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________________________ ____________

Jaime Harris Date

Clientele Effects in Mutual Funds

By

Jaime Harris
Master of Business Studies

Finance

____
Clifton Green
Advisor

Accepted:

____
Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

____
Date

Clientele Effects in Mutual Funds

By

Jaime Harris
M.A., Duke University, 2008
B.A., University of California, Santa Barbara, 2003

Advisor: Clifton Green, Ph.D.

An abstract of
A thesis submitted to the Faculty of the
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Abstract

Clientele Effects in Mutual Funds
By Jaime Harris

Mutual funds are important investment vehicles for both households and institutions. Prior research has established that these two groups of investors have different flow characteristics. Investor flow characteristics impact mutual fund manager behavior. The goal of this research is to understand how mutual fund managers respond to a change in their fund's clientele and how this response affects investors that remain in the fund. I find that the proportion of institutional investors has decreased relative to retail investors over time. In response, fund managers have selected more liquid securities.

Clientele Effects in Mutual Funds

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1 Introduction

Mutual funds are an important investment vehicle for both households and institutions. Prior research has established that these two groups of investors behave differently, especially in terms of flow characteristics (DelGuercio and Tkac (2002), Chen et al. (2010), and Evans and Fahlenbrach (2011)). In 1995, the Securities and Exchange Commission passed rule 18f-3 of the Investment Company Act of 1940. This rule change led to tremendous growth in mutual funds with multiple share classes. Of these, many cater to both institutional and retail investors. A purported benefit of the rule change was lower expenses, but existing evidence finds that this is not the case. As mutual fund managers react to flows, portfolios change, inducing trading costs and potentially increasing the amount of nonequity holdings.

The goal of this research is to understand how mutual fund managers respond to a change in their fund's clientele and how this response affects investors that remain in the fund. To measure changes in clientele, I will use a novel measure, the ratio of institutional share total net assets (TNA) to total fund TNA ($i2r$). Notably, the average $i2r$ has decreased over time. In addition, it changes over time for individual funds. This allows for the analysis of fund manager reaction to changes in clientele.

To test whether fund managers respond to clientele changes, I perform two main tests. The first test examines the relationship between fund holding characteristics and $i2r$. I regress a fund characteristic on the lagged percentage difference in $i2r$ and find that the liquidity of holdings indeed decreases. The second test examines benchmarks each dual fund to an institutional-only fund and a retail-only fund. The distance between the returns of the dual fund and benchmark fund is regressed on a clientele-change event indicator. The clientele-change event represents large changes in $i2r$. The hypothesis is that, after a shift in clientele toward retail (institutional), the fund's returns will be closer to the returns of its benchmark retail-only (institutional-only) fund. I find weak evidence in support of this hypothesis. The main hypothesis is that fund managers increase the liquidity of fund holdings when faced with a greater proportion of retail investors.

Tests of manager reaction are based on a sample of U.S.-based actively managed mutual funds from the CRSP Mutual Fund Database (CRSP MFDB). This sample is matched to Thompson Reuters Holding Data. Holdings data are used to calculate fund liquidity measures and to classify funds by style according to the 125 style portfolios of Daniel et al. (1997). Funds are then categorized by the types of share classes they offer: (i) institutional share classes only, (ii) retail share classes only, and (iii) both share classes offered (dual funds).

Existing research established two key empirical regularities: (i) the flow characteristics of retail and institutional investors are different, and (ii) mutual fund managers react to fund flows by changing their portfolio. For instance, Evans and Fahlenbrach (2011) show that, relative to institutional investors, institutional investors have lower flow volatility and more predictable flow. Additionally, DelGuercio and Tkac (2002) show that retail and institutional investors react to different measures of performance. Chen et al. (2010) provide evidence that institutional investors behave differently depending on whether they are surrounded by other institutional or retail investors. In illiquid funds where institutional investors are surrounded by retail investors, institutional investors react relatively more quickly to poor past performance than do retail investors. These outflows can cause more damage to future performance, affecting retail investors even more.

Coval and Stafford (2007) show that mutual fund managers do have to react to redemptions by selling. Chordia (1996) finds that funds hold more cash when there is uncertainty about redemptions. Yan (2006) shows that funds with more volatile fund flows hold more cash. First, these funds may not be able to capture the liquidity premium provided by relatively illiquid stocks (Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Pastor and Stambaugh (2003)). Additionally, Investment Company Institute (2011) shows that retail sentiment toward mutual funds moves with the level of the S&P 500. My data show that retail investor flows are more highly correlated with S&P 500 returns than are institutional flows. Because mutual funds are prohibited by law from short selling, managers are constrained to bet only on the long side. To generate returns, managers would bet on long-run convergence to fundamentals when the market is low. In general, it is risky for open-end funds to bet on longer horizon strategies (Shleifer and Vishny (1997) and Stein (2005)). With fewer institutional flows, managers are left with flows that are generally more volatile and particularly low following poor market performance. This suggests that dual and retail-only mutual funds should perform worse than institutional-only funds, especially following down markets. While the existing literature has not verified this hypothesis, James and Karceski (2006) shows that funds with both institutional and retail investors perform worse than funds with only institutional investors.

