# The Mutual Fund Fee Puzzle

Michael Cooper, Michael Halling and Wenhao Yang *

**August 2015**

**Keywords:** mutual funds, fund fees, fund expenses, price dispersion, price persistence.

**JEL Classifications:** G10, G11, G23.

---

* Cooper and Yang are with the David Eccles School of Business, University of Utah. Halling is with the Stockholm School of Economics and the Swedish House of Finance. We thank Jack Bogle, Darwin Choi, James Choi (WFA discussant), Magnus Dahlquist, Amit Goyal, Joseph Halford, Rachel Hayes, Keith Jacob, Stephan Jank (discussant), Dong Lou (discussant), Veronika K. Pool (discussant), Jonathan Reuter, David Robinson, Norman Schuerhoff, Mark Seasholes, Laura Starks, Paul Tetlock, and Charles Trzcinka. We also thank participants of the CEPR ESSFM meetings (2011, asset pricing week), the Northern Finance Association Meetings (2011), the 12th FBI Symposium in Karlsruhe, the 2012 WFA meetings and seminar participants at Arizona State, HEC Lausanne, the Institute of Advanced Studies in Vienna, KAIST, Nanyang Tech University, the Shanghai Advanced Institute of Finance, the University of Arizona, the University of Colorado, the University of Montana, the University of California, San Diego, and VU University Amsterdam for their comments. An earlier version of this paper was titled "Violations of the Law of One Fee in the Mutual Fund Industry."

# The Mutual Fund Fee Puzzle

**Abstract**

We find economically large fee dispersion in the mutual fund industry, even after controlling for a comprehensive set of fund characteristics such as performance, activeness or risk exposures. This dispersion is not driven by small funds, as it is also substantial among the very largest funds (top quintile). It is also not driven by the early years of the sample; rather in contrast, dispersion measures show a tendency to increase until the late-90ties, to then stay at elevated levels until the recent financial crisis, and to only decrease slightly in most recent years. Further tests reveal that competition and frictions help explain expected fees but do not substantially lower fee dispersion. Interestingly, shocks to US household participation in the mutual fund industry significantly predict future increases in dispersion (and, to a lesser extent, in average fees).

## 1. Introduction

A large literature exists that attempts to explain why similar products sell for different prices. For example, Lach (2002) documents considerable price dispersion for similar refrigerators, chicken, coffee, and flour.[1] He concludes that because stores change their pricing on a regular basis, consumers cannot learn which stores are the low cost sellers, and as a consequence, price dispersion persists.

In the mutual fund markets, Elton, Gruber, and Busse (2004) document price dispersion of more than 2% per year for essentially identical S&P500 index funds. They conclude that a combination of the inability to arbitrage (i.e., one cannot short sell open-ended mutual funds) and uninformed investors is sufficient to have the law of one price fail in the S&P500 index fund market. Other research, focusing on sub-categories of funds, provides evidence of differential prices being charged for funds with similar characteristics.[2]

In contrast, other papers suggest that the mutual fund markets are more or less competitively priced. For example, Khorana, Servaes, and Tufano (2009) examine mutual fund fees in 18 countries and find that most of the cross-sectional dispersion in fees can be explained by economic variables, such as investment objective, sponsor, national characteristics, and levels of investor protection.[3] More recently, Wahal and Wang (2011) provide evidence that incumbents with high overlap in their portfolio holdings with entrants subsequently engage in price competition by reducing their management fees. In addition, they also find evidence that incumbents with higher portfolio overlap with entrants have lower future fund inflows. They conclude that the mutual fund market has "evolved into one that displays the hallmark features of a competitive market." Overall, while the existing literature provides

---

[1] See also Bakos (2001), Brown and Goolsbee (2002), Brynjolfsson and Smith (2000), Nakamura (1999), Pratt, *et al.* (1979), Scholten and Smith (2002), and Sorensen (2000).

[2] See also Elton, Gruber, and Rentzler (1989) who find that public commodity funds exist that underperform the risk free rate, Christoffersen and Musto (2002) who find a wide dispersion in expenses across similar money market funds, and Hortacsu and Syverson (2004) who document fee dispersion within similar equity fund categories and within S&P500 index funds. There are also several papers that develop theoretical models of the mutual fund industry, including endogenous fee setting. Nanda, Narayanan and Warther (2000), for example, concentrate on the structure of mutual funds, i.e., on the combination of loads and fees; Das and Sundaram (2002) compare fulcrum fees to incentive fees. Pastor and Stambaugh (2010) use their model to study the aggregate size of the active management mutual fund market.

[3] See also Khorana and Servaes (2009) who examine determinants of mutual fund family market share. They document that fund families that charge lower style-adjusted expenses relative to other families and families whose expense ratios decline as the fund family size grows have higher market share. They also find that families whose expenses are above the mean increase their market share when they lower their expenses.

evidence of price dispersion in specific areas of the mutual fund market, there is little existing evidence on how widespread the phenomenon is or on how it has changed over time given the dramatic growth in the mutual fund market.

In this paper, we study the price dispersion among mutual funds and, specifically, investigate if similar funds, as measured by important fund characteristics, have roughly similar expenses. To do this, we examine the residuals from yearly, cross-sectional regressions of total annual expenses (i.e., annual operating expenses, including management fees and 12b-1 fees) on lagged fund characteristics, such as risk and performance characteristics, extent of active management, service levels, and fund size or age. On average, these regressions explain only about 28% of the dispersion in expenses, leaving a sizable unexplained dispersion in expenses. Specifically, we find that the average spread in residual expenses (between the 1st and 99th percentile) across all funds over the sample is 2.47%.

More interestingly, the dispersion in residual expenses has not decreased over time. In fact, the opposite is the case, as dispersion increased until the late-90ties, then stayed at high levels for some years and only showed a slight decrease in most recent years. In contrast, average fee levels – after increasing substantially until 2003 or so – did experience a noticeable decrease during the last 10 to 15 years. Importantly, our results hold for both the largest total net asset (TNA) funds as well as the smaller TNA funds; the average spread in residual expenses is 3.99% for the smallest quintile of TNA funds and is 1.77% for the largest quintile of funds. Our results are robust to multiple variations in the models used to estimate residual expenses, aggregation of share classes, the use of before-expense performance measures in estimating residual expenses, and the use of holdings data to identify similar funds.

We examine the implications of our findings for investors. Based on residual expenses, an investor purchasing the lowest expense funds would have earned compounded abnormal returns 84% higher than an investor purchasing the most expensive funds. If we do the same exercise using reported expenses (i.e., a fund's stated total annual expenses), the low fee investor would have been 162% ahead of the high fee investor. As a basis for comparison, the compounded differences in reported expenses (residual expenses) over the same period were 179% (147%). Thus, while the difference in abnormal returns between high expense and low expense funds is less than the cumulative difference in expenses, investors bear significant costs from investing in high expense mutual funds that are not recouped through higher performance of these funds.

One interpretation of our results on fee dispersion is lack of competition among mutual funds, consistent with Haslem, Baker and Smith (2006), Gil-Bazo and Ruiz-Verdu (2009), and Barras, Scaillet and Wermers (2010). In contrast, however, Wahal and Wang (2011) conclude that the mutual fund industry behaves like a competitive industry. To shed some more light on these differing results, we follow Wahal and Wang (2011) and create a fund-level competition measure based on holdings information. Consistent with their results and economic theory, we find some evidence that funds facing competition charge lower fees; however, controlling for competition in the fee regressions does not result in a substantial reduction of residual fee dispersion.

Finally, we investigate mechanisms that could potentially inhibit competition and boost dispersion. One such mechanism relies on the existence of frictions such as search costs or barriers to exit from funds. We define empirical proxies for these frictions and find strong and statistically significant evidence that they matter for expected fees – funds that seem to engage in randomization of fee changes and funds that make it costly for investors to exit are able to charge higher fees. Interestingly and surprisingly, however, controlling for these factors in the fee regressions does not reduce the spreads in residual fees.

Another mechanism that prevents competition and should increase fee dispersion is based on the existence of investor clienteles. Here we follow Christoffersen and Musto (2002) and Gil-Bazo and Ruiz-Verdu (2008) who argue that performance-sensitive investors withdraw assets from poorly performing funds leaving only performance-insensitive investors as holders of the funds' shares; in response, poorly performing funds tend to increase their fees. We find no support for this mechanism in our sample. Alternatively, we investigate whether the time-series dynamics of fee dispersion and average levels of fees are related to the participation of retail investors in the mutual fund industry. We find strong evidence that this is the case: positive shocks to the participation of retail investors resulted in subsequent increases in fee dispersion and average levels of fees.

The above results seem puzzling to us. While average fee levels have decreased in recent years, consistent with competition working well, levels of fee dispersion are still at economically large levels suggesting that competition does not work that well. Similarly, while our proxies for frictions help explain fees, they have only a negligible impact on fee dispersion. Maybe our proxies are not capturing the corresponding frictions well or we are missing important frictions in our analysis.

Alternatively, if one takes it as a given that the mutual fund markets are in a competitive equilibrium, then our finding of a large dispersion in prices for similar funds still represents a puzzle: what mutual fund product characteristics, missing from our analysis, can explain such large spreads in fees? Stated differently, what omitted product characteristics can be so important to investors that they are willing to lose 84% or more of the future value of their portfolio?

We see the broader contribution of this paper as threefold. First, we show that the S&P 500 index fund price dispersion effects documented in Elton, Gruber, and Busse (2004) and Hortacsu and Syverson (2004) extend to the entire US equity fund industry. We find that the spread in prices among similar funds is pervasive across investment styles, institutional and non-institutional funds, and for small and large TNA funds. In addition, despite enormous industry growth, the effect has not diminished much over time. Second, the heterogeneity of funds in our sample, relative to prior work in this area using index funds, allows us to test a rich set of hypotheses to explain fee dispersion, resulting in a deeper understanding of how funds set fees. Finally, we show important investor welfare effects that are industry wide and not just applicable to small subsets of funds.

