.888)
Buy3	3.252	5.879	0.502	-1.386	-0.773	-0.253	0.444
	(0.028)	(0.017)	(0.574)	(0.047)	(0.159)	(0.602)	(0.507)
Sell3	-5.230	-6.006	-0.774	2.272	1.506	0.834	-0.360
	(0.000)	(0.000)	(0.440)	(0.074)	(0.033)	(0.163)	(0.461)
Buy3-Sell3	8.482	11.885	1.276	-3.658	-2.280	-1.088	0.805
	(0.000)	(0.000)	(0.415)	(0.043)	(0.020)	(0.163)	(0.284)

Table 2.8: **Herding and Stock Returns: Small Vs Large Stocks**

This table reports mean DGTW-adjusted (Daniel, Grinblatt, Titman, and Wermers (1997)) quarterly return in percent on long-short portfolio of stocks, which is long on *Buy* portfolio (stocks sell-herded) and short on *Sell* portfolio (stocks sell-herded), herded by all funds in Panel A and by low and high managerial ownership funds in Panel B and C, respectively, by *firm size*. Panel D compares returns on stocks herded by low and high ownership funds, where funds are categorized into low and high categories as in Table 2.6. Panel E compares returns on stocks herded by low and high ownership funds, where funds are categorized into low and high categories as in Table 2.7. Each calendar quarter stocks buy- and sell-herded by low ownership funds are classified into two portfolios, *Buy* and *Sell*. Stocks in *Buy* and *Sell* portfolio are further divided into three groups by firm size at the start of each quarter. Firm size tercile break points are calculated at the start of each calendar quarter based on the market capitalization of firms listed on NYSE, AMEX and Nasdaq. In calculating the firm size tercile break points, only stocks with sharecode of 10 or 11 are included. Thus, there are six portfolios each at the start of each calendar quarter, *Buy:Small, Buy:Medium, Buy:Big*, and *Sell:Small, Sell:Medium, Sell:Big*. For each stock in each portfolio DGTW-adjusted return is calculated and then equal-weighted return is obtained for all portfolios for seven quarters: Q0 (herding quarter), 2 quarters prior (Q-2 and Q-1), 4 quarters ahead (Q+1, Q+2, Q+3, Q+4) of herding quarter. From six portfolios above, three *Buy-Sell* portfolios are constructed for each firm size group - small, medium and big. The table below in each panel reports mean DGTW-adjusted returns on these three *Buy-Sell* portfolios by firm size. Heteroscedasticity-consistent *P*-values are reported in parentheses.

Panel A: All Funds

Firm Size	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Small	9.983	11.398	0.402	-3.167	-2.229	-4.996	-19.987
	(0.003)	(0.000)	(0.900)	(0.387)	(0.535)	(0.057)	(0.038)
Medium	4.904	9.411	4.884	-1.078	-1.059	-1.314	-5.358
	(0.001)	(0.000)	(0.000)	(0.429)	(0.244)	(0.119)	(0.037)
Big	1.383	3.548	4.386	-0.028	-0.402	-0.653	-1.725
	(0.087)	(0.000)	(0.000)	(0.956)	(0.371)	(0.074)	(0.058)

Panel B: Low Ownership Funds (Median Separation)

Firm Size	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Small	10.238	7.728	0.690	-0.692	-3.967	-8.621	-13.789
	(0.007)	(0.023)	(0.916)	(0.884)	(0.479)	(0.064)	(0.316)
Medium	5.439	10.202	4.855	-1.618	-1.258	-1.505	-6.518
	(0.001)	(0.000)	(0.000)	(0.331)	(0.196)	(0.142)	(0.048)
Big	1.940	4.627	4.051	-0.215	-0.422	-0.583	-2.099
	(0.021)	(0.000)	(0.000)	(0.741)	(0.342)	(0.070)	(0.047)

Panel C: High Ownership Funds (Median Separation)

Firm Size	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Medium	-1.325	3.036	4.370	-0.943	-0.580	0.148	-1.470
	(0.169)	(0.002)	(0.003)	(0.245)	(0.733)	(0.783)	(0.567)
Big	-0.555	0.638	2.630	0.276	0.143	-0.033	0.302
	(0.243)	(0.112)	(0.000)	(0.330)	(0.789)	(0.930)	(0.740)

Panel D: Low Minus High (Median Separation)

Firm Size	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Medium	6.764	7.166	0.485	-0.675	-0.678	-1.653	-5.048
	(0.001)	(0.001)	(0.718)	(0.626)	(0.539)	(0.161)	(0.118)
Big	2.495	3.989	1.420	-0.491	-0.565	-0.550	-2.400
	(0.000)	(0.000)	(0.028)	(0.365)	(0.090)	(0.214)	(0.036)

Panel E: Low Minus High (Tercile Separation)

Firm Size	Q-2	Q-1	Q0	Q+1	Q+2	Q+3	Q+4
Medium	6.201	9.043	-1.876	-3.081	-0.051	-2.721	-4.000
	(0.000)	(0.009)	(0.347)	(0.050)	(0.977)	(0.177)	(0.391)
Big	2.791	4.489	0.895	-0.586	-1.063	-0.052	-2.238
	(0.002)	(0.000)	(0.254)	(0.301)	(0.049)	(0.928)	(0.877)

Table 2.9: **Multivariate Regression: Herding and Future Stock Returns**

This table reports mean coefficients from cross-sectional regressions of DGTW-adjusted (Daniel, Grinblatt, Titman, and Wermers (1997)) return on *ADJHERD*, *DLow*, *ADJHERD*DLow* and stock characteristics. The dependent variable is Q+i quarter DGTW-adjusted return for the ith quarter. See Section 2.2 for calculation of *ADJHERD*. *DLow* is dummy variable for stocks herded by the low ownership funds. *ADJHERD*DLow* is interaction of *ADJHERD* and *DLow*. *DivYield* is the dividend yield. Dividend yield is calculated as cash dividends divided by the size of the stock. *Log(Vol)* is the natural logarithm of standard deviation of daily returns of a stock during the herding quarter, *Turnover* is the volume divided by shares outstanding. Log(Size) is the natural logarithm of firm size in $millions, Log(BM) is the natural logarithm of book-to-market ratio, and Qret is the raw quarterly return. All stock characteristics are calculated at the end of the herding quarter. Heteroscedasticity-consistent *P*-values are reported in parentheses.

	Panel A: All Stocks				Panel B: Buy-Herded				Panel C: Sell-Herded			
DGTW	Q+1	Q+2	Q+3	Q+4	Q+1	Q+2	Q+3	Q+4	Q+1	Q+2	Q+3	Q+4
Intercept	8.462	5.821	5.665	12.602	6.216	1.698	5.366	15.570	8.940	9.890	6.398	9.318
	(0.401)	(0.468)	(0.526)	(0.228)	(0.466)	(0.801)	(0.551)	(0.173)	(0.444)	(0.281)	(0.480)	(0.334)
DLow	-0.064	-0.132	0.062	-0.168	0.136	-0.572	-0.739	-0.391	-0.050	-0.594	-0.352	0.863
	(0.590)	(0.594)	(0.626)	(0.339)	(0.781)	(0.236)	(0.198)	(0.572)	(0.929)	(0.266)	(0.485)	(0.150)
ADJHERD	2.513	0.891	-1.137	-2.137	4.426	-0.806	-3.377	-5.557	-0.006	2.313	-2.782	-2.271
	(0.069)	(0.487)	(0.486)	(0.015)	(0.019)	(0.747)	(0.219)	(0.036)	(0.998)	(0.510)	(0.377)	(0.381)
ADJHERD*DLow	-5.855	-3.939	-0.576	0.929	-6.919	0.350	4.896	0.276	-4.545	-7.657	-4.427	7.192
	(0.060)	(0.001)	(0.766)	(0.561)	(0.052)	(0.869)	(0.138)	(0.952)	(0.428)	(0.052)	(0.306)	(0.122)
DivYield	21.448	14.117	2.185	-7.442	12.050	12.471	-4.047	-4.927	28.385	15.768	8.398	-2.092
	(0.157)	(0.257)	(0.860)	(0.498)	(0.426)	(0.354)	(0.817)	(0.733)	(0.088)	(0.304)	(0.490)	(0.900)
Log(Vol)	2.399	1.780	1.000	2.493	1.857	0.460	1.060	2.997	2.650	2.970	0.989	1.764
	(0.433)	(0.499)	(0.590)	(0.329)	(0.483)	(0.821)	(0.568)	(0.277)	(0.458)	(0.353)	(0.605)	(0.457)
Turnover	-2.847	-3.192	-2.062	-2.630	-1.785	-3.029	-2.758	-2.503	-3.734	-3.393	-1.484	-2.469
	(0.021)	(0.051)	(0.149)	(0.035)	(0.153)	(0.072)	(0.069)	(0.105)	(0.029)	(0.063)	(0.373)	(0.076)
Log(Size)	-0.004	-0.207	-0.242	-0.122	0.036	-0.220	-0.158	-0.196	-0.013	-0.185	-0.317	-0.097
	(0.982)	(0.230)	(0.416)	(0.561)	(0.868)	(0.182)	(0.605)	(0.359)	(0.938)	(0.397)	(0.309)	(0.654)
Log(BM)	-0.167	-0.540	0.137	0.509	0.000	-0.708	-0.116	0.354	-0.274	-0.390	0.464	0.612
	(0.649)	(0.100)	(0.764)	(0.397)	(0.999)	(0.053)	(0.837)	(0.536)	(0.531)	(0.274)	(0.326)	(0.369)
Qret	-2.065	-1.623	-4.768	-1.238	-1.392	-1.367	-4.472	-0.701	-2.588	-1.427	-4.907	-1.500
	(0.460)	(0.666)	(0.173)	(0.412)	(0.620)	(0.755)	(0.180)	(0.521)	(0.368)	(0.653)	(0.207)	(0.533)

Chapter 3: **Customized Mutual Fund Peers**

3.1 Introduction

Money managers in the U.S. manage over \$13 trillion in assets, of which \$11.6 trillion is held in open-ended mutual funds. As of December 2011, there are 7,634 open-ended mutual funds, 4,581 of which invest primarily in equity. The shares held by mutual funds represent 29% of outstanding shares in the U.S. market (ICI Factbook, 2012).

Funds pursue varying investment objectives. Some funds invest in growth stocks while others seek income from dividend paying stocks or invest in specific sectors such as natural resources. Fund managers have broad latitude in setting investment strategies to attain their stated targets. Given these variation in fund objectives and investment strategies, academics and practitioners classify funds into a small number of investment "styles." For instance, the Thomson Reuters Lipper classification system lists 14 styles for U.S. diversified equity funds. Brown and Goetzmann (1997) identify 8 distinct equity investing styles.

A primary purpose of style classifications is to help investors evaluate fund performance. Fund managers are compensated, hired, and fired based on their returns relative to peer funds following similar styles. Individual investors face a complex search process when choosing among thousands of funds. Informative style classifications reduce the search costs for such investors. Misclassified peers can hurt investors because investor flows chase peer-adjusted returns even when the peers are imperfect (Sensoy (2009)). Thus, Brown and Goetzmann (1997) seek "... objectively and empirically determined style benchmarks that are consistent across managers and related to a manager's strategy." We develop methods to identify fund peers. A key feature of our classification system is that the fund peers we generate are customized and fund-specific. Thus, no two funds need have the same set of peers.

There are currently two main approaches towards specifying fund style benchmarks. One approach uses historical fund returns. Sharpe (1988), Sharpe (1992) regresses historical fund returns on benchmark indexes and uses the regression coefficients to generate fund benchmarks. Brown and Goetzmann (1997) use past returns to form clusters of funds, picking clusters such that they have low within-variation in historical returns. A second approach, which we develop, uses fund holdings to characterize style (Grinblatt and Titman (1989), Daniel et al. (1997), Chan et al. (2002), Chan et al. (2009), Brown et al. (2009)). The holdings based approach is extensively used in practice. The widely followed Lipper and Morningstar classifications use holdings data to construct peers. Our techniques contribute to this strand of the literature.

We propose a transparent and easily extendable method for identifying a fund's peers based on fund holdings data. We let both the number of a fund's peers and the composition of its peer group vary from fund to fund in fairly general ways. A distinguishing feature of our approach is that peers are fund-specific. If B is a peer of A and C is a peer of B, we do not require that C is a peer of A. A second feature is that our peer group size and composition are not static. They can vary from quarter to quarter to let the peer group adapt quickly to track the evolution in fund style shifts. We show that the peers we identify explain a significant component of fund performance out of sample. We use our customized peers to characterize performance, persistence and competition in the fund industry.

Briefly, our approach is as follows. We classify stocks according to k pre-specified dimensions of style. We represent a fund as a point in the resulting k-dimensional space based on its portfolio's value-weighted style characteristics. We compute a normed distance between a fund i and all other funds j. We classify a fund j as a peer of fund i if the normed distance $d_{i,j} \leq d^*$. An interesting question is what distance d^* one ought to choose in determining a fund's peer set. A tighter spatial radius generates more close fits but fewer funds as peers while wider bands may introduce excessive numbers of peers. We choose a granularity to match the widely used Lipper stock classification schemes. We do not impose any constraints on the number of peers of a fund. Some funds may have over 50 peers within spatial radius of d^*, while other funds may have less than 10 peers within the same radius.

A second question is what style dimensions should define the space in which funds are located. One extreme is to treat each stock as an independent dimension. However, this approach weights distances between all pairs of stocks symmetrically. For instance, the difference between two tech stocks would equal the difference between a young tech stock and an old tobacco firm. It seems more sensible to specify the spatial structure based on a smaller number of dimensions that capture likely drivers of stock co-movement. This is our approach. Here, it is worth emphasizing that expanding the spatial dimensions of style does not automatically improve fit. Irrelevant dimensions result in unrelated peers, noisy benchmarks, and worse fit.

Our peer selection process is flexible enough to accommodate variations in spatial dimensions and the distance function. For instance, the Morningstar or Lipper classifications use lexicographic orderings that preference size and then sequentially match on growth dimensions such as M/B, yield or earnings. We can accommodate such preferences. Our baseline spatial specifications are the drivers of co-movement studied in prior work, primarily size and B/M used by Morningstar and Lipper. However, we also consider momentum and find a surprisingly significant gain in power from doing so. Among other variables, dividend yield is somewhat beneficial but industry and several growth proxies such as P/E and sales growth show very little incremental value in our study. We do not experiment with other dimensions without a clear risk interpretation. However, our approach also accommodates other fund attributes such as fund size or expenses (Gruber (1996), Chevalier and Ellison (1999b), Kim et al. (2000)).