In 1995, the Securities and Exchange Commission (SEC) adopted rule 18f-3 as part of the Investment Company Act of 1940. This rule allowed mutual funds to offer different share classes of the same fund. While it was possible for funds to offer multiple share classes before 1995, funds had to submit requests to the SEC on a case-by-case basis (see Securities and Exchange release number IC-20915). Rule 18f-3 allows funds to offer share classes that hold the same underlying portfolio and share the same management but have different fees, expenses, loads, and minimum investment requirements. It is now common for funds to offer several different share classes to both institutions and individual investors. These share classes often have different fee structures, encouraging investors to pick a class based on investment horizon. For example, a fund may offer six classes for a given fund: three retail classes and three institutional classes, with each class offering different fees. For the purposes of this study, I aggregate all classes of a fund into two categories: retail and institutional. Funds can be comprised of both share classes or they may offer only one class or the other. I refer to these distinct fund types as dual, institutional-only, and retail-only funds.

To my knowledge, Lesseig et al. (2002) is the first academic paper to study multiple-class funds compared to single-class funds. They show that while multiple-class funds may reduce administrative costs, the fund sponsors charge higher management fees to make up for the cost savings. They do not make a distinction between multiple-class funds with offerings to retail or institutional clients only and funds that offer to both clientele. Chordia (1996) shows that funds that have load fees hold less cash than funds without loads. Edelen (1999) and Wermers (2000) show that liquidity-induced trading and holding liquid assets have a negative impact on fund performance. Morey (2004) notes that after rule 18f-3, a given fund may have classes with many different load options. He shows that the structure of multiple-class funds reduces the compositional gains from funds imposing loads.

James and Karceski (2006) study the cross-sectional differences in performance between retail mutual funds and across a spectrum of institutional mutual funds (institutional funds with large minimum investments compared to those with small minimum investments). Using a sample from 1995 to 2001, they find that institutional funds with large minimums outperform institutional fund with small minimums and institutional funds that have a retail mate. In line with the findings of DelGuercio and Tkac (2002), James and Karceski (2006) find that institutional investors and retail investors react differently to measures of performance. Specifically, institutional investors react to risk-adjusted performance measures while retail investors react to past raw returns and fund rankings. Further, institutional funds with retail mates or small minimum investments perform significantly worse than institutional funds with large minimum investments and retail funds. They explain this difference as arising from minimum purchase requirement acting as a proxy for monitoring. They do not analyze the holdings of funds.

As the goal of this research is to determine how the change in clientele affects the fund manager's behavior, it is not enough to simply look at fund returns. As explained in Daniel et al. (1997), when using actual fund returns, fees, expenses, and trading costs obfuscate the actions of the manager. Further, it is worthwhile noting that the sample in James and Karceski (2006) is short, and I document that the average dual-class fund experienced a decrease in institutional investing relative to retail investing over that period. By examining variation in $i2r$ is is possible to get a clearer picture of how fund managers react to both increases and decreases in institutional investors.

A very recent working paper, Evans and Fahlenbrach (2011), follows the spirit of James and Karceski (2006). Using a matched sample of institutional and retail investments, they find that when retail investors benefit from investing alongside institutions. Specifically, they find instances where a mutual fund and a separately managed account have highly correlated returns, the same manager, and the same objective. A separately managed account is a product that is available to institutional investors. Investors in a separate account own the underlying equities, as opposed to owning a share of a pool. In their sample, these separate accounts have lower turnover and a higher percentage of their portfolio invested in common stock. Their story parallels that of James and Karceski (2006), as they argue that the presence of institutional investors improves monitoring. Their study focuses on performance differences between mutual funds and similar institutional products. However, they do not investigate holdings, and there is clear evidence that the institutional products perform better due to lower turnover and lower nonequity investment. This research does not shed light on how a fund manager adjusts to changes in clientele in funds with multiple classes. Further, their paper differs from mine in that they do not differentiate between mutual funds that have separate shares for retail and institutional investors. In fact, they lump any mutual fund that offers a class to retail investors in the same category. In other words, they commingle what I refer to as retail-only and dual funds.