The remainder of the paper is organized as follows. In Section 2 we describe the data used in our analysis and describe the characteristics of high and low expense funds. In Section 3 we present results that document price dispersion in the residual expense distribution of funds and perform tests to quantify the economic effects of expense dispersion for fund investors. In Section 4, we test various hypotheses to explain the residual expense dispersion of funds. Section 5 concludes.

## 2. Data

### 2.1 Sample Construction

The sample selection follows Pastor and Stambaugh (2002). Accordingly, we select only domestic equity funds and exclude all funds not investing primarily in equities such as money market or bond funds. In addition, we exclude international funds, global funds, balanced funds, flexible funds, and funds of funds. The ICDI classification codes that were used by Pastor and Stambaugh (2002) are, however, no longer available. Thus, we follow Bessler et al. (2008) who use a combination of Lipper codes, Wiesenberger codes and Strategic Insight codes to identify domestic equity funds. Table A in the Data Appendix lists the specific codes that we use to identify the funds in our sample.

In short, the above screens result in our sample focusing on active and passive US domestic equity funds. Our sample includes approximately 38% of all funds covered in the CRSP Mutual Fund Database (our sample consists of a total of 20,926 funds while the CRSP Mutual Fund Database universe has approximately 55,109 funds). As measured by total net assets, our sample covers approximately 42.5% of the cumulative net assets represented in the database. The sample period spans 1966 to 2014 and the data frequency is yearly, as we focus on fund expenses.

### 2.2 Descriptive Statistics

Table 1 Panel A reports summary statistics of our fund sample. Details of the variable construction can be found in Table B in the Data Appendix. Throughout the paper we distinguish between a pre-1999 (up to and including 1998) and a post-1999 (including 1999) sample because several important variables such as fund family information (i.e., information on management companies) and flags for institutional funds only became available in the CRSP Mutual Fund Database in 1999.

The descriptive statistics show the dramatic increase in mutual funds over the past 30 years. In the pre-1999 sample the mean number of funds per year is 1051, while it increases to 7931 in the post-1999 sample. Note that the mean fund size (*TNA*) also increases from 361 Million USD pre-1999 to 530 Million USD post-1999. Thus, the mutual fund industry has experienced a considerable increase in assets under management.

Intuitively, given more funds and thus presumably increased competition, we would have expected to find that the rapid expansion of the mutual fund industry was also accompanied by a decrease in average expense ratios – but this is not the case.[4] Average annual expense ratios (*expense ratio*) increased from 121 basis points (bps) to 138 bps. It is also interesting to observe that yearly changes of expense ratios (*Δ(expense ratio)*) are on average close to zero. This is mostly driven by the fact that, on average, a similar fraction of funds increases and decreases their fees, namely 32% and 33% of all funds in a given year, respectively. Thus, if we remove the signs of the fee changes and calculate the time-series average of cross-sectional mean *absolute* fee changes, we find that it corresponds to 22 basis points; a relatively large number in economic terms.

The average performance of our sample funds, as measured by annual four-factor alphas (Carhart (1997)), is negative (-1.4% in pre-1999 and -1.2% in post-1999), consistent with Carhart (1997) and others who show that funds do not earn positive abnormal returns net of expenses. The average fund, over both time periods, has a market beta (*beta_mkt*) that is slightly less than 1, a small, negative exposure to HML (*beta_hml*), and small positive exposures to SMB (*beta_smb*) and UMD (*beta_umd*). After 1999, funds load more on the market, and less on SMB, HML, and UMD, consistent with an aggregate strategy shift to market indexing. The four-factor model works very well on average in explaining fund returns, yielding $R^2$ of 78% and 87%, in the pre and post-1999 periods, respectively.

Panel B (pre-1999 sample) and Panel C (post-1999 sample) of Table 1 report summary statistics by expense ratio deciles. Each year we split all funds into deciles by their expense ratios and then report contemporaneous means and standard deviations of fund characteristics.

Average expense ratios (*expense ratio*) of decile 10 exceed those of decile 1 by roughly 230 bps, in both the pre-1999 and post-1999 periods. In the pre-1999 sample, average expense ratio changes are most negative (-14 bps) in decile 1 and most positive (42 bps) in decile 10. These mean changes become smaller in the post-1999

[4] The averages reported in Table 1 are equal-weighted. If we value weight the expenses, we find a slight decrease from pre to post-1999. In this case, the corresponding values are 87 bps for pre-1999 expenses and 78 for post-1999 expenses. Figure 6 shows the complete time-series dynamics for value-weighted average fees.

sample: funds in the bottom expense ratio decile decrease their expenses on average by 1 bps in the same year, while funds in the top decile increase their expenses on average by 6 bps in the same year.

All of the fund performance variables decrease by expense ratio deciles. The spread in yearly four-factor Carhart alphas, for example, equals 2.0% pre-1999 and 1.8% post-1999, which is comparable to the spread in expense ratios, especially post-1999. Thus, these simple descriptive statistics suggest that funds with higher expense ratios on average underperform their cheaper competitors by approximately their expense ratios.

We also find that average fund size (*TNA*) in decile 1 is much larger than average size in decile 10, suggesting that economies of scale play a role for expense ratios. The average size in decile 1 is approximately 1.9 Billion USD larger in both the pre-1999 and post-1999 periods than the average size fund in expense ratio decile 10. We also find a greater concentration of fund families (*Family dummies*) in the lower expense deciles, although there are a non-trivial number of funds that belong to large fund families that reside in the higher expense deciles. For example, 57% of the funds in expense decile one are funds that belong to a fund family with more than 100 funds and 46% in expense decile ten are funds that belong to a fund family with more than 100 funds.[5] Moreover, we also find a greater concentration of institutional funds (*Institutional dummy*) and ETFs (*ETF dummy*) in the lower expense deciles.

Finally, Panel D of Table 1 shows pooled correlations between fund characteristics. These correlations are consistent with our previous interpretations of patterns between expense ratio deciles and other fund characteristics. In general, none of these correlations seem to be high enough to cause worries about multi-collinearity problems in the subsequent multivariate analysis.

Of course, the most important limitation of this univariate analysis from Table 1 is that it ignores that expense ratios may reflect different fund strategies and characteristics. This is something that we will explore in more detail in later sections of the paper. These simple summary statistics, however, already suggest that to some extent, expense ratios can be explained by economic determinants. For example, funds' risk characteristics seem to be

[5] In later cross-sectional tests we find that large families charge greater expenses.

correlated with expense ratios: more expensive funds tend to exhibit higher absolute loadings on standard risk factors (i.e., on MKT, SMB, and UMD). Similarly, the average $R^2$ of the four-factor model decreases as we move from decile 1 to decile 10, suggesting that the managers of the higher expense funds may be following "unique" strategies, likely in an attempt to outperform. However, these managers also trade much more (i.e., the *turnover* is much higher for the high expense funds relative to the low expense funds), which may contribute to their low return performance. Overall, these patterns between risk characteristics and expense ratios are intuitive and suggest that expensive funds do follow, at least to some extent, more active strategies, load more aggressively on individual risk factors, and implement strategies that go beyond the standard risk factors.

## 3. The Pricing of Mutual Funds

### 3.1 Residual Expense Estimation and the Pricing of Individual Fund Characteristics

Our goal is to compare prices (total expense ratios including management expenses and 12b-1 fees) across funds. Of course, not all funds are the same and differences in fund characteristics might justify price differences. Thus, we follow Lach (2002) and Sorensen (2000) to control for fund heterogeneity. As controls we use the standard fund characteristics that have been shown to be important in determining fund expenses (e.g., see Gil-Bazo and Ruiz-Verdu (2009) and Wahal and Wang (2011)).

We regress fund expenses on lagged fund characteristics including performance and risk characteristics. As our set of explanatory variables changes over time (e.g., fund family information is only available after 1998), we estimate a cross-sectional regression each year. Another advantage of this specification is that it allows for changing relationships (i.e., time-varying coefficients) between fund characteristics and expenses. The residuals of these regressions can be interpreted as deviations of fund expenses from expected expenses given the set of characteristics used in the regression. Thus, using the residuals, we can compare prices across "identical" funds, under the assumption that we have controlled for the correct fund characteristics.[6]

[6] We don't claim to have the absolutely correct expense models. We are careful to include fund characteristics that should matter to the average investor. Many of these characteristics are related to fund performance – items that should be the first order determinants of fund expenses. Mutual funds are, after all, investment portfolios and (most likely) not solely consumption

In Table 2 we present the details of the yearly cross-sectional regressions used to estimate the residuals. The reported coefficients are time series averages of cross-sectional regression coefficients obtained from the annual cross-sectional regressions. We estimate these models separately for the full sample and for the largest and smallest quintile of annually-ranked TNA funds. We also standardize the independent variables to have a mean of zero and a standard deviation of one. The standardized coefficients, thus, allow us to discuss a fund fee price estimate for a one standard deviation change in each independent variable, and also allow us to rank the fund characteristics in terms of economic importance.

For the full sample in the pre-1999 period, the models explain approximately 24% of the variation in expenses; in the post-1999 period, the model explains 28%. The signs of the coefficients are mostly consistent with the literature: e.g., across the two periods we observe that better performing funds (*Annual return*), less volatile funds (*sdmret*), larger funds (*TNA*), younger funds (*fund age*), lower turnover funds (*turnover*), institutional funds (*Institutional dummy*), ETFs (*ETF dummy*), and funds with higher $R^2$ from the Carhart four-factor model have lower expenses. Across the pre- and post-1999 periods, we essentially see the same relationships, with the exception of some sign switching of the coefficients from the four-factor model.

In terms of economic importance or "pricing" of individual fund characteristics, we observe substantial variation across variables. In the following, we discuss the fund characteristics from most to least expensive according to the full sample results in the post-1999 period. Looking at the results for the full sample of funds, in the post-1999 period, the coefficient on the institutional dummy is -53.62, suggesting that fund investors pay an extra 54 bps for non-institutional funds on average. Also, investors pay 45 bps to be in non-ETF funds. Interestingly, these prices of the institutional or the ETF feature vary significantly across our sub-samples of smallest and largest funds. Specifically, it is roughly speaking twice as expensive to be non-institutional and non-ETF in the small than in the large TNA fund universe.