We summarize the main results. Our sample comprises between open-ended mutual funds investing in U.S. equity that report quarterly holdings data. Following DGTW (Daniel, Grinblatt, Titman, and Wermers, 1997), the baseline results locate peers in a three dimensional space with size, growth, and momentum as the three axes. We find that there is considerable cross-sectional and temporal variation in the number and identity of peers of funds. For instance, about a sixth of funds have less than 25 peers, while about a quarter have more than 200 peers within the same maximal distance. A majority of funds exhibit churn in peer groups. For instance, almost a quarter of a fund's peer group consists of funds not in the peer group the previous quarter.

The customized peers intersect but do not entirely overlap with Lipper style peers. This is not surprising: the customized peers are updated every quarter so style drifts in funds or their peers result in quick reassignments. For example, funds switching to conservative styles to lock in early-year gains as in Brown et al. (1996b), will find themselves clustered along a new set of customized peers whose investing styles are closer to theirs. The new set of peers will likely still include many earlier-quarter peers absent complete churn in portfolio to a new style category. However, many new funds may now be better matches. Our approach permits this possibility with greater granularity than existing style buckets.

We next examine if the peers explain fund returns out of sample. For holdings announced in month T, we compute the equal weighted returns of a fund's spatially proximate peers for months $[T+1, T+3]$. In each month, we regress the cross-section of fund returns on the peer returns. In the baseline DGTW style space, our customized peers explain an average of 42% of fund returns compared to 32% for the 14-category Lipper style peers used widely in the fund industry. The R^2 is 42% when we include both the customized and Lipper peers. Funds also exhibit lower tracking error using our peers compared to Lipper peers.

We next examine whether performance relative to customized peers produces different rankings relative to conventional performance measures. If funds broadly follow consistent styles reflected in traditional risk factors, we should find both the customized peers and the traditional measures produces similar rankings of funds. On the other hand, if funds drift, the two rankings can be very different. Two-way sorts based on customized peer alphas and the DGTW characteristic selectivity (CS), Carhart, and Lipper style alphas reveal a large number of off-diagonal funds. Fund rankings using customized peers are imperfectly correlated with rankings using the other methods. The results suggest that funds exhibit significant style drift.

We consider out of sample prediction of fund alphas. Such predictability is not implausible. Our alpha rankings do not fully overlap with the CS and Carhart (1997) alphas. Moreover, funds must meet a relatively high bar to outperform relative to our customized peers, which are recalibrated every quarter. We conduct the alpha predictability tests by tracking future fund alphas as a function of alphas relative to customized peers. We find that outperformance relative to customized peers helps predict future risk-adjusted returns. For instance, for one quarter ahead, decile 10 minus decile 1 spreads are an annualized 317 basis points. Skill persists but declines with time, as the one year ahead alpha is about 206 basis points per year, about a third lower than the one-quarter ahead alpha spread.

We analyze competition in the mutual funds market. The number of fund-specific peers reflects the extent of competition faced by funds. Funds in less competitive markets earn higher alphas because they have unique or differentiated ideas coupled with skills that are hard to replicate. Alternatively, they may identify niche investment areas that investors desire, in which case such funds can charge higher fees. However, these managers may or may not earn higher alphas on average depending on whether *all* managers in the niche are skilled or not.

A second question is about persistence of alpha. Here, the tests focus not on average managerial ability but on the subset of managers with skill. We ask whether conditional on having skill, what types of markets display skill persistence. If our measure of customized peers reflects competition, we should find that skilled managers in a well populated area with many peers will likely not have persistent alphas. Even if such a manager earns alphas in a period, it is easier for competitors to enter and arbitrage away ideas. The same phenomenon can happen in a more concentrated market, but this can take longer as there are not enough peers to quickly move in the location of the successful manager. Thus, *persistence* of alpha should be higher in concentrated markets. We test these predictions.

We find evidence that customized peers proxy for competition in economically sensible ways. When funds have few customized peers, they appear to be specialized and differentiated. These funds are younger, have lower assets under management and higher expense ratio and management fees. Thus, our peer identification process sorts the style space by competition between funds. While the variation in alpha by concentration is low, there is economically significant alpha persistence in spatial locations with concentrated funds and few peers. The results suggest that *not* all managers have alphas, but those that do can sustain it in more concentrated markets with few customized peers. Further characterization of competition represents an avenue for further research, our view is that our peer identification methods can help this line of research by providing clean, dynamic, and ex-ante measures of the competitiveness of different market segments.

The rest of the paper is organized as follows. Section 2 provides some institutional background and reviews the current approaches towards peer identification. Section 3 describes our methodology in detail. Section 4 describes the data and Section 5 provides results. Section V6concludes.

3.2 Background and Related Literature

Current approaches for specifying fund style benchmarks are based on fund prospectuses, past fund returns, or fund holdings. We briefly review the methods and the related literature. We refer readers to Wermers (2011) for a detailed survey.

3.2.1 Prospectus-Based Peers

Fund prospectuses are potentially useful in understanding style because prospectuses have legal force. Prospectuses provide short descriptions of style that are extracted and categorized by fund databases such as Lipper. In practice, these descriptions are usually too unspecific to provide precise quantitative guidance on fund strategies. Moreover, the prospectuses explicitly permit managers to deviate from their stated strategies. For instance, the prospectus of T. Rowe Price Growth Funds says

... The fund seeks to provide long-term capital growth and *... dividend income through investments in the common stocks of well-established growth companies....* and *... the fund has the discretion to deviate from its normal investment criteria*

The description leaves managers enormous latitude in their baseline investment choices. Moreover, it explicitly permits managers to deviate from these choices. This is typical, even when funds are specific about their investing philosophies.[1]

SEC rules require mutual funds to report a benchmark peer index, which can

[1]See, e.g., T. Rowe Price's diversified madcap growth fund states *... The fund seeks to provide long-term capital growth by investing primarily in the common stocks of mid-cap growth companies. The fund defines mid-cap companies as those whose market capitalization falls within the range of either the S&P MidCap 400 Index or the Russell Midcap Growth Index. The fund has the flexibility to purchase some larger and smaller companies ... [and] some securities that do not meet its normal investment criteria.*

serve as a peer benchmark. However, the regulations offer little guidance about which index a fund should pick and why. the flexibility opens up the room for benchmark gaming, as pointed out by Brown and Goetzmann (1997) and Huang et al. (2011b). Sensoy (2009) finds that the benchmark in a large number of cases does not match with the actual fund style. Thus, the prospectus disclosed benchmarks are also unlikely to be reliable.

3.2.2 Returns Based Peers

A second approach towards constructing peers employs past fund returns. Sharpe (1988, 1992) is an early example of the returns-based approach. Sharpe suggests regressing fund returns on benchmark indexes with the restriction that the coefficients are positive and sum to unity. The coefficients can be interpreted as portfolio weights that are used to establish fund benchmarks. An alternative approach is to regress mutual fund returns on factors suggested in the asset pricing literature (Jensen (1968), Fama and French (1993), Carhart (1997)). Chan, Dimmock, and Lakonishok (2009) find that the procedure does not perform well in their sample of 199 managed equity portfolios. A third approach that employs historical fund returns is is suggested by Brown and Goetzmann (1997). They represent the fund benchmarking problem as a k-means return clustering problem. They identify 8 clusters of funds and find that the cluster returns explain fund returns better than regression based approaches.

3.2.3 Holdings Based Peers

A third approach generates peer benchmarks based on fund holdings. Under this approach each stock is classified into style dimensions. A fund's style characteristic on any dimension is the value weighted characteristic of the fund's stock holdings on that dimensions. The style dimensions usually employed in the literature include size, book-to-market (B/M), and past returns. Academic studies underline the value of holdings-based benchmarking, e.g., Chan, Chen, and Lakonishok (2002) for Morningstar funds from 1979 to 1997 and Chan, Dimmock, and Lakonishok (2009) for 199 actively managed equity portfolios.

Holdings are also widely employed by the fund industry. Here, the goal is to use holdings to generate *fund* peers. A fund is benchmarked by its performance relative to same-class peers. Here, the construction of peers is of particular economic interest because the excess returns above peer benchmarks are widely used to market funds to investors. While the exact process for generating peer classes has varied over time, one constant has been the use of two dimensions to classify funds: market capitalization and the growth/value orientation of a fund's stock portfolio. Both the Lipper and Morningstar classifications use this approaches to form fund peer groups.

To illustrate, consider the Lipper process used to classify funds.[2] Lipper defines a stock as large, medium, or small cap based on its capitalization relative to the 70th, 70th-85th, and above 85th percentiles of market capitalization going from large to small stocks. The growth/value orientation comes from a Z-score based on B/M, P/E, price-to-sales, dividend yield, return on equity, and 3-year sales growth.[3] Absolute Z-scores of 0.20 and above define growth/value orientation; "core" stocks are neither value nor growth. The growth and capitalization orientation of a fund is derived by aggregating fund holdings. For instance, Lipper characterizes funds as large, medium, or small cap based on whether 75% of its holdings fall into the relevant category of stocks, otherwise the fund is a multi-cap fund. Once funds are classed into groups, the peers and fund performance measures are well defined.

We develop and evaluate new methods to construct a fund's peer group from holdings data. Our approach addresses a number of open questions on the economics

[2]See, e.g., the *Holdings-Based Fund Classification Methodology* published by Lipper in June 2010. Morningstar employs a similar style classification process.

[3]The Z-score is a fund's characteristic minus the weighted average for its size bucket. The score used for ranking is a weighted average of Z's for current and prior quarter holdings.

of the peer peer identification process. One question concerns the specification of the style space. Neither Lipper nor Morningstar use momentum as a style dimension, nor do Chan, Dimmock, and Lakonishok (2009). However, the academic literature since Jegadeesh and Titman (1993) considers momentum an important style attribute. Likewise, does B/M suffice to capture a fund's growth/value orientation? Or is there value to supplementing B/M with attributes such as sales growth or dividend yield. If so, how do we incorporate them into the style space? Likewise, Kacperczyk et al. (2005) suggest that industry is a style dimension. Is it useful to incorporate industry as a style dimension? Our framework addresses such issues.

We also address a less familiar issue of *transitivity* in peer group formation. Current approaches, e.g., the Lipper 13-style classifications, construct transitive peers. The benchmarks for a fund comprise all other funds belonging to its class. Thus, if A is a peer of B and B is a peer of C, then C is also a peer of A. We show that the transitivity restriction is not necessary and is in fact costly, as it results in less precise benchmark peers.

Using intransitive peers can also address the economic issue of fund style drift (Brown, Harlow, and Starks (1996), Cremers and Petajisto (2009), Wermers, 2009). The literature points out that managers shift holdings relative to static benchmark classes, which can lead to incorrect performance attribution. In our approach, drifts in stock picking style are met with corresponding changes in peer groups. We can adjust peer groups without all-or-nothing reassignment of funds to new groups or redefining entire fund categories, which would be necessary with transitive groups. Because peer group changes match style changes, we can also identify the extent to which selectivity is an individual manager attribute or an attribute of groups of managers. Finally, intransitivity simplifies computation and permits flexible and easily scalable methods for peer identification.

3.3 Data

We obtain data on actively managed, open-ended U.S. equity mutual funds from CRSP Survivor-Bias Free US Mutual Fund database. Our sample starts from January 1980. We focus on diversified equity funds. To identify such funds, we follow a sequential algorithm. We first select funds whose Lipper Classification Code is one of the following: EIEI, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE. If the classification code is missing, we select funds whose "Strategic Insights" objective code is AGG, GMC, GRI, GRO, ING, or SCG. Where both codes are missing, we pick funds with Wiesenberger objective codes equal to G, G-I, GCI, LTG, MCG, or SCG or "Policy" code is CS. For the remaining funds, we require that the lifetime average invested in equity is at least 80%. We eliminate index funds by using CRSP defined index fund flags and by screening the names of funds for words such as "Index" or "S&P."

Our dependent variable in most specifications is the monthly fund return. The after-expense monthly return comes from CRSP. To obtain returns before expenses, we add back one-twelfth of the previous fiscal year end fund expense to the after-expense monthly return. To avoid multiple counting of funds, we value-weight fund class returns using prior month total net assets to obtain fund level before and after expense returns. Similarly, we also value-weight expense and turnover ratios. Fund size is the sum of total net assets of all fund classes. Fund age is in years, computed as of the month end relative to the fund's earliest first offer date. We exclude fund-months in which age is negative to eliminate young funds with limited histories.

We obtain snapshots of the quarterly holdings of funds from the Thomson Reuters mutual fund holdings database. We exclude all funds whose objective code is one of the following: International, Municipal Bonds, Bond & Preferred, Balanced, and Metals. For funds that do not report quarterly, which is less common towards the later years of our sample, we extrapolate the previous quarter holdings to the current quarter. This is done for at most one quarter to avoid excessively stale data. Holdings disclosures before a quarter end are carried forward to the quarter end.

From the fund-quarter portfolios identified through the holdings data, we remove all funds whose total net assets (TNA) are less than $5 million. We do not necessarily eliminate fund-quarters with missing TNA because these observations are sometimes for funds have large previously disclosed TNA. We eliminate survivorship bias due of newly incubated funds by excluding the first appearance of a fund-quarter in the Thomson Reuters dataset. These funds may appear in the funds only if their prior performance has been satisfactory. Evans (2009) points out that this bias is not eliminated by simply screening on size.

Because our focus is on diversified funds, we eliminate funds with less than 10 stocks in their portfolio. These funds are unlikely to be diversified. We then combine the CRSP sample with the Thomson Reuters holdings sample using the MFLINKS dataset developed by Wermers (2000). After matching the datasets, we further remove fund-quarters that do not have a valid Lipper class in CRSP. We implement this screen only for fund-quarters after December 1999 because Lipper classifications are unavailable before that date. Our final sample consists of 3081 unique funds for which we have at least one disclosed portfolio from quarter 2 of 1980 to quarter 2 of 2010.

3.4 Methodology

3.4.1 Specification of Characteristics Space

As discussed in Section 3.1, we place stocks into a k-dimensional characteristics space and value weight stocks held by a fund to locate funds in the characteristics space. We calculate the characteristic vector of each fund at the end of each quarter based on reported holdings. Following DGTW or Carhart (1997), our baseline characteristics axes are size, book-to-market (B/M) ratio and momentum.

Stock size is based on the the quarter-ending market capitalization of the firm in dollar millions from CRSP. B/M is calculated in June of year t using the book equity for the last fiscal year end in year *t-1* and market equity at the end of December in year *t-1*. The B/M ratio thus obtained is applied from July of year t to June of year *t+1*. We calculate book equity as defined in Daniel and Titman (2006). Momentum is the cumulative return of past 11 months $[t-2, t-12]$. Thus, we exclude the return for quarter-ending month when the portfolio is disclosed. We also require a minimum of 10 months of non-missing return data to calculate momentum.