To summarize, this study investigates the response of mutual fund managers to a change in clientele. Previously documented empirical regularities are that fund managers react to flows and that different clientele have different flow characteristics. I find that fund managers do indeed react to clientele. Specifically, when the proportion of institutional investors is large, they are able to invest in more illiquid equities. This paper is organized as follows. The next section describes the data and construction of the various measures of fund characteristics and establishes that institutional investors prefer illiquid stocks. I then explain in detail the empirical tests and their results, provide ideas for future research, and conclude.

2 Data

The CRSP Mutual Fund Database (CRSP MFDB) is used to construct the base sample. This sample is then matched to the Thompson Reuters fund holdings database, and CRSP provides security-level data. The CRSP MFDB provides share class-level data. Holdings data is available quarterly at the fund level. All classes of a fund will have the same holdings, though they will have different fees and loads. Classes are aggregated to the fund level by taking the value-weighted average of share-level fees and returns, where the weights are proportion of that share's TNA to the fund's TNA. To match frequencies monthly fund returns are cumulated to the quarterly frequency to match the holdings data.

My sample starts in January 1998 and runs through December 2009. Holdings data is available quarterly. The base sample consists of actively managed mutual funds. To get this sample, I first look at the fund's Lipper classification. If there is no Lipper code, I then look at the Wiesenberger objective code. If missing, I then look at the Strategic Insight code and then the policy. Using the first code in the aforementioned hierarchy, I require the code to be on a list that I have selected based on what has been previously used in the literature (Chen et al. (2010)). After generating this list, I use the index fund flag to exclude any funds that are denoted as index funds.

Next, it is necessary to classify each class of a fund as either institutional or retail. The institutional fund indicator determines if a share class is institutional or not. It is reasonable to think that a share class would not change from retail to institutional or vice-versa over the course of its life. If a class is ever denoted as institutional, it is always classified as institutional. Similarly, if a class is ever denoted as retail, it is always classified as retail. If a class always has missing values it is assumed to be retail. This classification roughly matches that of Chen et al. (2010). At this point, my sample contains three types of actively managed funds: (i) funds with both retail and institutional classes (referred to as dual funds), (ii) funds with only retail classes (retail only), and (iii) funds with only institutional classes (institutional only).

Table 1 shows the number of distinct funds in each category in each year. Panel A shows the number of funds from the base sample in CRSP each year, and the proportion of the total sample that they represent. There is rapid growth over all categories in the early years, though it is clear that there is a shift toward dual funds over time. My base sample accounts for approximately 25 to 30% of all mutual funds in existence in a given year Investment Company Institute (2011)) (the ICI includes mutual funds that invest primarily in other mutual funds). Panel B shows the number of funds from the base sample that were matched to holdings data. The composition of the sample changes slightly after matching funds. Fewer institutional-only funds and retail-only funds are matched than dual funds.

For each fund in the matched sample, liquidity and DGTW-based style measures are calculated from the holdings data merged with CRSP. The Amihud Illiquidity Measure (Amihud (2002)) is a low-frequency proxy for the price impact of a stock. It is calculated from daily data, and it is defined as

$$Illiq_{i,t} = \frac{1}{D_{i,t}} \sum_{t=1}^{D_{i,t}} \frac{|r_t|}{Vol_t},$$

where $D_{i,t}$ is the number of positive-volume days in the time period over which the measure is being calculated, r_t is the return on stock i on day t, and Vol_t is the trading volume in dollars of stock i on day t. The Amihud measure is simply an average of daily measures over the time period of interest. Stocks with high Amihud measures have large price responses to order flow. For this study, the Amihud measure is averaged at the monthly horizon, generating a monthly Amihud measure for each stock. To get a fund-level Amihud measure, the portfolio weights of the holdings from the previous quarter are used to value weight the individual stock illiquidty measures. These monthly fund-level measures are then averaged over the quarter and over the previous 12 months.

Hasbrouck (2004) introduces a estimator of Roll's measure of the effective spread[1] based on the Gibbs sampler of CRSP daily data. Hasbrouck (2009) provides empirical support that this is a strong proxy for high-frequency measures of effective cost. Hasbrouck provides the yearly estimates for each stock through 2009 on his website.[2] Hasbrouck liquidity measures at the fund level are calculated by value-weighting the holdings by the previous quarter's portfolio weights. Analogous to the Amihud measure over the previous 12 months, I also create a Hasbrouck measure of the holdings averaged over the previous 4 quarters.