---

products, and thus it seems reasonable to judge their performance using metrics from the asset pricing literature. However, we also include service and other non-performance related characteristics in the expense models. In Section 3.6, we estimate fees differences for similar funds using a model free approach that uses fund holdings information.

Investors pay 34 bps to purchase an extra unit of fund standard deviation of return, which can probably be viewed as the price of buying a more active and less diversified fund. Interestingly, the price of a unit of standard deviation is essentially zero within the large TNA group, and is 69 bps for the small TNA group.[7] This pattern, however, is different in the pre-1999 sample where investors paid around 25 basis points for an extra unit of fund standard deviation within the large and the small TNA sample.

The prices for the R-square variable, with the idea that lower R-square signals a more active fund, also features an interesting pattern: 22 (10) bps more for a unit of lower R-square for the small TNA funds and only 6 (0) bps more within the large TNA funds in the post-1999 (pre-1999) sample period. Across all fund groups, investors also pay more for smaller TNA funds; 24 bps per unit of Ln(TNA) for the full sample, with little variation across fund groups, at least in the post-1999 period. Investors pay more for style exposure, but only for value/growth exposure, and not size, market, or momentum exposure. For example, the price of an extra unit of SMB beta is 20 bps for the full sample, but only 1 to 2 bps for the HML and momentum beta (with slightly larger prices for SMB, market, and momentum betas for the small TNA funds).

As far as the price that investors pay for fund performance are concerned, the results seem counter-intuitive because of the negative coefficient on lagged returns in the fee regressions. The negative sign, however, is consistent with Christoffersen and Musto (2002) and Gil-Bazo and Ruiz-Verdu (2008) who argue that as fund returns go down, performance sensitive investors exit the fund, leaving a majority of performance insensitive investors, for whom fund management then raises the fees (see Section 4.3 for a more detailed discussion of this mechanism). Fund investors pay 14 bps for a unit standard deviation of lower annual returns, and are much more willing to pay this for the small TNA funds (i.e., they pay 40 bps for a one-standard deviation worse performance within the small fund group). Importantly, past fund performance does not seem to be of first order importance for fund fees. At least, in terms of the absolute magnitude of its price it consistently does not rank among the top priced

[7] Interestingly, these estimates are quite comparable to the annual cost of active investing estimated by French (2008) who quantifies it to be 67 basis points.

variables, which are the institutional dummy, the ETF dummy, fund size, volatility of funds returns and beta with respect to the value factor.

Finally, for an extra unit of service (as measured by a fund belonging to a large family with 100 or more funds) investors pay 13 bps. This premium for service seems to mainly be concentrated within the large TNA funds (19 bps) and is much less for the small TNA funds (3 bps). Finally, small fund investors pay 60 bps more for an extra unit of standard deviation of fund age, but large TNA investors pay essentially zero for older or younger funds.[8]

### 3.2 Detailed Analysis of Fee Dispersion

Our main point of interest, the spread in residual expenses, is presented in Table 3 and in Figure 1. In the figure, each year we plot the residual expense spread between the 25$^{th}$ and 75$^{th}$, 10$^{th}$ and 90$^{th}$, and 1$^{st}$ and 99$^{th}$ percentile points of the distribution (note that the mean residual is zero by construction) and the reported expense spreads. We do this for the full sample and for the largest and smallest quintile of annually-ranked TNA funds.

Given the arguably comprehensive array of mutual fund characteristics that we include in our fee regressions, the residual expense figures are striking. Essentially, these figures show that there exist huge dispersions in expenses for similar funds across all years. For the full sample, the residual expense dispersion (between the 1$^{st}$ and 99$^{th}$ percentile) is large and variable in the 1970-1990 period, with spreads ranging between 2 and 4%. After 1990, the spreads stabilize at approximately 2.5%. Overall, as reported in Table 3, Panel A, the mean 1$^{st}$ to 99$^{th}$ percentile spread from the basic expense model for the full sample (see the first row labeled *Base-case*) is 247 bps. For the 25$^{th}$ to 75$^{th}$ and 10$^{th}$ to 90$^{th}$ percentile points of the residual expense distribution, the spreads are 62 and 124 bps, respectively.

[8] Given the rather vast literature on the lack of persistence in mutual fund performance (Carhart, 1997, and many others), some readers may view it as a mystery that these fund characteristics are priced, given that they do not reliably predict higher fund returns. Obviously, fund consumers are willing to pay for fund product characteristics that do not map into better performance. Confirming the previous literature on the lack of fund return predictability, in unreported results, we estimate Fama-MacBeth regressions of annual returns regressed on the full set of lagged fund characteristic from the Table 2 post-1999 sample. We find that most of the priced fund fee regression characteristics are not significant in the return regressions. In the return regressions, the most important variable, by far, is simply the lagged fund expense ratio; the t-statistic on lagged expenses is -5.0 for the full sample in the post 1999 period. Thus, the simplest way to identify a fund that is likely to be high performing fund in the future (relative to the universe of all funds) is to invest in one with low fees.

Figure 1 also plots the growth in TNA. We see a clear pattern of enormous growth in the fund industry, but no decrease in the residual expense spread. In fact for the largest funds, we actually see an increase in the residual spread: the average spread is approximately 0.5% to 1% pre-1990 and grows to an average of approximately 2% for the 1st to 99th percentile points in the post-1999 period, with similar patterns for the inner breakpoints of the distribution. We note that the largest quintile of funds represent 83.6% of the market value of our sample, illustrating that high residual fee spreads are not by any means confined to smaller funds.

In addition to fund size, we also split the sample into retail and institutional funds (note that we explicitly control for this fund characteristic in our base-case specification). Indeed, the literature (see Christoffersen and Musto (2002), Bris, Gulen, Kadiyala, Rau (2007) and others) has shown that institutional funds tend to have lower expenses and are presumed to be held by more sophisticated investors relative to retail funds. Thus, if holders of institutional funds are more educated about funds and have a greater influence on prices, it is possible that our results do not hold for institutional funds. In figure 2, we plot reported expenses and estimate residual expenses separately for both retail and institutional funds. The reported and residual spreads are indeed higher for retail funds, but we still see evidence of relatively large spreads in residual expenses for institutional funds (ranging from about 0.98% to 2.4%) with no clear trend of decreasing expense spreads in more recent years. Thus, our results also apply to institutional funds.

### 3.3 Economic Magnitude of Fee Dispersion

Next, we implement a simple ex-ante trading strategy that trades funds based on the residual expense distribution, illustrating the negative wealth effects of investing in similar, but higher expense funds.[9] We assume no taxes. For comparison purposes, we also report a similar strategy using reported expenses. We compute the returns to a trading strategy that buys funds in the bottom decile and sells funds in the top decile of expenses. We

[9] Of course, this is not an implementable strategy since one cannot short sell open-ended mutual funds.

rebalance these portfolios every year and compute the cumulative four-factor model alphas over the 49 year sample period to equally-weighted portfolios.[10]

The results are reported in Table 4 and Figure 3. Interestingly, in Figure 3 (see the upper right hand graph – for the "All Funds" sample and the residual expense ratios) and in Table 4 Panel A, we observe that from 1968 to 1973, investors actually benefited (i.e., the strategy earned negative alpha, meaning that the high residual expense funds outperformed the low residual expense funds) from investing in higher residual expense funds, suggesting that managers of such funds were able to "earn their keep." Over the entire sample, from 1966 to 2014, based on residual expenses, an investor purchasing the lowest expense funds would have earned compounded abnormal returns 84% higher than an investor purchasing the most expensive funds. When we examine a similar strategy using reported expenses we see no evidence that managers "earn their keep" in the early part of the sample. In fact, over the entire sample, the low fee investors would have outperformed the high fee investors by 161%. We perform a similar trading strategy using just the annually ranked largest quintile of TNA funds. The results in Table 4, Panel B, and in the bottom row of Figure 3, are similar to the full sample; large TNA low-residual fee funds outperform large TNA high-residual fee funds by a cumulative four factor model abnormal return of 52% over the 49 year sample. Using reported fees, the abnormal return spread is even greater, at 190%. The cumulative alphas are never negative, so large fund managers never "earn their keep" within our sample.[11]

It is interesting to note that the abnormal return differences in Table 4 between high and low fee funds are quite persistent from year to year, especially after 1990, for both the reported expenses and the residual expenses. This seems to deepen the fund fee puzzle since this suggests that investors were likely to have known about these large

[10] We estimate the cumulative four-factor model alpha as follows. Using monthly returns from the annually rebalanced low-fee minus high-fee portfolio, we estimate the monthly 4 factor alpha each year and multiply it by 12 to obtain an estimate of the annual alpha. We then compound the annual alphas over time and report the cumulative alphas.

[11] We also estimate the monthly four-factor model alpha over the 1966 to 2014 period. To do this, we estimate a single time-series regression of the spread portfolio monthly returns on an intercept and the four factors. For the residual fee strategy, the alpha for all funds is 9 bps per month (t-statistic = 2.88) and the alpha for large funds is 8 bps (t-statistic = 2.62). For the reported fee strategy, the alpha for all funds is 14 bps per month (t-statistic = 3.62) and the alpha for large funds is 12 bps (t-statistic = 2.31). In the post 1999 period, the spreads are wider, especially for the large funds. Specifically, for the residual fee strategy, the alpha for all funds is 8 bps per month (t-statistic = 2.41) and the alpha for large funds is 11 bps (t-statistic = 3.95). For the reported fee strategy, the alpha for all funds is 16 bps per month (t-statistic = 3.78) and the alpha for large funds is 25 bps (t-statistic = 3.93).

wealth differences, yet their knowledge of these differences did not result in investors shifting their fund allocations enough to significantly affect residual fee spreads.

In Figure 3 and Table 4, we also report that the compounded differences in reported expenses (residual expenses) over the period were 179% (146%) for the full fund sample. Thus, while the difference in abnormal returns between high expense and low expense funds is less than the cumulative difference in expenses (with the exception for reported fee trading strategy based on large sample), investors bear significant costs from investing in high expense mutual funds that are not recouped through higher performance of these funds.[12]

### 3.4 Robustness Tests: Fund Characteristics

In this section, we examine the robustness of our results to variations in the mutual fund characteristics used to estimate residual expenses. The first sets of robustness tests examine different fund performance measures. Our main results use lagged yearly returns, net of expenses, as our performance measure. Rows 2 to 5 of Table 3 show that our estimates of expense dispersion do not materially change if we also include a *persistence dummy* or if we measure performance in terms of abnormal returns (we look at four-factor alphas (*alpha*), the t-statistics of the four-factor alphas (*tstat alpha*) and *Carhart alphas*[13]), rather than raw returns.