Each stock is assigned a 3-dimensional vector with each dimension representing a percentile value in the interval [0,1], based on the characteristic percentiles of stocks listed on the NYSE. For instance, to obtain size percentile, we first form size percentile breakpoints to one decimal point based on the firms listed on the NYSE with share codes of 10 or 11. We compare a stock's size with the NYSE size percentile breakpoints. For instance, if the firm size falls between the firm sizes corresponding to the percentiles 74.5 and 74.6, the size percentile for the stock is 0.745. We similarly assign the B/M and momentum percentiles. We then rescale stock weights in each fund's portfolio using stocks with non-missing size, B/M ratio and momentum percentiles. A fund's characteristic vector is the dollar-weighted average of its stock holdings vector.

3.4.2 Non-transitive Fund Peers

We compute fund pairwise similarity scores based on fund style to construct a fund-style-similarity network from which a customized set of peers can be identified for each fund. These similarity scores are constructed from each fund's 3 dimensional characteristic vector as described above. The methodology we employ uses a technique related to the cosine similarity method used in Hoberg and Phillips (2010) – HP – to construct industry classifications. However, there is one important difference. In HP, characteristic vectors are rescaled to have unit length before similarity is computed, as their objective is to score firms in a relative fashion based on the degree of relative vocabulary overlap. In the current application, we do *not* normalize our percentile vectors prior to computing similarity. This choice recognizes the fact that funds having low percentiles for all three characteristics are not peers for firms having proportional but uniformly high percentiles of all three characteristics.

For fund i in quarter t, we denote its N-element characteristic vector of percentiles as V_i. In our main specification, N is equal to three as we consider three characteristics. However, we express the methodology with greater generality as similarity can be based on a larger vector of characteristics, for which the computation is not unduly difficult. Each element of V_i lies in the interval $[0, 1]$ and denotes the fund's percentile ranking (expressed as a fraction). A fund j should be considered a peer of fund i if the elements of V_j are all very close to V_i in nominal magnitude. Denote the distance as d and similarity as $1 - d$, so high similarity denotes closeness in spatial distance. If $V_i[n]$ is the nth element of the vector V_i, the pairwise similarity of funds i and j, S_{ij} :

$$S_{ij} = \ 1 \ - \sum_{n=1,\ldots,N} \frac{|V_i[n] - V_j[n]|}{N} \tag{3.1}$$

Similarity S_{ij} is confined to the range $[0, 1]$. Scores closer to one indicate more similarity and scores closer to zero indicating less similarity. Also, because S_{ij} is known for every pair of funds, this calculation implies a fund "style network" in which the network is fully described by a pairwise similarity matrix.

To complete the process of using this network to construct a peer classification system, we need to identify a target level of granularity such that peers are funds within a cutoff distance $\bar{d}$ or a similarity exceeding $\bar{S}$. The choice of the cutoff is an empirical issue. We specify the target granularity based on the observed granularity of the Lipper classification. In particular, under the Lipper classification, 8.761% of randomly drawn fund pairs are in the same Lipper class. Because a goal of our study is to assess how the performance of our classifications to the Lipper classification, we will also require that our classification is equally granular such that 8.761% of randomly drawn funds will be members of one another's customized peer groups.

Analogous to the computational approach outlined in HP, the target granularity of 8.761% is achieved by identifying a "minimum required similarity" $\bar{S}$ such that i and j are deemed to be peers if $S_{ij} \geq \bar{S}$. This is equivalent to specifying $\bar{S}$ as the largest number such that 8.761% of randomly drawn S_{ij}'s are larger than $\bar{S}$. As a minor refinement, we further require that any particular fund have at least five peers. This refinement does not materially affect our results, but has the added benefit of ensuring that any given fund can be compared to a material set of counterfactual funds. Because the target granularity of 8.761% is relatively coarse, most funds have 100 or more peers and hence the minimum of five is binding only for a very small number of "unique" funds. Therefore, for any given fund i, its customized peers are defined as all other funds j such that $S_{ij} > \bar{S}$.

We note that the peers we identify are not transitive. Intuitively, peer funds can be visualized as funds within a sphere of a fixed radius. If two funds A and B lie within a sphere surrounding fund C, it is not necessary that B lies within a sphere of similar radius surrounding A. We also note that our specification of intransitive peers is parsimonious. We can easily expand the dimensions of the characteristic space – although more dimensions do not necessarily improve fit – or accommodate different loss functions such as ordered sorts with B/M and momentum following size.

We also do not further utilize information regarding the degree of similarity of each peer j relative to focal fund i. For example, some peers are more similar to i than others, and the degree of similarity can be used to generate a further-refined benchmark using weighted averages. We do not extensively pursue these refinements in this version to keep the focus on the value added by intransitive customized peers.

It is useful to compare our method for generating peers with other approaches used in the literature. Relative to the return based style analyses of Sharpe (1992) and Brown and Goetzmann (1997), there are important differences. We use current holdings rather than historical return patterns. Additionally, clustering identifies transitive peers while we focus on intransitive peers. Intransitivity is also a key difference between our methods and others such as Lipper or Morningstar classifications used in the industry.

Our analysis is also distinct from the DGTW approach of grouping the universe of all stocks by value, growth, and momentum and using these to generate benchmarks. The benefits of this technique in classifying funds are analyzed very carefully by Chan, Chen, and Lakonishok (2002) and more recently by Chan, Dimmock, and Lakonishok (2009). Our study can be viewed as complementing this line of work in two ways. One, we examine the performance of funds relative to other *funds* rather than passive benchmarks. In other words, we too use the classification of stocks by styles but marry it with data on actual fund holdings. Second, we relax the assumption of transitivity in fund peers by allowing each fund to have its own set of peers.

3.4.3 Transitive Fund Peers

Although the focus of our paper is on intransitive customized peers, we also construct a classification that imposes the transitivity restriction. A peer classification is said to satisfy the transitivity property if, for any funds i and j that are peers under the given classification, then a fund k that is among fund i's peers must also be among fund j's peers. As Hoberg and Phillips (2010) point out when constructing industry classifications, the transitivity property should be viewed as a constraint, as fund k might be quite dissimilar to fund j in the above example even if fund k is a strong peer for fund i. We consider transitive fund peers to assess the value added by relaxing the transitivity requirement, to better disentangle the source of the additional explanatory power from using our customized peers.

In order to compute transitive fund peers, we start with the same similarity matrix based on S_{ij} used constructing intransitive peers for each pair of funds i and j. Our objective is to now form 13 clusters of funds, matching the granularity of the Lipper classification to maximize the within-cluster similarity of fund holdings. Because the distribution of pairwise similarities for a small number of particularly unique funds can be quite low, we choose a clustering method that has the objective of maximizing the expected signal from peer effects under the assumption that signal strength is proportional to fund pairwise similarity scores S_{ij}. This algorithm recognizes that fund pairs with higher similarity scores should be deemed pairs. However, it also recognizes that more balance in the number of peers per group is also beneficial because for any fund, a more refined signal can be extracted if there are more peers.

The clustering algorithm follows the computational approach suggested by Hoberg and Phillips (2010). We start by initially pairing each fund with another fund that is highly similar to itself. For example, we first deem the two most similar funds (based on S_{ij}) to be a pair. Then, among remaining funds, the two most similar are deemed a pair. This process is continued until all funds are paired. We next combine these pair-clusters into larger clusters until only thirteen clusters remain (as Lipper has 13 groups). In any particular iteration, we choose which clusters to combine based on which combination will generate the maximum expected improvement in the signal strength, a process that requires considerable experimentation. This is especially true when are close to the target when a unitary move of a fund can impact the overall signal to noise ratio within a peer group. The details and an implementable computational algorithm are available from the authors upon request.

3.5 Results

3.5.1 Descriptive Statistics

Table 3.1 presents summary statistics for our dataset. Panel A shows that are 3,076 unique actively managed equity funds in our sample. The number of funds vary over time with 498 funds towards the start to around 2,000 towards the end of the sample period, reflecting the growth in the funds industry. The decline in the number of funds in 2010 represents exits in the industry due to the 2008 financial crisis. The total assets under management per fund expands over the period from an average of \$210 million in 1985 to \$1,328 million towards the end of the period. The weighted returns for our sample are comparable to those in prior studies such as Chan, Chen, and Lakonishok (2002), although the samples are not identical. For instance, Chan et al. use fund data from Morningstar and examine the time period between 1979 and 1997, while our study incorporates later time periods through 2010.

In Panel B, we report descriptive statistics classified by the 13 Lipper classes. The largest number of funds are in the "Large Cap Growth" and "Large Cap Core" style categories. The large cap floor is between the 316th and 317th stock in the S&P composite index. The multi-cap core category, with 210 funds, is the third largest category of funds, with the label "multi-cap" denoting the fact that less than 75% of fund assets are invested in specific category cutoffs defined by Lipper. Relatively few funds are in the "income" or "value" categories in terms of the number of funds, although the average assets under management are the highest for large cap value funds, which also have the lowest total expense ratios.

3.5.2 Do We Identify Different Peers?

Table 3.2 examines the differences in peer classifications between our methods and the Lipper classification methods. We ask whether the two methods generate similar peers, given our requirement that our classification methods should result in similar granularity as the Lipper methods.

The table reports three panels. Panels A and B report what is effectively a Venn diagram between the customized peer (CP) and the Lipper peer (LP) classifications. In Panel A, in each quarter q for year t, for each fund j_{qt}, we divide peers into three categories customized peers that are not Lipper peers $j_{qt}(CP \notin LP)$, common peers $j_{qt}(CP \cap LP)$, and Lipper peers that are not customized peers $j_{qt}(LP \notin CP)$. We add these numbers across all funds j and divide by the sum to normalize them into percentages. We then average these percentages for all four quarters $q = 1, 2, 3, 4$ for year t and report the average for each year. Panel B reports similar statistics, but here, we compute the percentage of each category of peers (e.g., $\frac{j_{qt}(CP \notin LP)}{j_{qt}(CP \notin LP) + j_{qt}(LP \cap CP) + j_{qt}(LP \notin CP)}$), average them for each quarter q in year t and then average the quarterly averages by year t. In either case, we find that there is significant non-overlap between the different types of peers. In fact, only about a fifth of the peers are common.

Panel C of Table 3.2 examines the dynamic variation in peer group composition. Here, we examine all pairs of funds in two successive quarters within the same year and report averages within a year. Our procedure does not imply complete instability in peer composition: about one half of peers in one quarter are likely to remain peers in the next quarter (the column labeled "Common" in Panel C). However, quite remarkably, few funds have *exactly* the same set of peers even between two successive quarters. The maximum number of funds that retain the same set of peers in any one quarter is under 0.2%, equivalently, more than 99.8% of funds churn peers from one quarter to another. Thus, the transitivity restriction has considerable bite. We then consider the extent to which old peers drop out. A fund peer has between a quarter and a third chance of dropping out in the successive quarter and about a third of a fund's peers are newly added that quarter.

3.5.3 Do Customized Peers Explain Returns?

The previous section suggests that that the fund-specific customized peers vary significantly from Lipper peers. Whether these peers explain future returns better is an interesting empirical question, to which we turn next. Tables 3.3 and 3.4 present the results.

Table 3.3 reports the results of a cross-sectional regression. For each fund j in month t, we compute the average return of the fund's customized (non-transitive) peer group, identified in the most recent *previous* quarter. We denote the peer group returns as $r_{NTCP,jt}$ and $r_{LC,jt}$ for Lipper class peers. We regress the fund's return $r_{j,t}$ on $r_{NTCP,jt}$ and $r_{LC,jt}$ individually and together to assess their explanatory power. We note that the peers are formed based on previous quarter disclosed holdings, so there is no look-ahead bias. We find that the non-transitive peers dominate. The average regression R^2 is close to 43% for the customized peers against 32% for Lipper peer groups. When both are included together, the R^2 budges very little from that for the non-transitive groups alone.

Our results have two explanations. One, Lipper classification schemes rely predominantly on size and B/M alone and sequentially sort B/M after adjusting for size. On the other hand, we use size, B/M, and prior 12 month returns to classify peers. A second difference is that we use intransitive peer groups, while Lipper classifications require transitivity. In unreported results, we explore the source of these differences in detail. When we impose transitivity, we get results similar to those achieved by Lipper. Thus, the additional power in our results comes from relaxing transitivity.

Panels B and C in Table 3.3 show additional regressions in which we include returns of funds classified by stated objectives in their prospectuses. Given the discussion in Section 2 on the latitude for fund managers to deviate from their stated investment strategies, it is not surprising that these returns add little to our baseline results. In unreported results, we also considered customized peers in which industry classifications of stocks are used as style dimensions. These peers produce about half the explanatory power of Lipper peers and add little to the explanatory power from our peer groups.

Following Chan, Dimmock, and Lakonishok (2009), Table 3.4 presents a different metric for explanatory power. We estimate the tracking error of fund returns relative to benchmarks. For each fund, we compute the difference between the fund's return and its benchmark derived in the nearest prior quarter. The standard deviation of the difference is the fund's tracking error volatility. We require that funds have at least twelve excess returns to compute the tracking error volatility. In Table 3.4, we present the mean tracking error classified by Lipper class. In all Lipper classes, the tracking error is lower when using customized peers. The standard deviation of tracking error volatility is also lower, indicating that our results are not driven by small outliers in the data. Figure 1 presents visual evidence consistent with this view. The tracking error distribution for customized peers (in the lower panel) is flatter than that for the Lipper peers with more mass towards zero (both figures are similarly scaled).

3.5.4 Predicting Alphas

3.5.4.1 Do Alphas Agree?

We consider whether alphas relative to customized peers agree with alphas relative to other methods. Alphas from Lipper peers impose transitivity and are less dynamic, unless funds have full transitions between classes. In contrast, our peer groups are intransitive and capture less extreme drifts. Other alphas are relative to traditional benchmarks, e.g., from Fama and French (1993), Carhart (1997). As Chan, Dimmock, and Lakonishok (2009) emphasize, different methods of analyzing fund performance can produce very different results. We examine if this is the case with the customized peer alphas.[4]

Table 3.5 divides funds into quartiles based on customized peer alphas (CPA) and Lipper peer alphas through independent sorts. We find that the (j, j) diagonal elements in the matrix account for between a quarter and a third of the observations in each quartile. The off-diagonal elements are significant. Table 3.6 presents a cross-tabulation between quartiles of alphas based on CS, Carhart, and customized peers. There is greater agreement between our alphas and the others but less agreement between CS and Carhart alphas. The CPA, CS, and Carhart classifications agree on about 60% of the observations in the two tails. show that these alphas tend to disagree more with the Lipper alphas. The diagonal elements represent only about a quarter to a third of the observations. The Pearson and Spearman correlations in Table 3.7 paint a similar picture. The CS alpha has lower correlation with the Carhart alpha. However, it is more correlated with our measure, which in turn is more correlated with the Carhart measure.