To assign mutual funds a style, I follow Daniel et al. (1997) and Wermers (2003) in assigning mutual funds to one of 125 holdings-based style portfo-

[1] The effective spread is 2[Execution Price-.5(Bid+Ask)].

[2] `http://people.stern.nyu.edu/jhasbrou/Research/GibbsCurrent/gibbsCurrentIndex.html`

lios. Russ Wermers provides yearly assignments to each stock in CRSP for the following three categories: size, book-to-market, and momentum (5 categories each).[3] Fund-level size is calculated as the value-weighted sum of size assignment of the holdings in the previous quarter, weighted by the portfolio weight of the stock in the previous quarter. Fund-level book-to-market and momentum are calculated analogously.

Table 2 presents medians of holdings-based measures, by year and by fund type (dual, institutional-only, or retail-only). By both measures of liquidity, dual funds have the most liquid holdings. The Amihud measure shows that dual funds have the most liquid holdings, as compared to both institutional and retail. Surprisingly, the retail-only fund has higher values than the institutional-only fund. Obizhaeva (2008) shows that the transactions in larger stocks are associated with a lower effective spread but a higher price impact. A potential explanation is that retail-only funds invest in larger stocks than institutional-only funds. The Hasbrouck measure also shows that dual funds have the most liquid holdings compared to the other two. The disagreement between the Amihud and Hasbrouck measures for institutional- and retail-only funds can be explained by the findings of Obizhaeva (2008) if it is true that retail-only funds invest in larger stocks than institutional-only funds. The holdings-based data also shows that dual funds are larger than retail-only funds, which are, in turn, smaller than institutional-only funds. Institutional-only funds hold more individual stocks than do dual funds, which hold more than retail-only funds.

[3] The DGTW benchmarks are available via `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`.

3 Empirical Strategy

The goal of this research is to determine how mutual fund managers respond to a change in clientele. I first show that there is a relationship between fund characteristics and my measure of clientele. I then investigate how extreme changes in the clientele measure affect the relative performance of the fund.

The first set of tests examines the relationship between fund characteristics and the $i2r$ measure of clientele. I run regressions of the following general form:

$$\text{Fund Characteristic}_{i,t} = \alpha_i + \beta\ i2r_{i,t-n} + \gamma\ \text{Controls}_{i,t-n},$$

where i is a dual-class fund, t is the observation quarter, and n is the number of lags. The specific left-hand side fund characteristics that I consider are the Amihud illiquidity measure, the Hasbrouck liquidity measure, the three fund-level DGTW characteristics, and the number of stocks. The main variable of interest is $i2r$. This variable is lagged for several reasons. First, the hypothesis is that the fund manager reacts to this by changing the holdings. While the manager may initially react by holding more cash, the expected equilibrium is that the manager will invest in more liquid equities.

Further, i2r is calculated from the quarter-end TNA values. Two funds may report the same i2r at the quarter end but may have had quite different clientele for the majority of the quarter. For example, assume that fund one had an influx of retail investors on the second day of the quarter and fund two experienced an influx of investors on the last day of the quarter. The quarter-end $i2r$ measure of both of these funds is the same, though it is likely that the manager of fund one had already started to shift holding characteristics. One way to mitigate this problem is to calculate rolling averages of i2r levels, though I leave this for a future version of this paper. For these regressions, I use the quarter-to-quarter percentage change in fund $i2r$.

For all regressions, I control for the age of the fund, and two lags of the dependent variable. Each regression includes fund fixed-effects and standard errors are clustered by fund style. For the two liquidity measures, the coefficients are in the correct direction and are statistically significant. Because the observations are not independent, the standard errors are clustered by fund style. By doing so, I assume the the errors are independent across fund styles. This series of regressions only consider dual funds since those are the only funds that have a measure of $i2r$. Results are in Table 3.

For the two illiquidity measures, the coefficients are in the correct direction and are statistically significant at the 1% level. The economic meaning of the first regression is that, for a one-standard deviation increase in institutional investors, the Amihud illiquidity measure increases by 0.01%, which is 1% of a standard deviation. While an increase in institutional investors does decrease the liquidity of the fund (as measured by the Amihud measure), the economic impact is quite small. For the Hasbrouck measure, a one-standard deviation increase in institutional investors leads to a decrease in liquidity of 0.34, which corresponds to 0.4% of a standard deviation. Again, the economic impact is quite small. However, both of these regressions do show that mutual fund holdings become more liquid after the clientele shifts toward retail investors. Additionally, the coefficient on the age of dual-class fund means that the longer the dual-class fund is around, the more liquid the holdings become. For both liquidity measures, the coefficients are statistically significant at the 1% level, though the economic impact is an order of magnitude smaller than that of the $i2r$ measure, which means there is very little economic effect of fund age on holdings characteristics.