All the performance measures discussed so far are based on after-expense returns. The motivation to focus on after-expense rather than before-expense returns is that investors, in the end, care about after-expense rather than before-expense performance. Nevertheless, Berk and Green (2004) and others suggest that there may exist a positive link between expense ratios and before-fee performance, as fund managers attempt to extract superior performance via fees. As a consequence, these papers suggest that there should be no or relatively little cross-fund variation in after-fee performance. If that is the case, then our specification using after-expense returns might miss the link between performance and fees. To address this concern, we calculate the same performance statistics as

---

[12] In contrast to our results, Ramadorai and Streatfield (2011) find little difference in performance across high and low management fees (i.e., the non-performance fee part of hedge fund expenses) for hedge funds. They conclude that high management fees are "money for nothing" in the hedge fund industry.

[13] The Carhart alphas use predicted four-factor model expected returns in estimating the pricing error. Please see the Data Appendix for details.

before but use before-expense returns. The mean spreads summarized in Table 3 (see rows 6 – 9 labeled "Before-expense") show that this does not affect our results; the residual expense dispersion remains qualitatively similar whether we use before-expense or after-expense returns. Next, we examine the robustness of our results to style fixed effects using a combination of Lipper codes, Wiesenberger codes and Strategic Insight codes (see Table A in the Appendix for details on the styles included in our sample). Row 10 of Table 3 shows that controlling for style fixed effects has very little impact on the spreads of the full sample and the size subsamples.

Finally, we analyze the level of expense dispersion for cases in which we vary the procedure used to estimate a fund's abnormal performance (four-factor alphas) and risk exposures (betas). Our main results are based on 3-year rolling-window regressions. The motivation is that via rolling windows we are able to capture time-variation in coefficient estimates. In contrast, however, it could be that by looking at relatively short windows of data we end up with noisy estimates of these fund characteristics that potentially inflate our measures of expense dispersion. To lessen this concern, we evaluate the following alternative estimation strategies: first, we replace our rolling-window estimates with expanding-window estimates (see rows 11 – 12 labeled "Expanding window") that exploit all information available up to a specific date; second, we replace all estimates of alphas and betas by 0 if they are not estimated precisely enough (i.e., if the absolute value of the t-statistic of any coefficient is below 3 – see row 13 labeled "Filtered alpha"); third, we use all available data per fund to estimate these parameters and then use these full-sample estimates at each point in time in our expense regressions (see rows 14 – 15 labeled "Full sample"). For all of these variations in how we measure fund performance, we do not see evidence in Table 3 of a noticeable reduction in the residual fee spreads.

### 3.5 Robustness Tests: Aggregation of Share Classes

In our main results we treat each share class as an individual fund. If share classes proxy for different distributional channels[14] or different investor clienteles, then different share classes of the same fund could (and

[14]Bergstresser, Chalmers and Tufano (2009) suggest a link between share classes and distribution channels.

often times do) have different expense ratios. Thus, we evaluate whether our levels of expense dispersion are driven by different share classes.

Share classes are not automatically identified within the CRSP Mutual Fund Database. We use the MFLINKS tables that are provided by WRDS for this purpose. The original idea of these tables is to link the funds in the CRSP Mutual Fund Database with the ones covered in the Thomson Reuters Mutual Fund Ownership Database. Our analysis in this section begins in March of 1980 since that is when the share class data starts. After identifying the individual share classes for a given fund, we aggregate the share classes (i.e., the expenses, returns, and other characteristics) into a common fund using equal and value weighting (using the total net asset values as weights). To avoid potential expense dispersion from share class aggregation, we also perform tests using the largest share class only for each fund. We re-estimate our main tests on these new, aggregated samples. Before discussing detailed expense dispersion results, it is interesting to look at some descriptive statistics regarding the use of different share classes in the mutual fund industry. First, we find that before 1995 it was very uncommon to have multiple share classes. Second, after aggregating multiple share classes into funds, we have on average more funds (798) with than funds without multiple share classes (542) each year. Third, the average size of funds without multiple share classes (approximately USD 548 million) is slightly smaller than the size for aggregated funds with multiple share classes (approximately USD 759 million using value-weighted aggregation).

Table 5 summarizes expense dispersion results for the full sample of funds (Panel A), the bottom size quintile (Panel B), and the top size quintile (Panel C) for the aggregated funds. Row 1 of each panel reports no share class aggregation results as a base case (using the basic expense models of Table 2 on the post 1980 sample) and rows 2-4 report results for the three aggregation methods. Overall, our results are robust to share class aggregation. Across different methods of aggregation, and for different size funds, we see low drops in residual expense spreads compared to the no-aggregation cases; the maximum drop in expense dispersion is 27 bps for the top quintile of funds using VW aggregation at the 1$^{st}$ to 99$^{th}$ percentile point.

Table 5 also re-emphasizes one of our previously discussed results that the spread in residual expenses has increased over time for the largest TNA-ranked funds. Comparing the values in Table 5 (1$^{st}$ row of Panel C) to the ones reported in Table 3 (again 1st row of each panel), highlights this point. Recall that the results in Table 3 use the entire sample period (1966 to 2014), while Table 5 only looks at more recent years (1980 to 2014). For the top quintile of funds, the percentage increase in residual expense dispersion in the recent period compared to the full period is approximately 22% for the 25th to 75th percentile points, 10% for the 10th to 90th percentile points, and 5% for the 1st to 99th percentile points.

Finally, Figure 4 compares the time-series dynamics of the residual expense distribution for our base-case (share class-level, 1st column) and the fund-level analysis (2nd column). For reasons of brevity we focus on the samples including all funds and largest funds. In general, the graphs look very similar across columns, documenting a minor impact of share classes on residual expense dispersion. Recall further that one of our key results is that expense dispersion does not decline over time; quite in contrast, it actually increases for the largest funds. The graphs clearly show that share class aggregation does not have a noticeable impact on this result.

### 3.6 Robustness Tests: Holdings Based Expense Differences

In this section, we explore a different approach for identifying similar funds. Instead of matching funds by multiple characteristics using linear regressions, we match funds using their holdings. This approach is inspired by Wahal and Wang (2011) who identify similar funds for their analysis based on holdings. One important advantage of this approach is that it is completely model-free; i.e., it does neither depend on the linear pricing framework nor on specific fund-expense models.

For each fund in our sample we obtain holdings information from the Thomson Financial CDA/Spectrum holdings database. This holdings database is linked with the CRSP mutual fund files using the MFLINKS file provided by Wharton Research Data Services. The sample starts in March of 1980 when the holdings information becomes available. To match funds in terms of holding we develop a pair-wise measure of fund overlap. We use a simple and intuitive measure, namely the sum, across all holdings, of absolute differences in weights for a given pair of funds. We deem this measure "uniqueness." The measure is bounded between zero (perfect overlap) and two (no overlap).[15] It is symmetric in the sense that the ordering of the funds does not matter.[16]

We calculate this measure yearly for all fund pairs (at the fund level, not at the share class level; to aggregate, we use the share class with largest TNA for a given fund). In total, the uniqueness measure is estimated for approximately 2.9 million pairs per year. For each fund, its matched fund is defined as the fund with the lowest uniqueness measure (i.e., the largest overlap in terms of holdings) in a given year. We refer to this sample of matched fund pairs as the "full pairs sample." We perform all our analysis for the full pairs sample and for pair sub-samples based on quintiles of the uniqueness distribution of matched fund pairs; i.e., based on the similarity in terms of holdings of the matched pairs. Thus, fund pairs in quintile one (five) are “most similar” (“least similar”) fund pairs. Note that “least similar” fund pairs are still relatively similar compared to the average of randomly drawn fund pairs. Finally, we also define “very similar funds" as the bottom decile of the uniqueness measure for the full pairs sample.

In Panel A of Table 6 we provide summary statistics on pair characteristics to provide a sense of how well the holdings algorithm performs in identifying similar funds. For each sample, we report the mean and interquartile range (IQR) for the uniqueness measure and the differences in average yearly returns (*Annual return*), four-factor model adjusted R-squared ($R^2$), and beta loadings on the four factors. The average uniqueness value for the full pairs sample is 1.05 with an IQR of 0.58. As we move from quintile five (i.e., “least similar funds) of uniqueness to quintile one (i.e., "very similar funds”) the mean of the uniqueness sorting variable decreases from 1.49 to 0.15. The differences in R-squareds, returns, and betas across fund pairs suggest that the uniqueness measure does a decent job identifying similar funds; all three difference metrics decrease as we move from less to more similar fund pairs.

[15] For example, consider two funds with holdings in only two stocks, A and B. If fund 1 holds 100% in A and 0% in B, and fund 2 holds 0% in A and 100% in B, then the uniqueness measure (the sum, across all holdings, of absolute differences in weights) is the absolute value of (1-0) plus (0-1) which is 2, resulting in the funds having no overlap. In contrast, if fund A and B both hold 100% in A and 0% in B, then the uniqueness measure is 0 (i.e., (1-1)+(0-0) = 0) signifying the same holdings.

[16] In contrast, the overlap measures used in Wahal and Wang (2011) are not symmetric: i.e., in their framework it matters which fund is the incumbent fund and which fund is the newly entering fund.

Next, we examine if funds with similar holdings charge similar expenses. In Panel B of Table 6, we report the absolute difference in reported expense ratios and residual expenses for matched pairs. The residual expenses are from our base-case expense regression models in Table 2. The expense differences are large: for the full pairs sample, the average reported expense difference is 49 bps, 54 bps for the inter-quartile range, 103 bps for the 10$^{th}$ to 90$^{th}$ percentile spread, and 219 bps for the 1$^{st}$ to 99$^{th}$ percentile spread. Expense spreads decrease monotonically from less similar funds to very similar funds, but are still economically large even for the very similar funds. For example, at the 1$^{st}$ and 99$^{th}$ percentile points, the quintile one uniqueness fund pairs have a 176 bps spread, and the very similar funds have a spread of 174 bps in reported expenses.