[4] We analyze but do not report results for the Fama-French regression alphas. The results are similar to the Carhart alpha results.

3.5.4.2 Predicting Alphas: Univariate Evidence

We next consider whether customized peer alphas (CPA) help predict future CS or Carhart alphas. If the latter represent risk-adjusted returns of funds, our analysis tests whether current customized peer alphas predict future risk adjusted returns. We sort funds in quarter t into quintiles based on their current-quarter returns over their customized peers. Using the time t characteristics, we compute the next-quarter alphas for each quintile of customized peer alpha portfolios. While the fund literature does not agree on whether momentum is a relevant attribute for assessing fund style (e.g., Chan, Dimmock, and Lakonishok, 2009), we follow the DGTW CS approach as our main specification.

Table 3.8 presents the results of a basic sort in which we predict the future CS alphas based on the deciles of their current CS and customized peer alphas. We predict the future CS alpha as it has the interpretation of a risk-adjusted return. We test whether performance relative to our customized peers predicts future risk-adjusted returns. We report results based on sorting according to past CS alphas to control for inherent persistency in alphas.

We find that performance persists. For instance, the 10-1 decile spread based on current quarter CS alpha is an annualized 263 basis points while the spread based on customized peer alphas is 317 basis points. The spread declines to 251 and 311 basis points at a six-month horizon and 118 and 206 basis points at a one year horizon. The results suggest that money manager skill is less persistent at longer horizons. At a shorter horizon, the alpha spread pattern is more monotonic when using our customized peer alphas compared to sorting based on CS alphas. At a one year horizon, the 10-1 spread based on ex-ante CS alphas is no longer significant, but the 10-1 spread based on customized peers persists.

3.5.4.3 Predicting Alphas: Multivariate Evidence

Given the evidence that both CS and Table 3.9 turns to bivariate sorts in which we first sort by both the current CS alphas and customized peer alphas. Panels A and B report two different sorts. In Panel A, we sort by CS alphas first and then by customized peers. In Panel B, we sort first by customized peers and then by CS alphas. In Panel A, we find that in all quintiles of past CS alphas, past customized peer alphas predict variation in alphas with a spread of between 107 and 209 basis points per year. The spread is especially pronounced in the high and low performing quintiles, a pattern that persists even out to 12 months and remains significant. In Panel B, we find the same pattern: spreads by our customized peers remain economically and statistically significant especially in the top and bottom quintiles of performers out to 12 months. The spreads *within* customized peer alpha quintiles are less monotonic and have insignificant p-values throughout the table.

As the evidence in Table 3.9 is based on bivariate sorts, we supplement the analysis with regression results to accommodate additional predictors of future performance. Tables 3.10 and 3.11 present the regression results for CS alphas and Carhart alphas, respectively, at different horizons. The regression predicts future alphas at three, six and twelve month horizons based on past-year customized peer and CS alphas. The additional controls are expense ratios, fund turnover ratios, fund assets under management, and fund age. We also include past flows to accommodate the possibility that flows predict future alphas and past standard deviations to control for fund return volatility. Finally, we include the size of the mutual fund family that a fund belongs to in order to control for cross-flows and benefits from other fund family firms. All regressions include year fixed effects.

The results show that our customized peer alphas predict future performance at all intervals. The coefficient for $CPA_{t-11,t}$ is significant at all three horizons.

The past CS-alphas are significant in univariate regressions but essentially drop in economic magnitude and significance when we control for customized peer alphas. Among the additional controls in the regressions, the funds with high expense ratio, oder funds, and funds with more volatile past returns have lower alphas. However, these have no effect on the significance and limited effects on the magnitudes of the coefficients for $CPA_{t-11,t}$. In Table 3.11, we repeat the regressions for the Carhart alphas and find essentially the same patterns.

3.5.5 Competition

The fund industry is now economically large. An important question concerns the nature of competition between funds. We consider whether competition predicts alphas and whether it predicts alpha *persistence*. We briefly motivate the tests before turning to the results.

Given the accumulating evidence that mutual funds underperform on average, the fund industry has seen a proliferation in both the size and assets under management of passive investing products such as index funds and exchange-traded funds. It is relatively straightforward to examine the nature of competition between index fund products. To a first degree, these funds have well-defined indexes that they must track so competition is likely to take the form of fees, especially when funds track well known indexes. For instance, funds tracking the S&P 500 index are likely to witness greater expense competition (Hortascu and Syverson, 2004).

In the active fund management industry, measurement of competition and its effects is more delicate. Managers have relatively flexible investment mandates and can pursue divergent styles, making performance measurement difficult relative to (say) an industrial corporation. Of course, the ability of investors to pull out funds serves as a disciplining channel, but evidence such as Sensoy (2009) suggests that this may be less than effective because investors (85% of whom are households) use inappropriate benchmarks to judge fund performance. Whether there is competition in the active fund management industry based on style and how this competition manifests itself are thus interesting questions.

Our customized peer approach suggests one way of examining competition in the fund industry. We characterize peers as all funds in a style space that lie within a given spatial radius. A greater number of peers indicates more competition in a given dimension of the style space. Thus, under the joint hypothesis that (a) funds compete on investing style; and (b) competition in the style space is captured by our peer measures, we can test hypotheses concerning competition in the actively managed fund industry.

We basically conduct two sets of tests. One is about the level of alphas and fees in the industry. Funds in less competitive markets earn higher alphas because they have unique or differentiated ideas coupled with skills that are hard to replicate. Alternatively, they may identify niche investment areas that investors desire, in which case such funds can charge higher fees but managers may or may not earn higher alphas on average depending on whether *all* managers in the niche are skilled or not.

The static tests can also be viewed as being akin to a negative relation between profitability and competition proxied by the number of firms within an industry. However, when products are not easily characterized (e.g., by simple 2-digit SICs), granular descriptions of products as in Hoberg and Phillips (2012) aid in identifying the number and nature of competitors and can help analyze its effects. In essence, this is our approach. Table 3.12 presents the results. We sort funds into buckets based on the number of customized peers: less than 25, 25-50, 50-100, 100-200, and more than 200 peers.

We find evidence consistent with competitive effects based on spatial location. Assets under management increase as the number of peers increases. One interpretation of this result is that greater investor demand for a particular style elicits a response from the supply side, with more funds willing to locate in that part of the style space. Older funds with established track records and styles attract greater competition with a greater number of peers. More specialized funds that have fewer peers are not only smaller and younger, but also have greater 12b-1 fees and expenses and charge greater management fees. There is rather minor spread in CS alphas, suggesting that while niche areas attract funds and give them ability to charge fees, these areas do not especially generate positive risk-adjusted returns. Thus, it is not the case that *all* managers in niche areas are specially skilled.

We also present evidence on a second question, the persistence of alpha. We ask whether skill is less persistent in a more populated area of the style space. The essential idea is that managers in all parts of the fund industry can have special ideas. However, managers in a well populated area with many peers will likely not be able to hold on to the performance persistently. Even if such a manager earns positive alpha in any one period, it is easier for competitors to enter and arbitrage away ideas when the portion of the style space is well populated. This is harder – or slower to accomplish – in concentrated markets with fewer funds. Thus, *persistence* of alpha should be higher in concentrated markets.

Tables 3.13-3.15 report evidence on these issues. In each Table, we regress future alphas on past alphas. Table 3.13 provides portfolio predictive evidence on future alphas of portfolios sorted by current period alpha decile *and* competition. We sort funds into portfolios based on their current period customized peer alpha. Within each decile of current period alpha, we sort funds by the amount of competition based on the terciles of the number of peers in the quarter in which we compute alphas. We then predict future CS alphas, which are the funds' risk-adjusted returns, over horizons ranging from one quarter to one year.

At each horizon, we find significant degradation in performance persistence based on levels of competition. For instance, in the one quarter results in Table 3.13, we find that the 10-1 spread is close to an annualized 499 basis points in low competition terciles but this drops to 99 basis points in the high competition tercile. The corresponding spread at a 12-month horizon is 331 and 96 basis points, respectively.

Tables 3.14 and 3.15 present these results in a regression format. Here, we regress future CS (Table 3.14) and Carhart (Table 3.15) alphas based on past customized peer alpha deciles and a host of controls and report separate regressions for low, medium, and high competition deciles. This is, in effect, similar to the portfolio results of Table 3.13 except that it incorporates additional fund controls such as fund size, expenses, age, or family characteristics.

In interpreting the regressions in Tables 3.14-3.15, we note that the regression coefficients are basis points per month. In Table 3.14, for instance, the 1-quarter ahead 10-1 spread in future alpha is 28.3 basis points per month, or about 340 basis points per year for the low competition tercile in univariate regressions, which becomes about 16.4 basis points per month or 197 basis points per year in multivariate regressions. This practically vanishes in the high competition tercile, where the spreads shrink by about 80% to 3.5 basis points per month, or 42 basis points per year. The patterns persist over a one year horizon, though the spread is attenuated suggesting that competitive effects kick in over a one-year horizon. In short, we find that the number of a fund's peers captures competitive effects in fees, less significantly in fund alphas but competition has a significant effect in the ability of fund managers to sustain current period alphas.

3.6 Conclusion

A key issue in the fund management industry is the benchmarking of fund managers by performance relative to peer funds. In this paper, we propose new techniques for identifying benchmark peers for mutual funds. We identify the location of funds in the space of stock style characteristics. All funds within a pre-specified normed distance are a fund's peers and peers are customized to each fund. While we develop implementation for the techniques we propose, they are easily scaled by incorporating multiple new dimensions or alternative specifications of loss functions to accommodate varying preferences for granularity.

We show that fund-specific customized peers differ significantly from peers identified under current industry practice. These differences are both in the cross-section and over time. In other words, at any point of time, our peers only partially overlap with peers used by the industry. Over time, a fund's best peers change, dynamics that are not captured in static fund classifications. The underlying drifts in fund style driving peer churn support the view that static classifications may be subject to gaming by funds. More dynamic classifications that accommodate drifts in fund styles are necessary for proper benchmarking. Our study is one step in this direction.

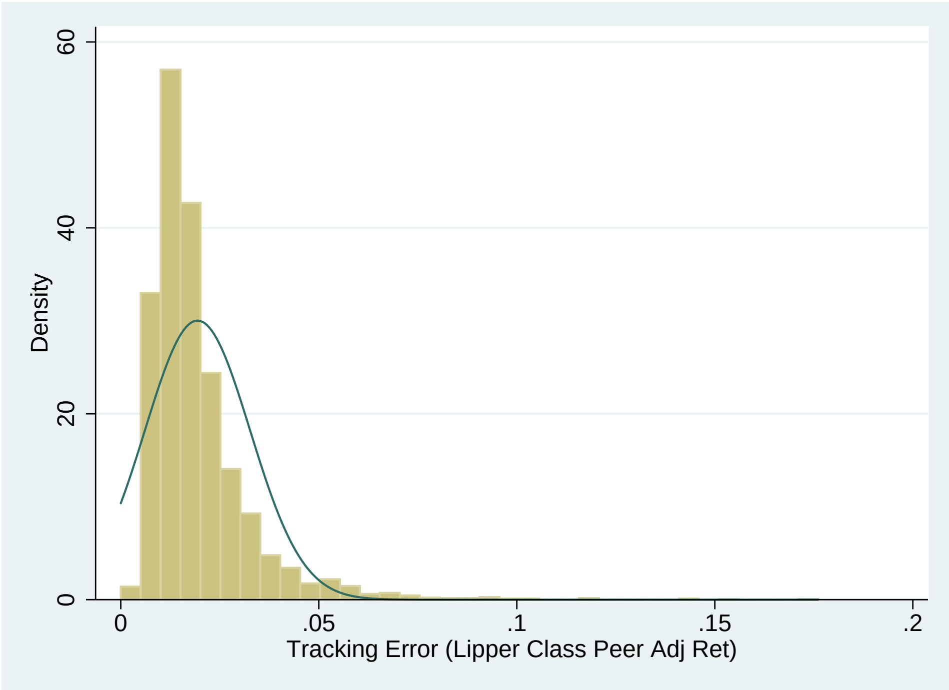
We affirm the value of style dimensions stressed in academic research such as Fama and French (1993) and Daniel, Grinblatt, Titman, and Wermers (1997). We find that additional industry and additional growth proxies such as P/E and sales growth that are sometimes used in practice add little explanatory power. However, (perhaps surprisingly) momentum, a trait not favored by industry, helps significantly in improving style classifications. However, we emphasize that the biggest boost in performance comes from considering *intransitive* peers, or fund-specific peers customized to each fund that do not require the property of transitivity.

We show that our fund-specific customized peers have out of sample predictive value. The produce close to 25% improvements in out of sample performance regressions and lower tracking error. Performance relative to customized peers also has predictive value for fund alphas. Our peer-excess alphas predict future risk-adjusted alphas of funds in univariate sorts, in bivariate sorts that control for past performance and in regressions that also control for other attributes.