3.1 Extreme Event Analysis

To determine how fund managers react to a change in the proportion of investors in a fund ($\Delta i2r$), I only examine events where there is a significant change in this ratio. I follow Coval and Stafford (2007) and define an event by looking at the distribution of $\Delta i2r$ over all observations. I define an up event as a $\Delta i2r$ in the 90th percentile or above and a down event in the 10th percentile or below. Additionally, events are defined over the distribution of the percentage change of $i2r$ instead of the absolute change. Regardless of the specification, the events account for approximately 7% of the sample. When a retail-only (institutional-only) fund launches a institutional (retail) class, there will be a large change in $i2r$. In terms of the reaction of the mutual fund manager, it is reasonable to think that the creation of a new class is a different type of event than an unanticipated change in the $i2r$. To allow for this possibility, two additional event indicators are created by ignoring the first two or four quarters after the introduction of a new class.

To determine if the returns of a dual fund become more like those of a institutional- or retail-only fund after an event, dual funds are assigned two benchmarks—an institutional-only and retail-only benchmark. Benchmarks are assigned by matching the fund style (DGTW characteristics) and then picking the fund with the closest size. Benchmarks are assigned in a given year and held fixed for the rest of the sample. The following regression is then run:

$$\text{Dual Return}_{i,t} - \text{Benchmark Return}_{i,t} = \alpha_i + \beta_1 \text{ Up Event}_{i,t} + \beta_2 \text{ Down Event}_{i,t}$$

. Fund fixed effects are included, and the standard errors are clustered by fund style. Each dual fund has two benchmarks (retail-only and institutional-only), so the above regression is run twice—once for each set of benchmarks. The predicted signs on the event coefficients are opposite in these two regressions. The particular event specification that is used ignores the first two quarters that a dual fund exists, and is based on percentage changes in $i2r$. After an up event occurs, the dummy is set to one for the next eight quarters and then is reset to zero. The same is done for the down event dummy. The first regression uses benchmarks that were assigned based on fund characteristics in 1998. The second regression uses benchmarks that were assigned based on fund characteristics in 1999 and includes only observations in 1999 onwards. Additional regressions are performed in an analogous manner, benchmarking yearly through 2008.

The top panel of table 5 shows the results from benchmarking the dual funds against the institutional funds. Following an extreme up event (an increase in the proportion of institutional investors), the hypothesis is that the distance between the dual fund and its institutional-only benchmark will decrease, as the dual fund acts more like an institutional-only fund. Similarly, an extreme down event means that the proportion of institutional investors decreases, making the fund less like an institutional fund. This coefficient should be positive. For institutional benchmarks, the direction of the signs is correct for every year through 2005, though the coefficients are not always statistically significant. Given the reduction in sample sizes and the relatively short period of time over which fund managers have to react, not many conclusions can be drawn from the low statistical significance for years after 2005. The bottom panel of table 5 shows the results from benchmarking the dual funds against the retail funds. For the events when the proportion of institutional investors decreased, many of the coefficients have the wrong sign. Specifically, when dual funds experience a decrease in the proportion of institutional investors, the distance between the dual fund and the retail benchmark actually increases, which is the opposite of what is expected.

Future work will try to determine the relationship between other fund characteristics, like cash holdings and tracking error, with the fund's clientele. The summary statistics from the sample suggest that institutional-only funds and retail-only funds have different characteristics. By looking at funds where both investors are present, it is possible to determine how the mutual fund manager reacts to changes in clientele. The first set of tests show that there is a relationship between the liquidity of the holdings and the clientele, and the second set of tests show that, following extreme increases (decreases) in institutional clientele, dual fund returns become more like (less like) the returns of the institutional-only funds.

4 Conclusion

Using a SEC rule change that led to a change in the organization of mutual funds, I test whether mutual fund managers react to changes in the type of investor—retail or institutional—in their fund. Prior research has established that these two groups of investors behave differently, especially in terms of flow characteristics. I document that the proportion of institutional investors to retail investors in dual funds has decreased over time. To react to changes in clientele, I show that fund managers change the composition of their portfolios to be more liquid. I also test whether extreme changes in clientele cause a fund to behave more like a single-class fund and find mixed support.