Thus, matching on holdings gives us qualitatively similar expense spreads as we get from the model-based residual expense spreads of Table 3. In fact, when we examine the model-based residual spreads for these matched pairs (as reported in the right-hand side of Panel B of Table 6), we see that the spreads decrease to some extent relative to the reported expenses (e.g., for quintile-one pairs spreads drop from 176 bps to 172 bps), consistent with the idea that controlling for fund characteristics has explanatory power on top of holdings, but including characteristics along with holdings still leaves a large unexplained spread in expenses.

In Figure 5 we plot the time-series of the annual distributions of reported and residual expense differences for the full pairs sample, most similar funds (i.e., the quintile one sample of uniqueness), and least similar funds (i.e., the quintile five sample of uniqueness). In addition, the plots also include the yearly average uniqueness value of the pairs included in each figure (solid line). Similar to the time series plots of the residual spreads in Figure 1, there is a lot of time series variation in these plots but only a slight drop in average expense differences in more recent years. In fact, for the most similar funds, we see evidence that despite becoming much more similar in terms of holdings (i.e., the average uniqueness represented by the solid line is decreasing, meaning that these funds become more similar over time), there is no commensurate drop in expense differences.

To conclude, the robustness tests show that the phenomenon of fee dispersion among US equity funds is strong and unaffected by different residual estimation methods, different ways of defining similar funds, and share class aggregation. Overall, our finding of large pricing differences for close-to-identical products across all US equity funds is a new finding with wide-spread implications for both fund investors and for our understanding of how prices are set in the mutual fund industry.

## 4. Discussion

### 4.1 Fee Dispersion and Price Competition

A potential interpretation of large levels of fee dispersion in the mutual fund industry is lack of price competition among funds (see among others Haslem, Baker and Smith (2006), Gil-Bazo and Ruiz-Verdu (2009), and Barras, Scaillet and Wermers (2010) to support this view). This interpretation, however, is at odds with other papers that argue that competition works well among funds. Most prominently, Wahal and Wang (2011) conclude that the mutual fund industry behaves like a competitive industry, as incumbent funds decrease their expenses when new funds with similar holdings enter the industry. To investigate these conflicting conclusions further, we extend their idea to all funds and construct a measure of competition per fund per year, aggregated from each fund's holdings overlap with all other funds available in a given year.[17]

More specifically, our competition measure is based on the pair-wise uniqueness measure introduced in section 3.5. To come up with a fund-level uniqueness measure (Fund Average Uniqueness) we calculate the simple average of a fund's pair-wise uniqueness measures with all other funds. This measure is constructed so that as it increases (i.e., average holdings with other funds become less similar), competition is assumed to decrease. A fund whose average uniqueness is close to two, has completely unique holdings and, thus, faces little competition. In contrast, a fund with a low average uniqueness measure has holdings that are similar to the holdings of many other funds and, thus, it is most likely exposed to substantial competition.

[17] As an alternative to matching on holdings, we identify competing funds as funds that have similar betas to a given fund. To estimate fund betas, we regress the time series of monthly returns for the fund against an intercept, MKT, SMB, HML and UMD using 3 years of data from year *t* to *t*-2. We require a minimum of 12 monthly returns to estimate the betas. Then we determine each beta's quartile and match funds if all four betas are in the same quartile of their respective distributions. Results from this strategy are not reported in the paper for reasons of brevity and are available from the authors upon request. However, these results are similar to the matching on holdings results.

Table 7, Panel A, reports summary statistics of fund average uniqueness across deciles of reported expense ratios. There is a monotonically decreasing relation between fund competition and reported expense ratios: as we move from low to high reported expense deciles, the fund average uniqueness increases. Next, we add the competition measure to the base-case expense models of Table 2. If the mutual fund industry behaves like a competitive market, in the sense of Wahal and Wang (2011), we expect funds that face more competing funds to have lower expenses; i.e., a positive coefficient on the competition measure. This is exactly what we find for the pre-1999 period (see Panel B of Table 7). However, for the post-1999 period (see Panel C of Table 7), the coefficient on fund average uniqueness turns out to be negative and insignificant suggesting that the mechanism became weaker during more recent years.

Panel D, finally, shows that controlling for fund average uniqueness has a moderate impact on the spreads of the residual expense distributions. For example, for the full sample of funds over the entire sample period, the drop in the residual expense spread is 11 bps at the 10$^{th}$ to 90$^{th}$ points. Interestingly, the reduction in spreads is somewhat more pronounced for the largest funds for which the 10$^{th}$-to-90$^{th}$ spreads drop by 25 basis points (or, 27% in relative terms).

Bottom line, we find some support for the competitive mechanism documented in Wahal and Wang (2011) in our sample, at least during the earlier years, as funds with more unique asset holdings tend to charge higher fees. Importantly, however, controlling for this variation in competition across funds does not substantially lower the dispersion in fees. One way to reconcile these results is to observe that there is an issue of magnitudes: a one standard deviation shock to our measure of competition corresponds to an expected increase in expense ratio by 3.6 basis points (see Panel B of Table 7); compared to the levels of fee dispersion, for example the 10-90$^{th}$ spread of 124 basis points, this is a tiny effect. Thus, while price competition seems to exist, it does not seem to be strong enough to narrow down fee spreads in any substantial way.

### 4.2 Fee Dispersion and Frictions in the Mutual Fund Industry

The results on competition raise another question; namely, what mechanisms might prevent price competition from taking place? One answer to this question is the existence of frictions in the mutual fund industry such as randomized fee changes (Varian (1980, Lach (2002)) or captive investors. The idea of randomized fee changes[18] is that they prevent investors from learning about the true prices of funds. To explore the importance of this friction, we create a random fee changes variable (*Random fee changes*) that is defined in the following way: for each fund and each year, we determine the fraction of positive and negative expense changes relative to all changes that we have observed for the fund since its first appearance in the CRSP Mutual Fund Database; then we use the minimum value as our variable, motivated by the idea that randomized pricing requires both increases and decreases of expenses (and not just unidirectional changes).

Panel A of Table 7 shows summary statistics of this proxy across reported expense ratio deciles. While we do not observe a monotonic pattern, we find more randomization of expenses in the top decile than in the bottom decile. If we include the proxy in our base case regression specifications, we find significantly positive coefficients pre-1999 (Panel B of Table 7) and post-1999 (Panel C of Table 7). Thus, after controlling for other fund characteristics, the influence of randomization on expenses is consistent with theory. An important question, however, is whether controlling for randomization results in a material reduction in residual expense dispersion. Panel D of Table 7 provides the corresponding results and shows that this is not the case.

The second friction that we consider is related to fund characteristics that inhibit easy investor exit from or switching across funds (e.g., rear loads or switching costs for pension products), thus creating captive investors. Ideally, one would like to condition directly on the existence of such features or the magnitudes of such costs but data availability is usually very poor in this respect. However, we conjecture that one implication of investor captivity is that flows into captivating funds will be highly auto-correlated. Thus, we estimate auto-correlation coefficients for the flows of each fund using the entire time-series of monthly flows and use these coefficients as a proxy for the level of captivity of investors. Additionally, we define a second variable, called "pension plans”, as funds in the top decile of the flow autocorrelation distribution.[19]

[18] If investors are less than fully aware of the expenses they pay, and given that fund expenses are typically subtracted daily from mutual fund net asset values, and not paid by the fund holder in one (presumably more salient) annual payment, it is plausible that funds could successfully engage in frequent switching of expenses without garnering the attention of fund holders.
[19] Empirical evidence on flow patterns of pension money is scarce. Sialm, Starks and Zhang (2014) study flow patterns of defined-contribution (DC) and non-DC money within the same funds and find that DC-money is not highly autocorrelated (due

Panel A of Table 7 reports the corresponding summary statistics across reported expense ratio deciles and shows that high expense funds have much more auto-correlated flows and a larger fraction of "pension plans" than low expense funds. This is clearly a desirable correlation from a fund manager's standpoint. Panels B and C report coefficient estimates for these variables if we include them in our base case expense regressions. Consistent with our expectations, we find positive and strongly significant coefficients, especially post-1999 (e.g., funds in the top decile of flow autocorrelations add, on average, another 11 bps to their expenses after controlling for the linear effect of flow autocorrelation on expenses and all other control variables). Surprisingly, however, we are not able to substantially reduce the level of residual expense dispersions (see Panel D of Table 7) using these proxies for captive investors.

Thus, we arrive at a similar conclusion as in the previous section on price competition: our results support the notion that frictions matter for fund fees, as both proxies for randomized fee changes and for captive investors are significant in the fee regressions; however, they do not help much in reducing or explaining the dispersion in fees.

### 4.3 Fee Dispersion and Investor Clienteles

As a last empirical test, we investigate whether clientele effects are able to explain the dispersion in fees. This is another potential mechanism that might prevent price competition. Specifically, we consider two types of clienteles, performance-insensitive investors and retail investors. Christoffersen and Musto (2002) and Gil-Bazo and Ruiz-Verdu (2008) show that performance-sensitive investors withdraw assets from poorly performing funds leaving only performance-insensitive investors as holders of the funds' shares. Funds respond to the fact that the fund flows of the remaining investors are not sensitive to fund performance by raising expenses. To evaluate whether this mechanism can help explain fee dispersion, we first estimate each fund's flow-performance sensitivity

---

primarily to plan sponsors' adjustments of plan investment options) and is sensitive to performance. Our results in this section are not dependent on fund flow autocorrelations signifying the presence of retirement plan investors; we view it as interesting in its own right that fund flow autocorrelations may be correlated with fees. An alternative story for a link between fund flow autocorrelations and fees is related to the "strategic fee setting hypothesis (SFSH)" discussed in the next section. In the SFSH, price insensitive investors fail to exit poorly performing funds and fund managers then raise the fees on these investors. Thus, it may be that a positive relation between flow autocorrelations and fees may be due to persistent fund flows being a good proxy for the presence of price insensitive investors. Finally, flow autocorrelations might also be driven by funds' marketing and advertising activities and expenses, which are included in our measure of total expenses.