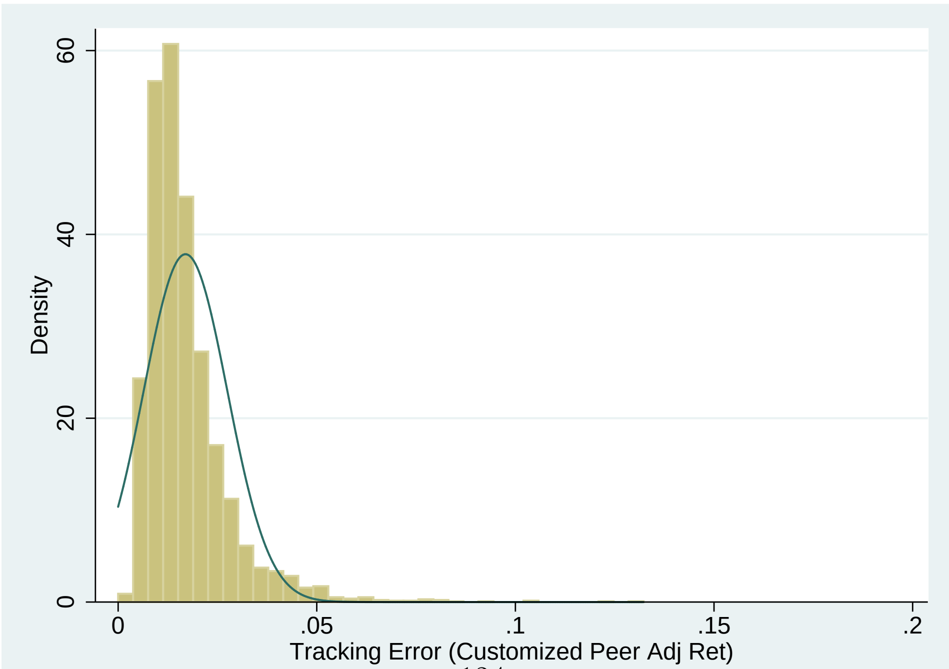
We also use the customized peers to assess the nature and persistence of competition in the actively managed fund industry. Under the joint hypothesis that funds compete on investing style and competition in the style space is captured by our peer measures, we test hypotheses concerning competition, performance, and performance persistence. We find that when funds have fewer fund-specific peers, funds are smaller, younger, have greater 12b-1 fees, expenses, and greater management fees. The source of these rents is likely the ability of funds to identify niche investing areas rather than their ability to generate alphas, as the average manager in the niche low population areas is not especially skilled. However, the managers with skill in niche areas are able to sustain them more than managers in more well populated areas in the style space. While our characterization of competition employs a simple count of the number of peers, further characterization of competition with other industry concentration measures merged with our customized peers represents an interesting avenue for further research.

Figure 3.1: **Tracking Error Volatility Distribution**

This figure shows distribution of tracking error volatilities estimated from monthly Lipper class adjusted return and customized peer adjusted return in sub-figure (a) and (b), respectively. Tracking error volatility of a fund is defined as the standard deviation of fund return minus its benchmark return. For each fund, its monthly Lipper class benchmark return is obtained by averaging monthly return of its peers (excluding own fund return). Similarly, customized peer benchmark return is obtained by averaging monthly return of its peers (excluding own fund return). Then, for each fund, its Lipper class adjusted and customized peer adjusted return is obtained. Finally, standard deviation of adjusted returns yields tracking error volatilities. We calculate tracking error volatilities of a fund using all months during which it belongs to a particular Lipper class, and require at least 12 observations monthly observations. If a fund changes its Lipper class and has more than one Lipper classification over its lifetime, then we calculate multiple tracking error volatilities for the same fund over different periods during which it belongs to different Lipper classifications. The sample duration used is 2000:01 to 2010:09. The figure also shows an overlaid normal distribution with the same mean and standard deviation, as of the underlying distribution.



(a) Tracking Error Distribution (Lipper Class Peer Adj Ret)



(b) Tracking Error Distribution (Customized Peer Adj Ret)

Table 3.1: **Summary Statistics**

This table reports mean statistics by year in Panel A and by Lipper Classification in Panel B. To obtain observations in Panel A, first, from the full sample of fund-month observations from July 1980 to September 2010, observations at the fund-year level are obtained by averaging monthly total net assets (TNA), expense ratio, and net and gross raw return for each fund and for each year. Then for each year average is taken over the funds in the sample in that year. Finally, average is taken over all years. *Nfunds* in Panel A represents average number of funds in the sample per year. *Total funds* represents total unique funds in the sample. For Panel B, first, observations at the Lipper Class-year level are obtained by averaging monthly TNA, expense ratio, and net and gross raw return raw return for each Lipper Class and for each year. Then average is taken over each Lipper Class. *Nfunds* in Panel B represents average number of funds in the sample for each Lipper Class per year.

Panel A: Mean Statistics By Year

Year	Nfunds	TNA ($M)	Expense Ratio (%)	Raw Ret (Gross) (%)	Raw Ret (Net) (%)
1985	498	210	0.905	2.364	2.330
1990	841	265	1.148	-0.412	-0.433
1995	1465	559	1.303	2.344	2.265
2000	2222	1179	1.382	0.112	0.076
2005	2287	1190	1.379	0.742	0.620
2010	1783	1328	1.281	0.890	0.790
1980-2010	1392	667	1.200	1.139	1.038
Total funds	3076				

Panel B: Mean Statistics By Lipper Classification

Lipper Class	Nfunds	TNA ($M)	Exp Ratio (%)	Raw Ret (Gross) (%)	Raw Ret (Net) (%)
Small-Cap Growth	175	421	1.514	1.963	1.854
Small-Cap Core	183	545	1.359	1.553	1.458
Small-Cap Value	110	517	1.376	1.327	1.200
Mid-Cap Growth	163	777	1.399	1.856	1.718
Mid-Cap Core	106	822	1.321	1.788	1.677
Mid-Cap Value	86	1010	1.363	1.274	1.160
Large-Cap Growth	226	1651	1.246	0.968	0.854
Large-Cap Core	273	1664	1.182	0.650	0.547
Large-Cap Value	139	2821	1.128	0.506	0.414
Multi-Cap Growth	170	2170	1.419	1.553	1.436
Multi-Cap Core	210	1220	1.353	0.964	0.887
Multi-Cap Value	181	1169	1.239	0.680	0.578
Equity Income	75	1329	1.211	0.514	0.406

Table 3.2: **Peer Comparisons**

This table reports average statistics from peer comparisons (Lipper Peers Vs Customized Peers) and Customized Peers (*t-1 Vs t*) for the years 2000 to 2009. In Panel A, for each quarter t and each fund i, we first calculate the number of Customized Peers that are not Lipper Peers *(CP(t,i) Minus LP(t,i))*, the common peers *(Common(t,i))*, and the Lipper Peers that are not Customized Peers *(LP(t,i) Minus CP(t,i))*. We then obtain sum of these numbers across across all funds in quarter t and obtain *CP(t) Minus LP(t)*, *Common(t)* and *LP(t) Minus CP(t)*. For each quarter t, we normalize *CP(t) Minus LP(t)*, *Common(t)* and *LP(t) Minus CP(t)* by dividing these numbers by the sum of [*CP(t) Minus LP(t)* + *Common(t)* + *LP(t) Minus CP(t)*]. Finally, we report average for each year across four quarters. In Panel B, we first obtain ratios for each fund i in each quarter t by dividing *CP(t,i) Minus LP(t,i)*, *Common(t,i)* and *LP(t,i) Minus CP(t,i)* with the sum of [*CP(t,i) Minus LP(t,i)* + *Common(t,i)* + *LP(t,i) Minus CP(t,i)*]. We then obtain average ratio for each quarter t across all funds in that quarter. Finally, we report average for each year across four quarters. In Panel C, we compare Customized Peers across two consecutive quarters, *t-1* and *t*. We only include funds that have Customized Peers in both quarters, *t-1* and *t*. We first report the fraction of funds that have same peers in both the quarters, *t-1* and *t*. This is obtained by normalizing the number of funds that have same peers in consecutive quarters with the total number of funds in quarter *t*. We report average for each year across four quarters. This number is represented by *SamePeer*. We also calculate for each quarter t and each fund i, the number of old Customized Peers in quarter *t-1* that are no longer peers in the current quarter t, the number of common peers in *t-1* and t, and the number of new peers in quarter t that were not peers in the last quarter *t-1*. We then obtain ratio for each fund i in quarter t by dividing the old peers, common peers and new peers by the sum of old, common and new peers. Next, we calculate average for each quarter, and finally report average for each year across four quarters.

	Panel A: Fraction			Panel B: Ratios			Panel C: Customized Peers (t Vs t+1)			
Year	CP Minus LP	Common	LP Minus CP	CP Minus LP	Common	LP Minus CP	SamePeer	Old Rival	Common	New Rival
2000	0.422	0.171	0.407	0.340	0.158	0.513	0.0006	0.334	0.351	0.315
2001	0.391	0.190	0.419	0.317	0.162	0.531	0.0000	0.317	0.331	0.352
2002	0.386	0.209	0.406	0.313	0.178	0.516	0.0002	0.302	0.373	0.325
2003	0.369	0.239	0.392	0.311	0.207	0.490	0.0003	0.278	0.411	0.311
2004	0.380	0.224	0.396	0.319	0.201	0.488	0.0008	0.285	0.429	0.287
2005	0.391	0.216	0.393	0.332	0.200	0.474	0.0014	0.250	0.483	0.268
2006	0.401	0.207	0.392	0.340	0.197	0.469	0.0005	0.260	0.490	0.250
2007	0.407	0.205	0.388	0.346	0.201	0.460	0.0005	0.248	0.486	0.266
2008	0.409	0.207	0.383	0.348	0.201	0.459	0.0003	0.283	0.465	0.252
2009	0.392	0.227	0.380	0.333	0.213	0.463	0.0006	0.309	0.412	0.279

Table 3.3: **Comparison of Fund Classifications**
The table reports R-squared and adjusted R-squared from cross-sectional monthly regressions of a fund's monthly return on its monthly benchmark return. Monthly benchmark return is the average return of a fund's peers (excluding own fund return) in case of Lipper Class Peers *(LC)*, Lipper Objective Peers *(LObj)* and Non-Transitive Customized Peers *(NTCP)*. Lipper Classification for each month into 13 peer categories (see Table 3.1) is obtained from CRSP. Funds in 13 Lipper Classifications have 7 Lipper defined fund objectives: Capital Appreciation, Equity Income, Growth, Growth and Income, Mid-Cap, Micro-Cap, and Samll-Cap funds. The classifications, fund objectives and all peer groups are obtained at the start of each quarter and carried over the next three months. For any of these three months, only the surviving funds are considered to be peers. For instance, if a fund has 100 peers based on its disclosed portfolio on March 2004 and if 2 funds do not have data for April 2004, then this fund has 98 peers in April 2004. The table also reports average number of monthly observations (*NObs/Mon*) used in cross-sectional regressions. The monthly period used in regressions is from 2000:01 to 2010:09.

Panel A: Ret on Ret Regression, NTC Peers Vs Lipper Class Peers			
Ind Vars	NObs/Mon	AvgR2/Mon	AvgAdjR2/Mon
NTCP	1517	42.75%	42.71%
LC	1517	32.14%	32.09%
NTCP, LC	1517	43.96%	43.89%
Panel B: Ret on Ret Regression, NTC Peers Vs Lipper Objective Peers			
NTCP	1512	42.71%	42.68%
LObj	1512	18.01%	17.95%
NTCP, LObj	1512	43.07%	42.99%
Panel C: Ret on Ret Regression, NTC Peers Vs Lipper Peers			
NTCP, LC, Lobj	1512	44.05%	43.94%

Table 3.4: **Tracking Error Volatility: Lipper Classifications Vs Customized Peers**

This table reports mean and standard deviations of tracking error volatilities of funds. The statistics are reported by Lipper Classification and for the full sample (in the last row). Tracking error volatility of a fund is defined as the standard deviation of fund return minus its benchmark return. For each fund, its monthly Lipper class benchmark return is obtained by averaging monthly return of its Lipper Peers (excluding own fund return). Similarly, customized peer benchmark return is obtained by averaging monthly return of its Customized Peers (excluding own fund return). Then, for each fund, its Lipper class adjusted *(Lipper)* and customized peer adjusted *(CPA)* return is obtained by subtracting the benchmark return from the fund's return. Finally, standard deviation of adjusted returns yields tracking error volatilities. We calculate tracking error volatilities of a fund using all months during which it belongs to a particular Lipper class, and require at least 12 monthly observations. If a fund changes its Lipper class and has more than one Lipper classification over its lifetime, then we calculate multiple tracking error volatilities for the same fund over different periods during which it belongs to different Lipper classifications. The sample duration used is 2000:01 to 2010:09.

	Mean		Std Dev	
Lipper Class	CPA	Lipper	CPA	Lipper
Small-Cap Growth	0.0209	0.0229	0.0115	0.0116
Small-Cap Core	0.0180	0.0198	0.0124	0.0137
Small-Cap Value	0.0197	0.0213	0.0089	0.0099
Mid-Cap Growth	0.0203	0.0231	0.0123	0.0160
Mid-Cap Core	0.0182	0.0212	0.0102	0.0134
Mid-Cap Value	0.0214	0.0244	0.0127	0.0142
Large-Cap Growth	0.0152	0.0171	0.0090	0.0119
Large-Cap Core	0.0115	0.0131	0.0064	0.0087
Large-Cap Value	0.0127	0.0138	0.0063	0.0072
Multi-Cap Growth	0.0220	0.0276	0.0135	0.0189
Multi-Cap Core	0.0156	0.0184	0.0099	0.0127
Multi-Cap Value	0.0163	0.0191	0.0081	0.0118
Equity Income	0.0148	0.0151	0.0057	0.0080
Full Sample	0.0170	0.0194	0.0105	0.0133

Table 3.5: **Performance Ranking Comparison: Customized Peer Adjusted Vs Lipper Adjusted**

This table reports percentage of funds that are ranked similarly (differently) in the diagonal (off-diagonal) cells according to the Customized Peer-Adjusted *(CPA)* and Lipper Peer-adjusted performance. At the end of each year, from 2000 to 2009, for each fund, average monthly Customized Peer-Adjusted and Lipper Peer-adjusted returns are obtained. To obtain these returns, first, for each fund its monthly Lipper class benchmark return is obtained by averaging monthly return of Lipper Peers (excluding own fund return). Similarly, customized peer benchmark return is obtained by averaging monthly return of Customized Peers (excluding own fund return). Then, for each fund, its monthly Lipper Peer-adjusted and Customized Peer-Adjusted return is obtained by subtracting the benchmark return from the fund's return. Finally, at the end of the year, average abnormal performance is calculated over 12 months. Funds are then ranked independently into quartiles according to the performance measures for each year. We then find out the proportion of funds that are ranked by Lipper Peer-adjusted return within each *CPA* ranked quartile. This results in a row with four column entries, containing proportion of funds that are ranked by Lipper Peer-adjusted return. For instance, if there are 300 funds in the first quartile according to the *CPA* measure, and within these 300 funds if there are 100 funds which are in the second quartile according to the Lipper Peer-adjusted, then the cell entry (1,2) is 33.33%. Thus, for each year and each *Rank_CPA*, the sum of column entries is 100. Finally, we take average across years for each *Rank_CPA*. A diagonal cell in the table below represents the average percentage of funds that are ranked similarly by two methods.