5 Figures and Tables

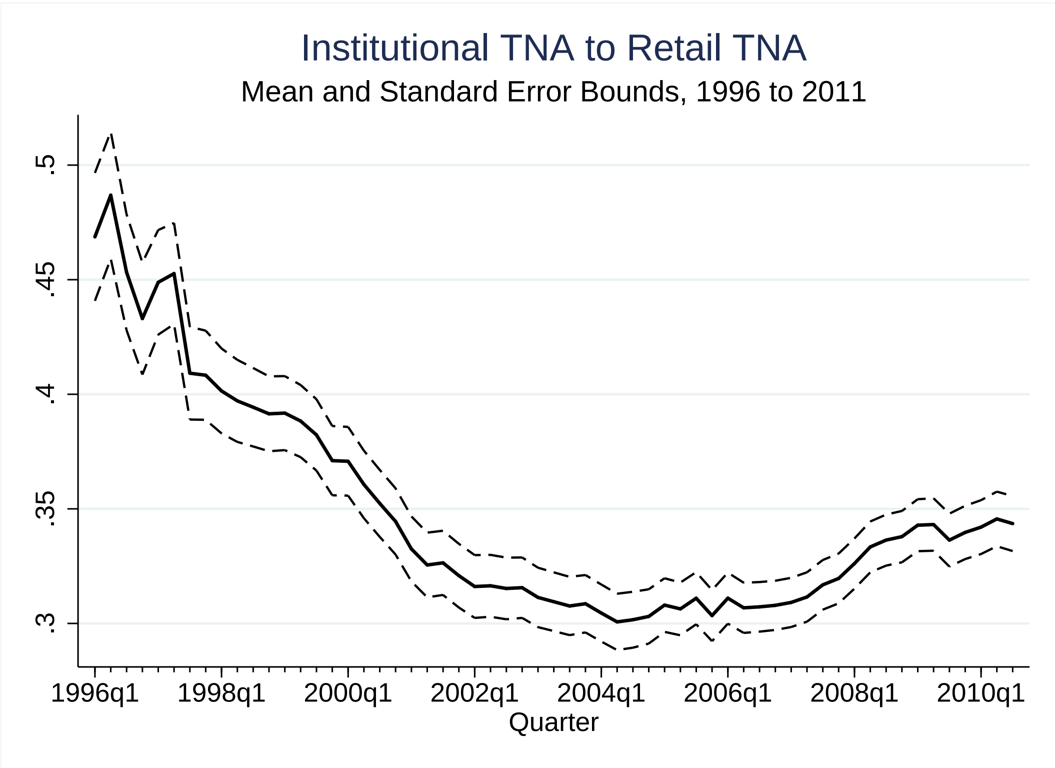

Figure 1: Mean Ratio of Institutional to Retail TNA

Table 1: Observations

Panel A: Base Sample Composition

Year	Dual		Institutional Only		Retail Only		Total Funds
	N	% of Sample	N	% of Sample	N	% of Sample	N
1998	135	19.5%	124	17.9%	432	62.5%	691
1999	661	27.9%	219	9.2%	1,492	62.9%	2,372
2000	709	27.0%	239	9.1%	1,677	63.9%	2,625
2001	720	27.2%	218	8.2%	1,706	64.5%	2,644
2002	758	28.3%	198	7.4%	1,723	64.3%	2,679
2003	802	30.3%	199	7.5%	1,648	62.2%	2,649
2004	851	32.3%	214	8.1%	1,566	59.5%	2,631
2005	912	35.3%	194	7.5%	1,481	57.2%	2,587
2006	961	38.2%	193	7.7%	1,361	54.1%	2,515
2007	946	38.5%	206	8.4%	1,307	53.2%	2,459
2008	910	39.0%	197	8.5%	1,224	52.5%	2,331
2009	849	38.9%	179	8.2%	1,153	52.9%	2,181
2010	759	38.2%	150	7.5%	1,080	54.3%	1,989

Panel B: Matched Sample Composition, Fund-Quarter Observations Per Year

Year	Dual		Institutional Only		Retail Only		Total
	N	% of Sample	N	% of Sample	N	% of Sample	N
1998	287	17.2%	347	20.8%	1,036	62.0%	1,670
1999	2,320	29.1%	638	8.0%	5,022	62.9%	7,980
2000	2,465	29.2%	729	8.6%	5,262	62.2%	8,456
2001	2,643	29.3%	713	7.9%	5,657	62.8%	9,013
2002	2,776	29.9%	605	6.5%	5,902	63.6%	9,283
2003	2,873	31.1%	614	6.7%	5,744	62.2%	9,231
2004	3,093	33.5%	664	7.2%	5,486	59.4%	9,243
2005	3,311	36.3%	621	6.8%	5,186	56.9%	9,118
2006	3,382	38.6%	578	6.6%	4,798	54.8%	8,758
2007	3,335	39.1%	644	7.5%	4,558	53.4%	8,537
2008	3,251	39.6%	616	7.5%	4,349	52.9%	8,216
2009	2,930	39.0%	532	7.1%	4,045	53.9%	7,507