(*Flow-perf sensitivity*) by regressing monthly flows on lagged monthly net-of-expense returns using an expanding window (with a minimum of 12 monthly observations). Because monthly TNA data is sparse in early years, we only calculate this proxy for our latter sample period. We then regress fund expenses on flow-performance sensitivity (and other controls) and expect to find a negative coefficient.

Panel A of Table 7 shows simple summary statistics of our flow-performance proxy across reported expense ratio deciles. Looking across deciles, we do not find a monotonic pattern. Also, comparing the most extreme expense deciles, we observe that the most expensive funds show higher flow-performance sensitivity estimates than the cheapest funds. Similarly, Panel C of Table 7 reports a positive and significant coefficient of flow-performance sensitivity in our standard expense regressions. Finally, in Panel D of Table 7 we examine if residual expense dispersion decreases once we control for flow-performance sensitivity and find no change.[20]

In our last empirical test we evaluate whether the fraction of retail investors investing in mutual funds plays a role in explaining the level of fund fees and their dispersion. The underlying idea is that retail investors are considered to be less skilled in picking funds and less informed about asset management. Unfortunately, we do not observe the fraction of retail investors invested in each fund. We only observe the overall fraction of retail investors, i.e., US households, participating in the mutual fund industry at the yearly frequency starting in 1980 from reports published by the Investment Company Institute (ICI 2014). Thus, we need to follow a different empirical strategy in evaluating the relevance of this variable.

Specifically, we run time-series regressions in which we use one of the following four, aggregated variables as dependent variable: (i) the equal-weighted average expense ratio, (ii) the value-weighted average expense ratio, (iii) the spread between the 90$^{th}$ and 10$^{th}$ percentile for reported expense ratios, and (iv) the spread between the 90$^{th}$ and 10$^{th}$ percentile for residual expenses. We run all these regressions using percentage changes of dependent and

[20] In unreported results, we evaluate the dispersion of residual fees after controlling for our standard controls and jointly for all variables introduced in this section, i.e., fund average uniqueness, randomization of fees, captivity of investors, and flow-performance sensitivity of investors, and find no noticeable differences to the existing results.

independent variables and lag the percentage change of US household participation in the mutual fund industry by one year. We focus on the full sample of funds and largest funds in this analysis.[21]

Table 8, Panel A, summarizes the descriptive statistics of the above variables in levels and percentage changes. Average US household participation in the mutual fund industry is 33% during the period 1980 to 2014 and increased, on average, by more than 7% every year. Interestingly, growth rates of average fees and fee spreads are all positive with the exception of value-weighted average fees for the full sample. Figure 6 provides a more detailed view on the dynamics of US household participation, value-weighted average fees and 90-to-10$^{th}$ percentile residual fee spreads. Roughly speaking, all series show a somewhat hump-shaped pattern peaking around 2000. US household participation stays at a relatively constant level of 45% afterwards while value-weighted average fees show a pronounced decrease over the last 15 or so years, resulting in slightly lower levels of average fees in 2014 than in 1980. Over the same period of time, dispersion in residual fees shows a flat or slightly decreasing pattern for the full sample of funds and a substantial reduction in spreads for largest funds. Nevertheless, in both cases levels of dispersion at the end of the sample, 2014, are noticeably higher than at the beginning of the sample shown in the figure, i.e., 1980.

These patterns further deepen the puzzle about mutual fund fees. On one hand, the substantial decrease in average fees that is particularly pronounced if we use value-weighting shows that capital tends to flow more into low-expense funds nowadays. This effect is also consistent with learning by investors and corresponding responses by the industry such as the rise of low-fee providers (e.g., Vanguard) and low-fee products. On the other hand, dispersion in reported and residual fees shows much weaker decreases recently and remains at historically high levels indicating that there is still a substantial fraction of capital invested in inefficient, high-fee funds. These patterns also imply that relative to average fees, the dispersion of fees has substantially increased recently. This is particularly true for largest funds: in the early 80ties the ratio of 90-10$^{th}$ spread in residual fees to value-weighted average fees was around 70% while it jumped to nearly 200% in 2014.

[21] In unreported results, we also control for additional macro-economic variables such as GDP growth or the business-cycle in these time-series regressions. As we find our main results unchanged, we decided to focus on the simple univariate regressions to make our point.

Panel B of Table 8 evaluates whether growth rates in US household participation help explain growth rates in average fees and fee dispersions using simple, univariate time-series regressions. In the case of all funds, we find positive coefficients on household participation across all dependent variables, but the coefficients are significant in only half of the models. In the case of the largest funds, we find the same result but now coefficients are statistically significant across the board (three models are significant at the 1% p-value, and one model is significant at the 10% level). These results suggest that a positive shock to US household participation last year is related to an increase in average levels of fees and dispersion in fees next year. The effects are economically meaningful: an average increase in US household participation by 7.2% is related to an expected increase in average value-weighted fees of 1.3% and in 90-10$^{th}$ residual fee spreads of 3.0% for largest funds.[22] Quite impressively, lagged changes in US household participation are able to explain 14 to 15% of variation in residual and reported fee spreads. Thus, it seems that both average levels of fees and measures of fee dispersion are related to the fraction of retail investors participating in the mutual fund industry.

## 5. Conclusion

In this paper we examine how mutual funds price their services for a large cross-section of mutual funds (i.e., all mutual funds that focus on investing in US equities) and a long time-series of 49 years. Surprisingly, after we control for a variety of fund characteristics related to performance, service, and other features that investors are likely to care about, we find that the unexplained portion of fund expenses exhibits considerable dispersion and that this dispersion has not declined over time, with the exception of small decreases during the last few years. The level of dispersion that we find is huge in economic terms. For example, the costs for getting it wrong – investing in high expense funds when close-to-identical low expense funds are available – are large; we show that a low-expense fund investor would have earned approximately 84 to 162% more in cumulative abnormal returns than a high-expense fund investor over our sample period.

[22] The value of 7.2% represents the average %-change in US household participation as shown in Panel A of Table 8. We then plug this number into the time-series regressions and multiply it with the reported coefficients in Panel B; i.e., 0.18 for value-weighted average fees and 0.42 for the 90-10 residual expense spread.

While we find it already puzzling not being able to explain more of the variation in reported fund fees, the puzzle becomes even deeper once we investigate different explanations. For example, average fees in the fund industry dropped considerably during recent years indicating an increase in competition or learning by investors. However, over the same period of time levels of fee dispersion only experienced very moderate and not comparable decreases. Thus, while average fees at the end of 2014 are as low as or even slightly lower than in the early 80ties, the level of fee dispersion is much higher. Similarly, we also find evidence that expected fund fees are related to frictions in the fund market but controlling for these frictions has basically no impact on the dispersion in fees. One variable that seems to be strongly related to fee dispersion is the participation of US households in the mutual fund industry. Unfortunately, however, this measure is only available at the industry level and, thus, we cannot directly control for it in our fund-fee regressions.

Overall, our results pose an important and multi-dimensional puzzle regarding the fees charged in the mutual fund industry. Potential explanations of our results are, of course, that we do not control for the complete set of fund characteristics that affect fund fees[23] or that we do not capture relevant characteristics of the fund industry such as frictions accurately. While we are unable to completely rule these out, we also find it implausible to expect them to substantially reduce the enormous spreads in fees, particularly given the comprehensive set of robustness tests that we employ in the paper.

One explanation for the large fee dispersion, for which we find some empirical evidence, is related to investor clienteles and, specifically, the dramatic inflow of retail investors with limited knowledge of financial products during the sample period. Thus, issues such as financial literacy and advising of households should be of first order importance for regulators. Of course, it is not obvious that enabling (retail) investors with the basic tools to select funds would solve the issue of fee dispersion. As pointed out by Carlin and Manso (2011) funds may optimally react to investor learning by increasing the level of obfuscation (i.e., by making it harder for investors to learn). They argue, however, that an increase in competition should lower the incentives for obfuscation and, thus, should

[23] One specific example for such a fund characteristic is trust in the fund manager. Gennaioli, Shleifer, and Vishny (2015) develop a model in which investors pick portfolio managers on performance and trust. Investor trust in the manager lowers an investor's perception of the portfolio's risk, and allows managers to charge higher expenses to investors who trust them more.

enable investors to learn more quickly.[24] Thus, from a regulator's perspective it is also important to increase transparency and comparability in the industry.

[24] Ellison and Wolitzky (2012) develop a static model of obfuscation and find that competition might actually lead to more confiscation, increased search costs and more price dispersion.

## References


Aigner, D., C. A. K. Lovell, and P. Schmidt, 1977, Formulation and Estimation of Stochastic Frontier Production Function Models, *Journal of Econometrics*, 6, 21-37.

Bakos, Y., 2001, The Emerging Landscape of Retail E-commerce, *Journal of Economic Perspectives,* 15, 69-80.

Barber, B. M., T. Odean, and L. Zheng, 2005, Out of Sight, Out of Mind: The Effects of Expenses on Mutual Fund Flows, *Journal of Business*, 78 (6), 2095-2119.

Barras, L., Scaillet, O. and R. Wermers, 2010, False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas, *The Journal of Finance*, Vol. LXV, No. 1, 179-216.

Bergstresser, D., J. M. R. Chalmers and P. Tufano, 2009, Assessing the Costs and Benefits of Brokers in the Mutual Fund Industry, *The Review of Financial Studies*, 22, 4129-4156.

Berk, J. B., and R. C. Green, 2004, Mutual Fund Flows and Performance in Rational Markets, *Journal of Political Economy*, 112, 1269-1295.

Bessler, W., D, Blake, P. Luckiff, and I. Tonks, 2010, Why is Persistent Mutual Fund Performance so Difficult to Achieve? The Impact of Management Turnover and Fund Flows, working paper.

Bris, A., H. Gulen, P. Kadiyala, and P. Raghavendra Rau, 2007, Good Stewards, Cheap Talkers, or Family Men? The Impact of Mutual Fund Closures on Fund Managers, Flows, Fees, and Performance, *The Review of Financial Studies*, 20, 953-982

Brown, J. and A. Goolsbee, 2002, Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry, *Journal of Political Economy,* 110, 481-507.