	Rank_Lipper			
Rank_CPA	1	2	3	4
1	31.25	23.64	23.84	21.27
2	27.88	27.23	22.48	22.40
3	22.06	27.25	25.76	24.93
4	18.70	21.95	28.00	31.35

Table 3.6: **Performance Ranking Comparison: Customized Peer Adjusted, Lipper Adjusted Vs Other Measures**

This table reports percentage of funds that are ranked similarly (differently) in the diagonal (off-diagonal) cells according to the customized peer adjusted *(CPA)* and other performance measures in Panel A, and also according to the Lipper peer adjusted and other performance measures in Panel B. At the end of each year, from 2000 to 2009, for each fund, average monthly customized peer adjusted performance and Lipper peer adjusted returns is obtained. To obtain these returns, first, for each fund its monthly customized (Lipper) peer benchmark return is obtained by averaging monthly return of customized (Lipper) peers, excluding own fund return. Then, for each fund, its customized (Lipper) peer adjusted return is obtained by subtracting the benchmark return from the fund's return. Next, monthly Characteristic-Selectivity performance *(CS)* is obtained as in Daniel, Grinblatt, Titman, and Wermers (1997). Risk-adjusted monthly 3-factor *(FF)* and 4-factor *(Carhart)* alpha are obtained by subtracting the estimated fund return from the fund's return. The estimated return is obtained by multiplying estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. Finally, at the end of the year, average abnormal performance is calculated over 12 months according to all performance measures. Funds are then ranked independently into quartiles according to the performance measures. The quartile rankings are then arranged as in Table 3.5. A diagonal cell in the table below represents the average percentage of funds that are ranked similarly by two methods.

Panel A: CPA Vs other perf measures					Panel B: Lipper-adj perf Vs other perf measures				
	Rank_CS					Rank_CS			
Rank_CPA	1	2	3	4	Rank_Lipper	1	2	3	4
1	60.44	23.79	10.20	5.57	1	37.00	29.51	20.28	13.21
2	25.72	39.14	26.29	8.85	2	25.84	27.97	25.60	20.59
3	9.42	27.21	38.02	25.36	3	19.36	23.76	27.39	29.49
4	4.36	9.91	25.55	60.18	4	17.69	18.84	26.81	36.66
	Rank_Carhart					Rank_Carhart			
Rank_CPA	1	2	3	4	Rank_Lipper	1	2	3	4
1	58.72	25.27	10.77	5.25	1	31.87	28.11	22.22	17.80
2	24.55	38.53	24.92	12.00	2	22.80	26.51	28.23	22.45
3	10.49	25.12	39.69	24.69	3	24.66	24.03	25.45	25.86
4	5.99	10.94	24.72	58.35	4	20.67	21.40	24.17	33.76

Table 3.7: **Correlation Among Performance Measures**

This table reports Pearson and Spearman Rank correlations among various performance measures in Panels A and B, respectively. First, performance measures are obtained at the fund level. Characteristic-Selectivity *(CS)* is obtained as in Daniel, Grinblatt, Titman, and Wermers (1997). It is dollar-weighted characteristic-adjusted (or DGTW-adjusted) return of a fund's holdings. Customized Peer-Adjusted return, *CPA*, is obtained by subtracting average return of Customized Peers, *RPeer*, (excluding own fund return) from a fund's return, *RFund*. Then average monthly *CS* and *CPA* are obtained over a fund's lifetime. 4-factor alpha *(Carhart)* is obtained by regressing a fund's excess return on 4 factors over its lifetime (Carhart (1997)). A fund must have at least 30 observations for its *Carhart* performance to be calculated. While *CS* is gross of expenses and transactions costs, *CPA* and *Carhart* measures are both net and gross of expenses. For instance, *CPA (Net) = RFund (Net) - RPeer (Net)*, and *CPA (Gross) = RFund (Gross) - RPeer (Gross)*. All correlations are statistically significant at 1% level.

Panel A: Pearson Correlation

	Gross			Net		
Perf Measure	CS	Carhart	CPA	CS	Carhart	CPA
CS	1.00			1.00		
Carhart	0.33	1.00		0.33	1.00	
CPA	0.51	0.60	1.00	0.52	0.61	1.00

Panel B: Spearman Rank Correlation

	Gross			Net		
Perf Measure	CS	Carhart	CPA	CS	Carhart	CPA
CS	1.00			1.00		
Carhart	0.45	1.00		0.45	1.00	
CPA	0.51	0.62	1.00	0.53	0.62	1.00

Table 3.8: **Future Performance Prediction from Past Characteristic-Selectivity and Customized Peer-Adjusted Performance**

This table reports results on future Characteristic-Selectivity prediction from past Characteristic-Selectivity *(CS)* and past Customized Peer-Adjusted *(CPA)* performance. At the start of each calendar quarter, we sort funds into decile portfolios based on the past 12 months average *CS* and *CPA* performance. Next, we calculate equal-weighted *CS* performance over the next three months after portfolio formation, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 10-1 represents zero-investment long-short portfolio that is long on decile ten and short on decile one. Returns are percentage annual (monthly return multiplied by 12). *P*-values are reported in parentheses.

	3 Month		6 Month		12 Month	
Decile	CS	CPA	CS	CPA	CS	CPA
1	-0.693	-1.013	-0.538	-0.784	0.037	-0.204
	(0.383)	(0.177)	(0.453)	(0.253)	(0.961)	(0.759)
2	-0.075	0.052	-0.021	-0.130	0.503	0.016
	(0.884)	(0.907)	(0.966)	(0.761)	(0.298)	(0.970)
3	0.417	-0.056	0.501	0.227	0.595	0.172
	(0.309)	(0.883)	(0.213)	(0.553)	(0.141)	(0.651)
4	0.059	0.316	0.181	0.390	0.457	0.458
	(0.861)	(0.379)	(0.589)	(0.251)	(0.174)	(0.188)
5	0.328	0.315	0.405	0.200	0.372	0.481
	(0.323)	(0.339)	(0.266)	(0.560)	(0.261)	(0.149)
6	0.623	0.413	0.495	0.202	0.301	0.301
	(0.042)	(0.202)	(0.102)	(0.538)	(0.327)	(0.364)
7	0.502	0.709	0.513	0.799	0.607	0.456
	(0.146)	(0.027)	(0.151)	(0.013)	(0.074)	(0.185)
8	0.713	0.909	0.703	0.935	0.409	0.903
	(0.058)	(0.013)	(0.063)	(0.011)	(0.293)	(0.016)
9	1.228	1.244	1.025	1.097	0.740	0.802
	(0.010)	(0.004)	(0.022)	(0.011)	(0.094)	(0.054)
10	1.939	2.157	1.977	2.331	1.217	1.856
	(0.015)	(0.002)	(0.009)	(0.001)	(0.109)	(0.006)
10-1	2.632	3.170	2.515	3.115	1.180	2.060
	(0.031)	(0.001)	(0.019)	(0.001)	(0.278)	(0.016)

Table 3.9: **Bivariate Sorts Comparing Characteristic-Selectivity and Customized Peer-Adjusted Performance**

This table compares future Characteristic-Selectivity prediction from past Characteristic-Selectivity *(CS)* and past Customized Peer-Adjusted *(CPA)* performance, using bivariate sequential sorts. At the start of each calendar quarter, we form 25 portfolios using sequential sorts. We next calculate equal-weighted *CS* performance over the next three months after portfolio formation in Panels A1 and B1, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 5-1 represents zero-investment long-short portfolio that is long on quintile five and short on quintile one. Returns are percentage annual (monthly return multiplied by 12). *P*-values are reported in parentheses.

Panel A: First sort by CS, second sort by CPA																		
	Panel A1: 3 Months						Panel A2: 6 Months						Panel A3: 12 Months					
	CPA Quintile						CPA Quintile						CPA Quintile					
CS Quintile	1	2	3	4	5	5-1	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	-1.563	-0.652	-0.073	0.089	0.306	1.869	-1.518	-0.599	-0.233	0.361	0.607	2.125	-0.843	-0.589	0.312	1.171	1.251	2.094
	(0.155)	(0.351)	(0.902)	(0.878)	(0.623)	(0.028)	(0.118)	(0.353)	(0.667)	(0.525)	(0.314)	(0.006)	(0.370)	(0.366)	(0.594)	(0.038)	(0.063)	(0.003)
2	-0.352	0.335	0.126	0.357	0.718	1.070	-0.169	0.239	0.314	0.458	0.878	1.046	0.827	0.200	0.474	0.670	0.489	-0.338
	(0.502)	(0.394)	(0.741)	(0.343)	(0.136)	(0.028)	(0.751)	(0.511)	(0.393)	(0.238)	(0.077)	(0.049)	(0.109)	(0.603)	(0.209)	(0.093)	(0.292)	(0.472)
3	-0.380	0.441	0.806	0.319	1.162	1.542	0.069	0.439	0.207	0.480	1.055	0.985	0.021	0.337	0.221	0.229	0.887	0.866
	(0.415)	(0.218)	(0.024)	(0.290)	(0.005)	(0.001)	(0.888)	(0.230)	(0.557)	(0.148)	(0.011)	(0.035)	(0.962)	(0.349)	(0.517)	(0.481)	(0.036)	(0.039)
4	0.192	0.152	0.451	0.853	1.389	1.198	0.345	-0.195	0.565	0.795	1.517	1.172	0.011	0.177	0.608	0.926	0.795	0.784
	(0.681)	(0.706)	(0.203)	(0.024)	(0.007)	(0.026)	(0.488)	(0.609)	(0.106)	(0.040)	(0.004)	(0.027)	(0.982)	(0.659)	(0.109)	(0.016)	(0.109)	(0.183)
5	0.806	1.175	1.495	1.580	2.892	2.086	0.609	0.878	1.481	1.572	2.892	2.283	-0.706	0.977	0.940	1.232	2.287	2.993
	(0.221)	(0.055)	(0.008)	(0.020)	(0.002)	(0.004)	(0.346)	(0.119)	(0.010)	(0.012)	(0.001)	(0.002)	(0.272)	(0.080)	(0.096)	(0.047)	(0.014)	(0.000)
5-1	2.369	1.827	1.568	1.491	2.585		2.127	1.477	1.713	1.211	2.285		0.138	1.566	0.628	0.061	1.036	
	(0.053)	(0.060)	(0.061)	(0.099)	(0.015)		(0.049)	(0.088)	(0.028)	(0.149)	(0.021)		(0.892)	(0.066)	(0.409)	(0.942)	(0.315)	

Panel B: First sort by CPA, second sort by CS																		
	Panel B1: 3 Months						Panel B2: 6 Months						Panel B3: 12 Months					
	CS Quintile						CS Quintile						CS Quintile					
CPA Quintile	1	2	3	4	5	5-1	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	-1.308	-0.564	-0.502	-0.404	0.405	1.713	-1.521	-0.721	-0.221	-0.178	0.390	1.911	-0.662	-0.492	0.173	0.607	-0.092	0.570
	(0.247)	(0.402)	(0.393)	(0.387)	(0.502)	(0.122)	(0.120)	(0.233)	(0.711)	(0.719)	(0.531)	(0.053)	(0.507)	(0.420)	(0.748)	(0.224)	(0.878)	(0.569)
2	-0.021	0.699	-0.410	-0.068	0.475	0.496	0.189	0.537	0.018	0.276	0.516	0.327	0.903	0.722	0.236	0.127	-0.374	-1.277
	(0.973)	(0.115)	(0.237)	(0.846)	(0.339)	(0.461)	(0.753)	(0.205)	(0.959)	(0.453)	(0.276)	(0.624)	(0.174)	(0.075)	(0.505)	(0.733)	(0.423)	(0.060)
3	0.055	0.338	0.423	0.447	0.570	0.515	0.270	0.357	0.155	-0.116	0.366	0.097	0.740	0.420	0.259	0.123	0.432	-0.308
	(0.910)	(0.367)	(0.191)	(0.215)	(0.262)	(0.424)	(0.590)	(0.332)	(0.647)	(0.741)	(0.445)	(0.865)	(0.172)	(0.245)	(0.399)	(0.747)	(0.346)	(0.598)
4	0.478	0.771	0.838	0.622	1.345	0.867	1.005	0.780	0.937	0.655	0.947	-0.058	0.721	0.524	0.909	0.518	0.657	-0.064
	(0.351)	(0.025)	(0.014)	(0.103)	(0.030)	(0.248)	(0.053)	(0.018)	(0.004)	(0.094)	(0.089)	(0.928)	(0.174)	(0.174)	(0.005)	(0.219)	(0.267)	(0.927)
5	1.458	1.069	1.286	1.956	2.772	1.313	1.405	1.262	1.229	2.035	2.605	1.199	1.509	0.703	0.980	1.372	2.180	0.671
	(0.011)	(0.029)	(0.012)	(0.002)	(0.007)	(0.187)	(0.011)	(0.015)	(0.010)	(0.002)	(0.007)	(0.174)	(0.010)	(0.113)	(0.043)	(0.023)	(0.027)	(0.475)
5-1	2.767	1.633	1.788	2.360	2.367		2.926	1.983	1.450	2.213	2.214		2.171	1.195	0.808	0.765	2.272	
	(0.008)	(0.033)	(0.014)	(0.001)	(0.009)		(0.002)	(0.006)	(0.042)	(0.002)	(0.007)		(0.021)	(0.071)	(0.224)	(0.239)	(0.005)	

Table 3.10: **Characteristic-Selectivity Prediction: Regression Analysis**

This table reports coefficients from regression of future Characteristic-Selectivity on past Customized Peer-Adjusted *(CPA)* performance, past Characteristic-Selectivity *(CS)* and other controls. The dependent variable is $CS_{t+i,t+j}$, which represents the average *CS* performance over the months *t+i* to *t+j*. $CPA_{t\text{-}11,t}$ represents average *CPA* performance over the months *t-11* to *t*. $CS_{t\text{-}11,t}$ represents average *CS* performance over the months *t-11* to *t*. $ExpRatio_{t\text{-}11,t}$ and $TurnRatio_{t\text{-}11,t}$ represent average expense ratio and turnover ratio over the months *t-11* to *t*, respectively. $LogFundAge_{t\text{-}11,t}$ and $LogFundSize_{t\text{-}11,t}$ represent average natural logarithm of fund age (years) and fund size ($millions) over the months *t-11* to *t*, respectively. $Flow_{t\text{-}11,t}$ represents average monthly flow over the months *t-11* to *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly investor returns over the months *t-11* to *t*. $LogFamSize_{t\text{-}11,t}$ represents average natural logarithm of family size ($millions) over the months *t-11* to *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared. Standard errors are clustered by fund. *P*-values are reported in parentheses.