Table 2: Median Holdings-Based Characteristics, by Year

Year	Amihud Illiquidity (VW Holdings Prev 12 Mos)			Hasbrouck Liquidity (VW Holdings Prev 12 Mos)			Fund TNA (CRSP, millions)			Size, VW Holdings (1=small, 5=large)		
	Dual	Inst	Retail	Dual	Inst	Retail	Dual	Inst	Retail	Dual	Inst	Retail
1998	0.0023	0.0041	0.0028	67.9	71.9	75.6	147	205	88	3.91	3.66	3.91
1999	0.0020	0.0019	0.0033	85.8	72.1	75.6	287	63	108	3.80	3.78	3.61
2000	0.0011	0.0013	0.0019	101.5	86.3	89.0	351	85	127	3.82	3.89	3.59
2001	0.0010	0.0011	0.0017	114.1	92.0	98.1	309	81	93	3.98	3.95	3.80
2002	0.0009	0.0013	0.0015	120.4	98.1	104.2	260	82	75	4.05	3.96	3.84
2003	0.0009	0.0014	0.0016	117.0	80.2	98.7	277	77	83	3.84	3.71	3.67
2004	0.0006	0.0008	0.0010	140.4	80.5	117.3	331	83	118	3.85	3.57	3.62
2005	0.0005	0.0006	0.0007	158.5	90.0	133.9	338	98	136	3.82	3.52	3.63
2006	0.0004	0.0005	0.0006	169.0	96.2	149.2	415	132	142	3.56	3.35	3.40
2007	0.0004	0.0004	0.0005	182.6	112.4	165.2	435	142	168	3.54	3.40	3.38
2008	0.0004	0.0005	0.0006	171.5	113.7	159.3	318	113	133	3.57	3.40	3.44
2009	0.0008	0.0011	0.0012	144.5	92.2	131.5	285	122	126	3.72	3.62	3.62

Year	Book-to-Market, VW Holdings (1=low,5=high)			Momentum, VW Holdings (1=low, 5=high)			Number of Stocks in Holdings		
	Dual	Inst	Retail	Dual	Inst	Retail	Dual	Inst	Retail
1998	2.35	2.19	2.34	2.82	2.77	2.87	78	101	70
1999	2.21	2.17	2.19	2.74	2.69	2.72	90	84	71
2000	2.09	2.07	2.06	3.07	2.99	2.99	92	91	74
2001	2.14	2.10	2.09	2.85	2.86	2.82	95	93	73
2002	2.23	2.21	2.17	2.48	2.55	2.45	96	96	74
2003	2.12	2.09	2.12	2.43	2.51	2.40	93	104	73
2004	2.26	2.25	2.27	2.87	2.90	2.83	91	109	74
2005	2.27	2.25	2.26	2.68	2.67	2.66	83	101	71
2006	2.18	2.18	2.16	2.55	2.53	2.48	81	103	73
2007	2.17	2.16	2.11	2.58	2.61	2.53	82	110	72
2008	2.28	2.21	2.22	2.71	2.67	2.61	81	114	68
2009	2.21	2.15	2.17	2.75	2.79	2.72	83	117	69

Table 3: Regressions

VARIABLES	(1) amihud_avg_p12m_vw	(2) hasbrouck_avg_p12m_vw	(3) size_vw	(4) bm_vw	(5) mom_vw	(6) nstocks
L2.d1i2r_pct	7.22e-06***	-0.0172***	-0.000258*	1.41e-05	-0.000351***	-0.00331
	(1.01e-06)	(0.00603)	(0.000137)	(8.34e-05)	(0.000112)	(0.00224)
i2r_tenure	-6.75e-07***	0.00384***	1.01e-05*	1.50e-05***	-1.21e-05	-0.00147***
	(2.06e-07)	(0.000658)	(5.52e-06)	(5.08e-06)	(1.01e-05)	(0.000537)
L.amihud_avg_p12m_vw	0.851***					
	(0.0685)					
L2.amihud_avg_p12m_vw	-0.117					
	(0.0739)					
L.hasbrouck_avg_p12m_vw		1.032***				
		(0.0510)				
L2.hasbrouck_avg_p12m_vw		-0.188***				
		(0.0520)				
L.size_vw			0.779***			
			(0.0463)			
L2.size_vw			0.0113			
			(0.0328)			
L.bm_vw				0.724***		
				(0.0403)		
L2.bm_vw				0.0494*		
				(0.0280)		
L.mom_vw					0.698***	
					(0.0249)	
L2.mom_vw					-0.0443*	
					(0.0257)	
L.nstocks						0.716***
						(0.0763)
L2.nstocks						0.0993
						(0.0739)
Constant	0.00262***	13.59***	0.741***	0.460***	0.949***	22.84***
	(0.000714)	(1.477)	(0.188)	(0.0620)	(0.0869)	(4.269)
Fixed Effects	Fund	Fund	Fund	Fund	Fund	Fund
Clustered SE	Style	Style	Style	Style	Style	Style