Brynjolfsson, E. and M. Smith, 2000, Frictionless Commerce? A Comparison of Internet and Conventional Retailers, *Management Science,* 46(4), 563-585.

Carhart, M., 1997.On persistence in mutual fund performance. *Journal of Finance*, 52, 57-82.

Carlin, B. I. and G. Manso, 2011, Obfuscation, Learning, and the Evolution of Investor Sophistication, *The Review of Financial Studies*, 24, 754-785.

Choi, J. J., D. Laibson, and B. C. Madrian, 2010, Why Does the Law of One Price Fail? An Experiment on Index Mutual Funds, *The Review of Financial Studies*, 23, 1405-1432.

Christoffersen, S. and D. Musto, 2002, Demand Curves and the Pricing of Money Management, *Review of Financial Studies, Vol. 15, No. 5.*

Collins, S., 2005, Are S&P 500 Index Mutual Funds Commodities?, *Investment Company Institute Perspective*, 11(3).

Das, S. R. and R. K. Sundaram, 2002, Fee Speech: Signaling, risk-sharing, and the impact of fee structures on investor welfare, *The Review of Financial Studies*, 15, 1465-1497.

Diamond, P., 1971, A Model of Price Adjustments, *Journal of Economic Theory*, 3 (3), 156-168.

Ellison, G. and A. Wolitzky, 2012, A Search Cost Model of Obfuscation, *Rand Journal of Economics*, 3, 1756-2171.

Elton, E., M. Gruber, and J. Busse, 2004, Are Investors Rational? Choices Among Index Funds, *Journal of Finance*, Vol. 59, No. 1.

Elton, E., M. Gruber, and J. C. Rentzler, 1989, New public offerings, information, and investor rationality: the case of publicly offered commodity funds, *Journal of Business*, Vol. 62, 1-15.

French, K. 2008, Presidential Address: The Cost of Active Investing, *Journal of Finance*, Vol. 63, No. 4.

Gennaioli, N., A. Shleifer, R. W. Vishny, 2015, Money Doctors, The *Journal of Finance*, 70, 91-114

Gil-Bazo, J., and P. Ruiz-Verdu, 2008, When Cheaper is Better: Fee Determination in the Market for Equity Mutual Funds, *Journal of Economic Behavior and Organization*, pp. 871-885.

Gil-Bazo, J., and P. Ruiz-Verdu, 2009, The Relation between Price and Performance in the Mutual Fund Industry, *Journal of Finance*, 64, 2153-2183.

Graham, John R. and Harvey, Campbell R., 2015, The Equity Risk Premium in 2015. Available at SSRN: http://ssrn.com/abstract=2611793 or http://dx.doi.org/10.2139/ssrn.2611793.

Greene, R. C., B. Hollifield, and N. Schuerhoff, 2007, Financial Intermediation and the Costs of Trading in an Opaque Market, *Review of Financial Studies*, 20 (2), 275-314.

Greene, W. A., 2002, *Econometric Analysis*, Prentice Hall, 5th Edition.

Habib, M. and A. Ljungqvist, 2005, Firm value and managerial incentives: A stochastic frontier approach, *Journal of Business* 78, 2053-2094.

Haslem, J. A., Baker, H. K. and D. M. Smith, 2006, Are retail S&P 500 index funds a financial commodity? Insights for investors, *Financial Services Review*, 15, 99-116.

Hortacsu, A., and C. Syverson, 2004, Product Differentiation, Search Costs, and Competition in the Mutual Fund Industry: A Case Study of S&P 500 Index Funds, *Quarterly Journal of Economics*, 403-456.

Investment Company Institute, 2014, "Ownership of Mutual Funds, Shareholder Sentiment and Use of the Internet", downloaded from https://www.ici.org/research/perspective.

Khorana, A., H. Servaes, and P. Tufano, 2009, Mutual Fund Fees around the World, *Review of Financial Studies*, 22 (3), 1279-1310.

Khorana, A., and H. Servaes, 2012, What Drives Market Share in the Mutual Fund Industry? *Review of Finance*, 16, 81-113.

Lach, S., 2002, Existence and Persistence of Price Dispersion: an Empirical Analysis, *The Review of Economics and Statistics*, 84 (3), 433-444.

Liang, B., 2000, Hedge Funds: The Living and the Dead, *Journal of Financial and Quantitative Analysis*, 35, 309-326.

Nakamura, L., 1999, The Measurement of Retail Output and the Retail Revolution, *Canadian Journal of Economics,* 32(2), 408-425.

Nanda, V., M. P. Narayanan and V. A. Warther, 2000, Liquidity, investment ability, and mutual fund structure, *Journal of Financial Economics*, 57, 417-443.

Nanda, V. K., Z. J. Wang and L. Zheng, 2009, The ABCs of mutual funds: On the introduction of multiple share classes, *Journal of Financial Intermediation*, 18, 329-361.

Pástor, L. and R. Stambaugh, 2002, Mutual fund performance and seemingly unrelated assets, *Journal of Financial Economics,* 63, 315-349.

Pástor, L. and R. Stambaugh, 2012, On the Size of the Active Management Industry, *Journal of Political Economy* 120, 740–781

Pratt, J., D. Wise and R. Zeckhauser, 1979, Price Differences in Almost Competitive Markets, *Quarterly Journal of Economics,* 939, 189-211.

Ramadorai, T. and M. Streatfield, 2011, Money for Nothing? Understanding Variation in Reported Hedge Fund Fees, Working Paper.

Scholten, P. and S. Smith, 2002, Price Dispersion Then and Now: Evidence from Retail and E-tail Markets, *Advances in Microeconomics: Economics of the Internet and e-Commerce* 11, 63-88.

Sialm, C., L. Starks and H. Zhang, 2014, Defined Contribution Pension Plans: Sticky or Discerning Money?, The *Journal of Finance* forthcoming.

Sorensen, A., 2000, Equilibrium Price Dispersion in Retail Markets for Prescription Drugs, *Journal of Political Economy,* 108(4), 833-862.

Varian, H., 1980, A Model of Sales, *American Economic Review*, 70 (4), 651-659.

Wahal, S., and A. Wang, 2011, Competition among mutual funds, *Journal of Financial Economics,* 99, 40-59.

## Data Appendix

### Table A. Sample Selection

We follow Bessler et al. (2008) who use a combination of Lipper codes, Wiesenberger codes and Strategic Insight codes to identify domestic equity funds. Specifically we include funds in our sample with the following classification codes:

1. Lipper: CA, EI, EIEI, G, GI, I, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, FS, H, NR, S, SESE, TK, TL, UT.
2. Wiesenberger: AGG, G, G-I, G-I-S, G-S, G-S-I, GCI, GRI, GRO, IG, I-G-S, I-S, I-S-G, IEQ, ING, LTG, MCG, S-G, S-GI, S-I-G, S-I, SCG, ENR, FIN, HLT, TCH, UTL.
3. Strategic Insight: AGG, GMC, GRI, GRO, ING, SCG, ENV, FIN, HLT, NTR, SEC, TEC, UTI.

**Table B. Variable Construction and Definitions**

| Variable Name | Variable Definition | Source |
|---|---|---|
| $\Delta$*(expense ratio)* | Yearly change in the expense ratio. | Calculated |
| *12b-1 fees* | Ratio of the total assets attributed to marketing and distribution costs. Available since 1992. | CRSP MF Database |
| *Alpha* | Four factor alpha. For each December and each fund, we estimate a monthly four-factor alpha using three years of monthly after-expense, excess fund returns. Alpha is the estimated monthly alpha (i.e., the constant in the time-series regression) multiplied by 12. *Before-expense alphas* are estimated in the same way using monthly before-expense fund returns, which are calculated by adding the total expense ratio to monthly after-expense returns. *Expanding window alphas* are estimated from an expanding estimation window rather than a rolling window of three years. *Filtered alphas* replace alpha estimates by zero when the corresponding t-statistic of the alpha estimate is below three in absolute terms. *Full sample alphas* are unconditional alphas estimates exploiting all available data per fund. | Calculated |
| *Annual flow* | Annual fund flow. It is estimated as $Flow_t = \left(TNA_t - TNA_{t-12}\left(1 + return_t\right)\right)/TNA_{t-12}$ and is winsorized at the 1% level. | Calculated |
| *Annual return* | Annual fund return. Calculated by compounding monthly after-expense returns within the previous 12 months. Monthly return values are calculated as a change in NAV including reinvested dividends from one period to the next. NAVs are net of all management expenses and 12b-fees. Front and rear load fees are excluded. *Before-expense annual returns* are calculated as the sum of annual after-expense returns and the total expense ratio. Annual return is in decimal form, that is 0.01 is 1%. | CRSP MF Database and Calculated |
| *Avgfamilyfee* | Value-weighted mean of expense ratios for funds within a fund family | Calculated |
| B*eta_mkt*<br>*Beta_hml*<br>*Beta_smb*<br>*Beta_umd* | Fund betas from the four-factor model. Each December and each fund, we estimate the monthly four-factor model betas using 3 years of monthly after-expense excess return. Refer to the information on the calculation of *Alpha* for details regarding *before-expense, expanding window, filtered* and *full sample* estimates of betas. | Calculated |
| *Carhart alpha* | For each month, and for each fund, we first estimate a monthly after-expense alpha as the difference between the fund's after-expense excess return in month *t* and the realized risk premium, defined as the vector of betas times the vector of contemporaneous factor realizations in month *t* (see Carhart (1997) and Gil-Bazo and Ruiz-Verdu (2009)). Betas are estimated from 3 years of monthly after-expense fund returns and lagged by one month. The Carhart alpha that we use in the analysis is yearly and is calculated by compounding monthly Carhart alphas estimated over the previous 12 months. Refer to the information on the calculation of *Alpha* for details regarding | Calculated |