Dep Var	$CS_{t+1,t+3}$				$CS_{t+1,t+6}$				$CS_{t+1,t+12}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.214	-0.230	-0.218	-0.143	0.014	0.000	0.012	-0.154	-0.109	-0.110	-0.106	0.464
	(0.001)	(0.001)	(0.001)	(0.475)	(0.776)	(0.999)	(0.808)	(0.326)	(0.001)	(0.001)	(0.002)	(0.001)
$CPA_{t\text{-}11,t}$	0.102		0.090	0.091	0.100		0.093	0.090	0.060		0.078	0.070
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
$CS_{t\text{-}11,t}$		0.075	0.019	0.012		0.069	0.011	0.008		0.020	-0.029	-0.031
		(0.000)	(0.076)	(0.297)		(0.000)	(0.308)	(0.504)		(0.023)	(0.010)	(0.014)
$ExpRatio_{t\text{-}11,t}$				0.026				0.021				0.012
				(0.011)				(0.045)				(0.283)
$TurnRatio_{t\text{-}11,t}$				0.006				0.007				0.007
				(0.196)				(0.170)				(0.160)
$LogFundAge_{t\text{-}11,t}$				0.006				0.006				0.003
				(0.262)				(0.273)				(0.530)
$LogFundSize_{t\text{-}11,t}$				-0.009				-0.009				-0.010
				(0.006)				(0.003)				(0.004)
$Flow_{t\text{-}11,t}$				0.001				0.001				-0.003
				(0.597)				(0.465)				(0.063)
$StdDev_{t\text{-}11,t}$				-1.636				-2.085				-1.600
				(0.000)				(0.000)				(0.000)
$LogFamSize_{t\text{-}11,t}$				0.003				0.002				0.001
				(0.188)				(0.441)				(0.675)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	91890	91890	91890	77610	46249	46249	46249	38643	23301	23301	23301	19130
AdjRSQ	0.053	0.052	0.053	0.051	0.048	0.045	0.048	0.051	0.059	0.057	0.060	0.068

Table 3.11: **Carhart Alpha Prediction: Regression Analysis**

This table reports coefficients from regression of future Carhart alpha on past Customized Peer-Adjusted *(CPA)* performance, past Characteristic-Selectivity *(CS)* and other controls. The dependent variable is $Carhart_{t+i,t+j}$, which represents the average *Carhart* performance over the months $t+i$ to $t+j$. For each month in $(t+i,\ t+j)$, we obtain monthly *Carhart* alpha by subtracting the estimated monthly return from the fund's raw return. We estimate monthly return by multiplying the estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. $CPA_{t\text{-}11,t}$ represents average *CPA* performance over the months *t-11* to *t*. $CS_{t\text{-}11,t}$ represents average *CS* performance over the months *t-11* to *t*. $ExpRatio_{t\text{-}11,t}$ and $TurnRatio_{t\text{-}11,t}$ represent average expense ratio and turnover ratio over the months *t-11* to *t*, respectively. $LogFundAge_{t\text{-}11,t}$ and $LogFundSize_{t\text{-}11,t}$ represent average natural logarithm of fund age (years) and fund size ($millions) over the months *t-11* to *t*, respectively. $Flow_{t\text{-}11,t}$ represents average monthly flow over the months *t-11* to *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly investor returns over the months *t-11* to *t*. $LogFamSize_{t\text{-}11,t}$ represents average natural logarithm of family size ($millions) over the months *t-11* to *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared. Standard errors are clustered by fund. *P*-values are reported in parentheses.

Dep Var	$Carhart_{t+1,t+3}$				$Carhart_{t+1,t+6}$				$Carhart_{t+1,t+12}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.222	0.210	0.246	1.208	0.369	0.358	0.388	1.230	0.966	0.969	0.969	1.307
	(0.009)	(0.013)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$CPA_{t\text{-}11,t}$	0.087		0.124	0.101	0.091		0.124	0.098	0.073		0.118	0.087
	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
$CS_{t\text{-}11,t}$		0.020	-0.058	-0.061		0.025	-0.052	-0.056		0.003	-0.071	-0.062
		(0.043)	(0.000)	(0.000)		(0.011)	(0.000)	(0.000)		(0.763)	(0.000)	(0.000)
$ExpRatio_{t\text{-}11,t}$				-0.056				-0.059				-0.060
				(0.000)				(0.000)				(0.000)
$TurnRatio_{t\text{-}11,t}$				-0.007				-0.009				-0.011
				(0.338)				(0.181)				(0.135)
$LogFundAge_{t\text{-}11,t}$				-0.005				-0.004				-0.009
				(0.369)				(0.525)				(0.144)
$LogFundSize_{t\text{-}11,t}$				-0.019				-0.018				-0.018
				(0.000)				(0.000)				(0.000)
$Flow_{t\text{-}11,t}$				0.002				0.002				-0.001
				(0.166)				(0.193)				(0.351)
$StdDev_{t\text{-}11,t}$				-2.093				-1.803				-1.563
				(0.000)				(0.000)				(0.000)
$LogFamSize_{t\text{-}11,t}$				0.010				0.010				0.011
				(0.000)				(0.000)				(0.000)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88860	88860	88860	75926	45158	45158	45158	38163	23207	23207	23207	19110
AdjRSQ	0.097	0.095	0.097	0.095	0.133	0.130	0.134	0.129	0.182	0.178	0.183	0.177

Table 3.12: **Average Fund Characteristics by Peer Competition**

This table reports average fund characteristics by the degree of peer competition faced by the fund. We categorize funds by the number of customized peers *(NPeers)*. We obtain peers at the end of each quarter and apply over the next three months. For observations in the table below, first, for each month of the sample from 1980:07 - 2010:09, we classify each fund into five peer groups by the number of its customized peers. We then obtain observations at the peer group-year level by averaging monthly observations for each group and for each year. Finally, we take average over each category. *Nfunds* represent average number of funds per month in a peer group. *TNA* and *Family Assets* represent total net assets of a fund and total net assets of a fund family. *Fund Age* represents fund age of a fund in years. *Turnover Ratio*, *Expense Ratio* and *Mgmt Fee* are obtained as of the last fiscal year for each month. *Raw Ret* represents monthly raw return of a fund. We obtain risk-adjusted monthly 4-factor Carhart alpha by subtracting the estimated fund return from a fund's return. We calculate estimated return, for each fund and each month, by multiplying the estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. *CS* and *CPA* represent Characteristic-Selectivity and Customized Peer-Adjusted return of a fund. All performance measures except *CS* are net of expenses. *Flow* represents monthly flow.

Peer Group	Nfunds	TNA ($M)	Family Assets ($M)	Fund Age (Years)	Turn Ratio (%)	Exp Ratio (%)	Mgmt Fee (%)	Raw Ret (%)	Carhart (%)	CS (%)	CPA (%)	Flow (%)
NPeers $\leq$ 25	335	416	10965	12.63	0.999	1.324	0.793	1.062	0.324	0.059	-0.001	1.107
25 < NPeers $\leq$ 50	340	637	15046	16.46	0.900	1.204	0.747	0.954	0.301	0.051	-0.011	0.578
50 < NPeers $\leq$ 100	390	732	18231	18.25	0.834	1.145	0.700	0.821	0.433	-0.008	-0.007	0.565
100 < NPeers $\leq$ 200	397	1202	24316	16.95	0.812	1.149	0.652	-0.383	0.240	-0.113	-0.197	0.598
NPeers > 200	513	1989	34565	16.91	0.722	1.138	0.588	0.521	0.107	-0.010	-0.010	0.288

Table 3.13: **Competition and Future Characteristic-Selectivity Performance: Portfolio Analysis**

This table reports results on future Characteristic-Selectivity *(CS)* prediction from past Customized Peer-Adjusted *(CPA)* performance, conditional on past peer competition. At the start of each calendar quarter, we first sort funds into terciles by the number of fund peers. These terciles are represented by *Low*, *Med* and *High*. Then we sort funds into deciles within terciles to arrive at 30 portfolios. Next, we calculate equal-weighted *CS* performance over the next three months after portfolio formation, and then re-balance the portfolios. Finally, we obtain average monthly *CS* post-ranking portfolio performance by taking average over the entire time-series. Similarly, we form portfolios at the start of each half-year (year) and then re-balance portfolios after six (twelve) months and obtain future *CS* performance. 10-1 represents zero-investment long-short portfolio that is long on decile ten and short on decile one. Returns are percentage annual (monthly return multiplied by 12). *P*-values are reported in parentheses.

	3 Month			6 Month			12 Month		
Decile	Low	Med	High	Low	Med	High	Low	Med	High
1	-1.729	-0.923	-0.692	-1.278	-0.579	-0.517	-0.542	-0.345	-0.528
	(0.115)	(0.204)	(0.119)	(0.213)	(0.398)	(0.210)	(0.607)	(0.581)	(0.220)
2	-0.027	0.055	-0.415	-0.416	-0.246	-0.408	0.366	0.209	-0.311
	(0.971)	(0.916)	(0.253)	(0.555)	(0.633)	(0.247)	(0.597)	(0.662)	(0.369)
3	0.795	-0.099	0.081	1.064	0.102	-0.081	0.178	0.354	0.129
	(0.223)	(0.831)	(0.797)	(0.088)	(0.829)	(0.790)	(0.784)	(0.426)	(0.692)
4	0.714	-0.110	0.051	0.977	0.285	0.232	1.051	0.336	0.514
	(0.231)	(0.805)	(0.861)	(0.124)	(0.490)	(0.473)	(0.090)	(0.419)	(0.098)
5	1.106	0.175	0.313	0.691	0.111	0.076	0.730	0.067	0.258
	(0.090)	(0.680)	(0.270)	(0.289)	(0.790)	(0.791)	(0.217)	(0.881)	(0.385)
6	0.455	0.471	0.018	0.336	0.177	0.092	0.922	0.335	0.178
	(0.377)	(0.253)	(0.950)	(0.514)	(0.667)	(0.766)	(0.126)	(0.414)	(0.566)
7	1.320	0.356	0.550	1.425	0.736	0.363	1.069	0.573	-0.107
	(0.022)	(0.415)	(0.069)	(0.015)	(0.090)	(0.229)	(0.058)	(0.189)	(0.711)
8	1.634	0.969	0.529	1.660	0.788	0.645	1.352	1.176	0.156
	(0.006)	(0.030)	(0.116)	(0.004)	(0.081)	(0.046)	(0.032)	(0.014)	(0.637)
9	1.925	1.752	0.615	1.797	1.277	0.471	1.749	0.719	0.363
	(0.003)	(0.002)	(0.060)	(0.005)	(0.020)	(0.152)	(0.004)	(0.188)	(0.263)
10	3.258	1.682	0.296	3.377	2.197	0.576	2.769	1.562	0.435
	(0.000)	(0.039)	(0.519)	(0.000)	(0.007)	(0.192)	(0.004)	(0.045)	(0.325)
10-1	4.988	2.605	0.988	4.654	2.775	1.094	3.311	1.906	0.963
	(0.000)	(0.012)	(0.115)	(0.000)	(0.005)	(0.046)	(0.009)	(0.040)	(0.083)

Table 3.14: **Competition and Future Characteristic-Selectivity Performance: Regression Analysis**

This table reports coefficients from regression of future Characteristic-Selectivity on past Customized Peer-Adjusted *(CPA)* performance and other controls for low, medium and high competition sub-samples. At the start of each time period (three months, six months and twelve months), we first sort funds into terciles depending upon the average number of monthly peers in the past one year. We refer to the samples in the lowest, medium and highest terciles as as *Low*, *Med* and *High* competition sub-samples, respectively. We then sort funds into deciles within terciles based on the past 12 month *(t-11,t)* average CPA performance. *CPA_Decile1* and *CPA_Decile10* are dummy variables for funds corresponding to the funds in the bottom and top decile, respectively. The dependent variable is $CS_{t+i,t+j}$, which represents the average *CS* performance over the months *t+i* to *t+j*. $CS_{t-11,t}$ represents average *CS* performance over the months *t-11* to *t*. $ExpRatio_{t-11,t}$ and $TurnRatio_{t-11,t}$ represent average expense ratio and turnover ratio over the months *t-11* to *t*, respectively. $LogFundAge_{t-11,t}$ and $LogFundSize_{t-11,t}$ represent average natural logarithm of fund age (years) and fund size ($millions) over the months *t-11* to *t*, respectively. $Flow_{t-11,t}$ represents average monthly flow over the months *t-11* to *t*. $StdDev_{t-11,t}$ is the standard deviation of monthly investor returns over the months *t-11* to *t*. $LogFamSize_{t-11,t}$ represents average natural logarithm of family size ($millions) over the months *t-11* to *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared. Standard errors are clustered by fund. *P*-values are reported in parentheses.

Panel A: Dep Var = $CS_{t+1,t+3}$

	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.078	-0.739	-0.739	-0.310	0.124	0.123	-0.265	0.028	0.021
	(0.563)	(0.108)	(0.110)	(0.008)	(0.329)	(0.338)	(0.002)	(0.885)	(0.913)
CPA_Decile1	-0.116	-0.064	-0.027	-0.057	-0.031	-0.004	-0.044	-0.043	-0.035
	(0.000)	(0.066)	(0.456)	(0.008)	(0.197)	(0.862)	(0.001)	(0.003)	(0.022)
CPA_Decile10	0.167	0.173	0.137	0.103	0.122	0.093	0.002	0.009	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.896)	(0.546)	(1.000)
$CS_{t-11,t}$			0.051			0.050			0.025
			(0.002)			(0.002)			(0.131)
$ExpRatio_{t-11,t}$		0.034	0.031		0.003	0.002		0.004	0.003
		(0.122)	(0.151)		(0.850)	(0.917)		(0.726)	(0.759)
$TurnRatio_{t-11,t}$		-0.003	-0.003		0.025	0.025		-0.005	-0.005

		(0.762)	(0.772)		(0.001)	(0.001)		(0.337)	(0.347)
$\text{LogFundAge}_{\text{t-11,t}}$		0.032	0.030		0.008	0.006		-0.004	-0.004
		(0.016)	(0.022)		(0.392)	(0.474)		(0.438)	(0.412)
$\text{LogFundSize}_{\text{t-11,t}}$		-0.016	-0.017		-0.008	-0.009		0.000	0.000
		(0.052)	(0.033)		(0.109)	(0.094)		(0.894)	(0.904)
$\text{Flow}_{\text{t-11,t}}$		0.004	0.002		0.003	0.001		-0.000	-0.000
		(0.163)	(0.467)		(0.243)	(0.539)		(0.898)	(0.793)
$\text{StdDev}_{\text{t-11,t}}$		-3.466	-3.441		-2.471	-2.497		-1.240	-1.186
		(0.000)	(0.000)		(0.000)	(0.000)		(0.053)	(0.063)
$\text{LogFamSize}_{\text{t-11,t}}$		0.004	0.005		0.006	0.006		-0.000	-0.000
		(0.456)	(0.338)		(0.142)	(0.124)		(0.908)	(0.952)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	30606	25755	25755	30651	25970	25970	30633	25885	25885
AdjRSQ	0.064	0.057	0.057	0.071	0.073	0.074	0.056	0.057	0.057