Table 4:

VARIABLES	(1) ret_diff_98inst	(2) ret_diff_99inst	(3) ret_diff_00inst	(4) ret_diff_01inst	(5) ret_diff_02inst	(6) ret_diff_03inst	(7) ret_diff_04inst
event_up_pct4q_fwd8	-0.00111	-0.00514	-0.00625	-0.0220***	-0.0117	-0.0157***	-0.00485*
Predicted: −	(0.00982)	(0.00681)	(0.00564)	(0.00663)	(0.00895)	(0.00493)	(0.00271)
event_down_pct4q_fwd8	0.0145	0.0174**	0.0189**	0.0103	0.00350	0.0106**	0.00223
Predicted: +	(0.0102)	(0.00723)	(0.00853)	(0.00628)	(0.00482)	(0.00492)	(0.00405)
Constant	-0.00195**	-0.00165**	-0.00134	0.000749	-0.00414***	-0.00340***	-0.00208***
	(0.000858)	(0.000801)	(0.000830)	(0.000812)	(0.000961)	(0.000509)	(0.000383)
Observations	2,471	2,322	2,014	1,649	1,522	1,282	1,086
R-squared	0.041	0.028	0.053	0.071	0.052	0.075	0.053

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) ret_diff_98rtl	(2) ret_diff_99rtl	(3) ret_diff_00rtl	(4) ret_diff_01rtl	(5) ret_diff_02rtl	(6) ret_diff_03rtl	(7) ret_diff_04rtl
event_up_pct4q_fwd8	-0.00847	-0.0107	-0.00426	0.000394	-0.00265	-0.00358	-0.00145
Predicted: +	(0.00801)	(0.00846)	(0.00590)	(0.00785)	(0.00604)	(0.00581)	(0.00605)
event_down_pct4q_fwd8	0.0204	0.0147**	0.00851	0.00144	0.00198	0.0100	0.0145**
Predicted: −	(0.0121)	(0.00557)	(0.00507)	(0.00471)	(0.00658)	(0.00968)	(0.00588)
Constant	0.000639	0.00375***	1.74e-05	-0.00126	-0.00178*	-0.00162*	-0.00181**
	(0.00134)	(0.000874)	(0.000841)	(0.000779)	(0.000893)	(0.000951)	(0.000777)
Observations	2,586	2,368	2,196	1,897	1,778	1,514	1,279
R-squared	0.027	0.043	0.042	0.048	0.041	0.035	0.053

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) ret_diff_05inst	(2) ret_diff_06inst	(3) ret_diff_07inst	(4) ret_diff_08inst
event_up_pct4q_fwd8	-0.000362	0.00138	-0.00658	-0.0167
Predicted: −	(0.00306)	(0.00449)	(0.00793)	(0.0130)
event_down_pct4q_fwd8	0.0140**	0.0146**	0.00844	0.0144
Predicted: +	(0.00585)	(0.00646)	(0.00751)	(0.00853)
Constant	-0.00139***	-0.00331***	-0.00256***	-0.000757
	(0.000373)	(0.000576)	(0.000518)	(0.00101)
Observations	923	717	562	443
R-squared	0.067	0.068	0.074	0.084

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) ret_diff_05rtl	(2) ret_diff_06rtl	(3) ret_diff_07rtl	(4) ret_diff_08rtl
event_up_pct4q_fwd8	-0.00564	-0.00725	-0.0103	0.00393
Predicted: +	(0.00663)	(0.00617)	(0.00655)	(0.0130)
event_down_pct4q_fwd8	0.00536	0.00316	0.00844	0.0248**
Predicted: −	(0.00569)	(0.00521)	(0.00724)	(0.0120)
Constant	0.000160	0.000841	0.000415	-0.00264**
	(0.000600)	(0.000635)	(0.000777)	(0.00119)
Observations	1,038	854	659	523
R-squared	0.048	0.052	0.051	0.073

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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