Panel B: Dep Var = $CS_{t+1,t+6}$

	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.060	0.105	0.104	-0.011	-0.257	-0.258	-0.019	-0.238	-0.240
	(0.583)	(0.752)	(0.756)	(0.889)	(0.173)	(0.173)	(0.755)	(0.279)	(0.275)
CPA_Decile1	-0.112	-0.038	0.001	-0.076	-0.057	-0.040	-0.026	-0.023	-0.022
	(0.000)	(0.285)	(0.970)	(0.000)	(0.019)	(0.117)	(0.081)	(0.143)	(0.183)
CPA_Decile10	0.156	0.167	0.129	0.105	0.108	0.090	0.021	0.027	0.025
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.156)	(0.092)	(0.135)
$CS_{t-11,t}$			0.056			0.032			0.005
			(0.001)			(0.058)			(0.742)
$ExpRatio_{t-11,t}$		0.035	0.032		-0.017	-0.018		0.003	0.003
		(0.146)	(0.173)		(0.347)	(0.318)		(0.749)	(0.756)
$TurnRatio_{t-11,t}$		0.003	0.003		0.021	0.021		-0.007	-0.007
		(0.744)	(0.724)		(0.009)	(0.007)		(0.255)	(0.256)
$LogFundAge_{t-11,t}$		0.026	0.024		0.012	0.011		-0.004	-0.004
		(0.058)	(0.076)		(0.208)	(0.242)		(0.440)	(0.436)

$\text{LogFundSize}_{t\text{-}11,t}$		-0.018	-0.020		-0.010	-0.010		-0.000	-0.000
		(0.029)	(0.016)		(0.066)	(0.060)		(0.978)	(0.974)
$\text{Flow}_{t\text{-}11,t}$		0.004	0.002		0.004	0.003		-0.001	-0.001
		(0.198)	(0.573)		(0.129)	(0.240)		(0.716)	(0.698)
$\text{StdDev}_{t\text{-}11,t}$		-3.815	-3.801		-3.181	-3.218		-1.268	-1.253
		(0.000)	(0.000)		(0.000)	(0.000)		(0.053)	(0.057)
$\text{LogFamSize}_{t\text{-}11,t}$		0.006	0.008		0.002	0.003		-0.001	-0.001
		(0.256)	(0.159)		(0.530)	(0.501)		(0.768)	(0.777)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15402	12808	12808	15429	12945	12945	15418	12890	12890
AdjRSQ	0.052	0.055	0.056	0.061	0.070	0.070	0.057	0.060	0.060

Panel C: Dep Var = $CS_{t+1,t+12}$

	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.169	-0.080	-0.070	-0.128	-0.195	-0.195	-0.000	0.593	0.586
	(0.015)	(0.237)	(0.302)	(0.036)	(0.000)	(0.000)	(0.992)	(0.000)	(0.000)
CPA_Decile1	-0.067	-0.009	0.003	-0.023	0.016	0.017	-0.019	-0.006	-0.022
	(0.061)	(0.815)	(0.934)	(0.315)	(0.536)	(0.545)	(0.217)	(0.714)	(0.203)
CPA_Decile10	0.129	0.140	0.127	0.049	0.069	0.069	0.012	0.017	0.035
	(0.000)	(0.001)	(0.003)	(0.034)	(0.008)	(0.010)	(0.446)	(0.318)	(0.057)
$CS_{t-11,t}$			0.017			0.001			-0.047
			(0.338)			(0.971)			(0.007)
$ExpRatio_{t-11,t}$		0.027	0.026		-0.020	-0.020		-0.007	-0.006
		(0.316)	(0.335)		(0.282)	(0.281)		(0.585)	(0.647)
$TurnRatio_{t-11,t}$		0.005	0.005		0.018	0.018		-0.004	-0.005
		(0.554)	(0.548)		(0.031)	(0.031)		(0.442)	(0.428)
$LogFundAge_{t-11,t}$		0.011	0.010		0.008	0.008		-0.001	-0.000
		(0.466)	(0.490)		(0.401)	(0.402)		(0.921)	(0.965)
$LogFundSize_{t-11,t}$		-0.020	-0.020		-0.009	-0.009		0.000	0.000
		(0.023)	(0.018)		(0.097)	(0.097)		(0.955)	(0.920)

$Flow_{t-11,t}$		-0.004	-0.004		-0.003	-0.003		-0.001	-0.000
		(0.218)	(0.161)		(0.181)	(0.189)		(0.637)	(0.808)
$StdDev_{t-11,t}$		-2.841	-2.836		-3.406	-3.407		-0.025	-0.181
		(0.000)	(0.000)		(0.000)	(0.000)		(0.974)	(0.813)
$LogFamSize_{t-11,t}$		0.007	0.008		0.004	0.004		-0.003	-0.003
		(0.227)	(0.201)		(0.373)	(0.372)		(0.299)	(0.258)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7762	6324	6324	7776	6425	6425	7763	6381	6381
AdjRSQ	0.066	0.076	0.076	0.069	0.084	0.084	0.063	0.070	0.071

Table 3.15: **Competition and Future Carhart Performance: Regression Analysis**

This table reports coefficients from regression of future Carhart alpha on past Customized Peer-Adjusted *(CPA)* performance and other controls for low, medium and high competition sub-samples. At the start of each time period (three months, six months and twelve months), we first sort funds into terciles depending upon the average number of monthly peers in the past one year. We refer to the samples in the lowest, medium and highest terciles as as *Low*, *Med* and *High* competition sub-samples, respectively. We then sort funds into deciles within terciles based on the past 12 month *(t-11,t)* average CPA performance. *CPA_Decile1* and *CPA_Decile10* are dummy variables for funds corresponding to the funds in the bottom and top decile, respectively. The dependent variable is $Carhart_{t+i,t+j}$, which represents the average *Carhart* performance over the months *t+i* to *t+j*. For each month in *(t+i, t+j)*, we obtain monthly *Carhart* alpha by subtracting the estimated monthly return from the fund's raw return. We estimate monthly return by multiplying the estimated factor loadings (obtained from past 36 month regression, with a minimum of 30 observations) with factor returns. $CS_{t\text{-}11,t}$ represents average *CS* performance over the months *t-11* to *t*. $ExpRatio_{t\text{-}11,t}$ and $TurnRatio_{t\text{-}11,t}$ represent average expense ratio and turnover ratio over the months *t-11* to *t*, respectively. $LogFundAge_{t\text{-}11,t}$ and $LogFundSize_{t\text{-}11,t}$ represent average natural logarithm of fund age (years) and fund size (\$millions) over the months *t-11* to *t*, respectively. $Flow_{t\text{-}11,t}$ represents average monthly flow over the months *t-11* to *t*. $StdDev_{t\text{-}11,t}$ is the standard deviation of monthly investor returns over the months *t-11* to *t*. $LogFamSize_{t\text{-}11,t}$ represents average natural logarithm of family size (\$millions) over the months *t-11* to *t*. All regressions include time *t* dummy. *N* and *AdjRSQ* represent number of observations and adjusted-Rsquared. Standard errors are clustered by fund. *P*-values are reported in parentheses.

Panel A: Dep Var = $\text{Carhart}_{t+1,t+3}$									
	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.390	1.592	1.418	0.666	0.496	0.495	0.232	0.951	1.054
	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.039)	(0.005)	(0.000)
CPA_Decile1	-0.199	-0.103	-0.083	-0.058	-0.004	-0.034	-0.022	0.014	-0.029
	(0.000)	(0.003)	(0.021)	(0.022)	(0.890)	(0.218)	(0.195)	(0.466)	(0.142)
CPA_Decile10	0.115	0.127	0.107	0.116	0.127	0.160	-0.044	-0.046	0.001
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.008)	(0.008)	(0.945)
$\text{CS}_{t\text{-}11,t}$			0.029			-0.058			-0.129
			(0.111)			(0.001)			(0.000)
$\text{ExpRatio}_{t\text{-}11,t}$		-0.057	-0.059		-0.094	-0.092		-0.077	-0.074

		(0.060)	(0.052)		(0.000)	(0.000)		(0.000)	(0.000)
$\text{TurnRatio}_{t\text{-}11,t}$		-0.019	-0.019		0.011	0.010		-0.009	-0.010
		(0.072)	(0.072)		(0.457)	(0.499)		(0.107)	(0.092)
$\text{LogFundAge}_{t\text{-}11,t}$		0.010	0.009		-0.002	-0.001		-0.014	-0.013
		(0.544)	(0.588)		(0.816)	(0.926)		(0.036)	(0.056)
$\text{LogFundSize}_{t\text{-}11,t}$		-0.033	-0.034		-0.021	-0.021		-0.002	-0.002
		(0.000)	(0.000)		(0.001)	(0.001)		(0.656)	(0.705)
$\text{Flow}_{t\text{-}11,t}$		0.006	0.005		-0.001	0.001		0.000	0.002
		(0.059)	(0.125)		(0.812)	(0.753)		(0.835)	(0.419)
$\text{StdDev}_{t\text{-}11,t}$		-4.004	-3.988		-2.120	-2.078		-1.976	-2.256
		(0.000)	(0.000)		(0.001)	(0.001)		(0.061)	(0.030)
$\text{LogFamSize}_{t\text{-}11,t}$		0.015	0.016		0.010	0.010		0.004	0.003
		(0.006)	(0.004)		(0.041)	(0.046)		(0.175)	(0.286)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	29330	25017	25017	29731	25470	25470	29799	25439	25439
AdjRSQ	0.108	0.112	0.112	0.122	0.124	0.124	0.144	0.137	0.140

Panel B: Dep Var = $\text{Carhart}_{t+1,t+6}$

	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.422	0.593	0.622	0.320	0.143	0.135	0.369	0.639	0.711
	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)	(0.005)	(0.000)	(0.001)	(0.000)
CPA_Decile1	-0.180	-0.090	-0.066	-0.082	-0.038	-0.074	-0.025	0.015	-0.019
	(0.000)	(0.014)	(0.080)	(0.002)	(0.183)	(0.010)	(0.140)	(0.425)	(0.352)
CPA_Decile10	0.121	0.125	0.102	0.115	0.113	0.152	-0.020	-0.021	0.017
	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.242)	(0.252)	(0.381)
$\text{CS}_{t-11,t}$			0.034			-0.068			-0.104
			(0.054)			(0.000)			(0.000)
$\text{ExpRatio}_{t-11,t}$		-0.053	-0.054		-0.097	-0.096		-0.077	-0.075
		(0.096)	(0.084)		(0.000)	(0.000)		(0.000)	(0.000)
$\text{TurnRatio}_{t-11,t}$		-0.017	-0.017		0.006	0.005		-0.013	-0.014
		(0.132)	(0.134)		(0.690)	(0.757)		(0.073)	(0.072)

$\text{LogFundAge}_{t-11,t}$		0.005	0.003		-0.002	-0.001		-0.009	-0.008
		(0.788)	(0.847)		(0.814)	(0.954)		(0.177)	(0.222)
$\text{LogFundSize}_{t-11,t}$		-0.034	-0.034		-0.018	-0.017		-0.003	-0.003
		(0.000)	(0.000)		(0.007)	(0.008)		(0.414)	(0.464)
$\text{Flow}_{t-11,t}$		0.006	0.005		-0.001	0.001		-0.001	0.000
		(0.056)	(0.136)		(0.661)	(0.838)		(0.774)	(0.853)
$\text{StdDev}_{t-11,t}$		-3.755	-3.742		-2.316	-2.229		-1.467	-1.769
		(0.000)	(0.000)		(0.000)	(0.000)		(0.077)	(0.030)
$\text{LogFamSize}_{t-11,t}$		0.018	0.019		0.008	0.008		0.004	0.004
		(0.001)	(0.001)		(0.095)	(0.108)		(0.117)	(0.186)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14959	12604	12604	15085	12796	12796	15114	12763	12763
AdjRSQ	0.133	0.139	0.139	0.172	0.172	0.173	0.191	0.181	0.183

Panel C: Dep Var = $\text{Carhart}_{t+1,t+12}$

	Low			Med			High		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.566	0.819	0.809	0.604	0.640	0.663	0.706	1.257	1.241
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CPA_Decile1	-0.181	-0.109	-0.102	-0.046	0.011	-0.019	-0.031	0.005	-0.030
	(0.000)	(0.004)	(0.011)	(0.089)	(0.713)	(0.521)	(0.124)	(0.824)	(0.186)
CPA_Decile10	0.064	0.083	0.076	0.112	0.116	0.149	-0.020	-0.022	0.016
	(0.081)	(0.040)	(0.072)	(0.000)	(0.000)	(0.000)	(0.262)	(0.247)	(0.421)
$\text{CS}_{t-11,t}$			0.010			-0.057			-0.102
			(0.588)			(0.005)			(0.000)
$\text{ExpRatio}_{t-11,t}$		-0.042	-0.043		-0.115	-0.113		-0.080	-0.078
		(0.180)	(0.174)		(0.000)	(0.000)		(0.000)	(0.000)
$\text{TurnRatio}_{t-11,t}$		-0.020	-0.020		0.004	0.003		-0.014	-0.014
		(0.076)	(0.077)		(0.828)	(0.868)		(0.089)	(0.087)
$\text{LogFundAge}_{t-11,t}$		0.002	0.001		-0.013	-0.012		-0.011	-0.010
		(0.921)	(0.938)		(0.225)	(0.282)		(0.157)	(0.189)

$\mathrm{LogFundSize}_{t\text{-}11,t}$		-0.039	-0.039		-0.017	-0.017		-0.000	0.000
		(0.000)	(0.000)		(0.009)	(0.009)		(0.952)	(0.981)
$\mathrm{Flow}_{t\text{-}11,t}$		-0.000	-0.001		-0.005	-0.003		-0.001	-0.000
		(0.877)	(0.788)		(0.090)	(0.212)		(0.654)	(0.964)
$\mathrm{StdDev}_{t\text{-}11,t}$		-3.701	-3.699		-2.432	-2.334		1.953	1.615
		(0.000)	(0.000)		(0.000)	(0.000)		(0.020)	(0.053)
$\mathrm{LogFamSize}_{t\text{-}11,t}$		0.021	0.021		0.010	0.010		0.003	0.003
		(0.001)	(0.001)		(0.039)	(0.046)		(0.281)	(0.390)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7723	6319	6319	7748	6416	6416	7736	6375	6375
AdjRSQ	0.161	0.170	0.170	0.219	0.219	0.220	0.252	0.242	0.246

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