| Variable Name | Variable Definition | Source |
|---|---|---|
| | *before-expense, expanding window, filtered* and *full sample* estimates of Carhart alphas. Carhart alpha is in decimal form, that is 0.01 is 1%. | |
| *Expense ratio* | Annual ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. | CRSP MF Database |
| *Family1 dummy*<br>*Family10 dummy*<br>*Family100 dummy*<br>*Family250 dummy* | A dummy variable equal to 1, 0 else, if a fund is part of a management company with more than 1 (10) [100] {250} funds associated with it. The standard case in our analysis is *Family100 dummy*. | Calculated. |
| *First expense ratio* | Total yearly expense ratio in the year when the fund was initiated. | Calculated |
| *Flow autocorrelation* | This is the autocorrelation of monthly fund flows. The flow autocorrelations is estimated using the entire time series of monthly flows. | Calculated |
| *Flow-perf sensitivity* | For each fund and each year, we estimate the fund's flow-performance sensitivity as the coefficient of lagged monthly performance in a regression that explains monthly flows. The regression starts with 3 years of monthly data and uses an expanding window. | Calculated |
| *Front load* | Front loads for investments represent maximum sales charges. They often change with the level of investment. The front load value is the equal weighted average of all front loads charged by a fund across different investment levels. | CRSP MF Database |
| *Fund age* | Age of fund calculated as the difference between current year and year of fund initiation. | Calculated |
| *Institutional dummy*<br>*Open dummy*<br>*ETF dummy* | A dummy variable equal to 1, 0 else, if a fund is an institutional fund, or open to new investment, or is an ETF. | CRSP MF Database |
| *ln(MgmtComp TNA)* | The natural log of each December's sum of total net assets of all funds belonging to the same management company. | Calculated |
| *ln(TNA)* | The natural log of total net assets per fund as of December-end. | Calculated |
| *Pension Plan dummy* | A dummy variable equal to 1, 0 else, if a fund's monthly autocorrelation is in the top decile of all funds. | Calculated |
| *Persistence dummy* | A dummy variable equal to 1 for a given fund in year t if the fund is among the top-20% funds with respect to yearly net performance in years t-1 and t-2. The term "*before-expense persistence dummy*" refers to a persistence dummy that is based on gross returns rather than net returns. | Calculated |
| $R^2$ | For each December and each fund, we estimate the four-factor model using 3 years of monthly fund returns. Then we collect the adjusted $R^2$ of these models. | Calculated |
| *Random fee changes* | For each fund and each year, we determine the fraction of positive and negative fee changes for the fund since its first appearance in the CRSP Mutual Fund Database. "Random fees changes" is the minimum value of the frequency of positive and negative fee changes. | Calculated |

| Variable Name | Variable Definition | Source |
|---|---|---|
| *Rear load* | The rear load is a fee charged by the fund when an investor withdraws funds. The rear load typically varies by investment level and duration of the investment. The rear load value is the equal weighted average across all reported rear load values across these dimensions. | CRSP MF Database |
| *Sdmret* | Standard deviation of monthly returns calculated from 3 years of monthly fund returns. Sdmret is in decimal form, that is 0.01 is 1%. | Calculated |
| *Style Fixed Effects* | Fund styles are defined using the classification codes described in Table A of the Data Appendix. | CRSP MF Database |
| *TNA* | Total net assets as of December-end in millions of USD. | CRSP MF Database |
| *Tstat alpha* | The t-statistic associated with *alpha.* Refer to the information on the calculation of *Alpha* for details regarding *expanding window* and *full sample* estimates of Tstat alpha. | Calculated |
| *Turnover* | Annual fund turnover is calculated as the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month total net assets of the fund. | CRSP Mutual Fund Database |
| *Uniqueness* | It is the sum, across all holdings, of absolute differences in weights for a given pair of funds, estimated yearly. The measure is bounded between zero (perfect overlap) and two (no overlap). The uniqueness variable is based on fund holdings which are available at the fund rather than the share class level. As a consequence, all results that involve this variable are at the fund level. For each fund, its uniqueness value is defined as the value of this sum for the fund pair that results in the maximal holdings overlap. | |
| *Fund average uniqueness* | For each fund, this is the average of its *Uniqueness* with all other funds, estimated yearly. | |

**Table 1. Summary Statistics**

The table reports summary statistics and a correlation table of our sample of domestic equity mutual funds (see Table A in the Data Appendix for a detailed description of the sample). The standard deviations in Panels A and B are computed as the mean of yearly cross-sectional standard deviations. The data covers the period of 1966 to 2014 and is a yearly panel. Variables are defined in Table B in the Data Appendix. The table focuses on the variables used in our base model of fund expense ratios. Some information is only available after 1999 (e.g., information on management companies) and, thus, we split the sample into a pre-1999 and a post-1999 subset. Panel A presents full period summary data. Panel B and C summarize the sample by expense ratio deciles in the pre- and post-1999 periods, respectively. Panel D contains correlations. The last column in Panel B and C reports the difference between decile 1 and decile 10. Stars indicate significance at the 1% (***), 5% (**) and 10% (*) level. *Annual return, Carhart alpha, the R-Squared,* the standard deviation of monthly returns (*Sdmret*) and all summary statistics of dummies are in decimal form, that is 0.01 is 1%. *Annual Flow* and *Turnover* are in percentages. *Expense ratio* and Δ(*Expense ratio*) are in basis points.

**Panel A. Full Sample**

| | Pre - 1999 | | Post - 1999 | |
|---|---|---|---|---|
| | **Mean** | **SD** | **Mean** | **SD** |
| **Number of funds per year** | 1051 | 968 | 7931 | 1157 |
| **Expense ratio** | 121.000 | 99.000 | 138.000 | 98.000 |
| **Δ(Expense ratio)** | 7.000 | 81.000 | 0.000 | 56.000 |
| **Annual return** | 0.130 | 0.181 | 0.075 | 0.232 |
| **Carhart alpha** | -0.014 | 0.101 | -0.012 | 0.092 |
| **Beta_mkt** | 0.857 | 0.309 | 0.978 | 0.331 |
| **Beta_smb** | 0.226 | 0.440 | 0.161 | 0.361 |
| **Beta_hml** | -0.012 | 0.420 | -0.008 | 0.378 |
| **Beta_umd** | 0.055 | 0.289 | 0.018 | 0.195 |
| $R^2$ | 0.779 | 0.241 | 0.870 | 0.155 |
| **Annual flow** | 1.008 | 4.696 | 0.972 | 4.878 |
| **ln(TNA)** | 3.699 | 2.293 | 3.537 | 2.592 |
| **TNA** | 361.379 | 1679.748 | 530.320 | 2849.820 |
| **Fund age** | 8.088 | 8.612 | 8.985 | 8.169 |
| **Sdmret** | 0.047 | 0.032 | 0.051 | 0.025 |
| **Turnover** | | | 1.009 | 2.551 |
| **ln(MgmtComp TNA)** | | | 8.864 | 2.657 |
| **Family1 dummy** | | | 0.882 | 0.323 |
| **Family10 dummy** | | | 0.802 | 0.399 |
| **Family100 dummy** | | | 0.524 | 0.499 |
| **Family250 dummy** | | | 0.250 | 0.433 |
| **Institutional dummy** | | | 0.232 | 0.422 |
| **Open dummy** | | | 0.727 | 0.446 |
| **ETF dummy** | | | 0.020 | 0.139 |

**Panel B. Summary Statistics by Expense Ratio Deciles --- Pre - 1999 Sample**

| | Decile 1 | | Decile 3 | | Decile 5 | | Decile 7 | | Decile 10 | | Decile 1 - 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Diff |
| **Expense ratio** | 31 | 28 | 75 | 29 | 104 | 21 | 136 | 28 | 268 | 154 | -237*** |
| **Δ(Expense ratio)** | -14 | 58 | -3 | 33 | 2 | 27 | 4 | 39 | 42 | 149 | -56*** |
| **Annual return** | 0.171 | 0.215 | 0.137 | 0.157 | 0.135 | 0.169 | 0.135 | 0.183 | 0.118 | 0.209 | 0.053*** |
| **Carhart alpha** | -0.010 | 0.080 | -0.010 | 0.072 | -0.010 | 0.084 | -0.016 | 0.109 | -0.030 | 0.137 | 0.020*** |
| **Beta_mkt** | 0.856 | 0.407 | 0.842 | 0.287 | 0.853 | 0.279 | 0.851 | 0.282 | 0.858 | 0.346 | -0.002 |
| **Beta_smb** | 0.072 | 0.446 | 0.113 | 0.330 | 0.197 | 0.392 | 0.273 | 0.432 | 0.384 | 0.540 | -0.312*** |
| **Beta_hml** | 0.034 | 0.469 | 0.002 | 0.316 | -0.018 | 0.383 | -0.013 | 0.406 | -0.041 | 0.536 | 0.075*** |
| **Beta_umd** | 0.008 | 0.254 | 0.034 | 0.209 | 0.053 | 0.245 | 0.072 | 0.288 | 0.085 | 0.396 | -0.077*** |
| $R^2$ | 0.810 | 0.268 | 0.809 | 0.235 | 0.797 | 0.225 | 0.765 | 0.242 | 0.702 | 0.256 | 0.108*** |
| **Annual flow** | 1.213 | 5.292 | 0.568 | 3.382 | 0.533 | 3.026 | 0.769 | 3.744 | 1.203 | 4.709 | 0.010 |
| **ln(TNA)** | 4.916 | 2.433 | 5.113 | 1.892 | 4.477 | 1.638 | 3.890 | 1.686 | 2.370 | 1.740 | 2.545*** |
| **TNA** | 1550.352 | 5290.461 | 691.041 | 1775.102 | 285.858 | 766.173 | 198.393 | 669.415 | 46.796 | 133.216 | 1503.556*** |
| **Fund age** | 9.778 | 10.120 | 12.047 | 9.861 | 11.178 | 9.026 | 8.490 | 7.369 | 6.753 | 7.154 | 3.024*** |
| **Sdmret** | 0.037 | 0.032 | 0.039 | 0.017 | 0.042 | 0.018 | 0.046 | 0.020 | 0.051 | 0.023 | -0.014*** |

**Panel C. Summary Statistics by Expense Ratio Deciles --- Post - 1999 Sample**

| | Decile 1 | | Decile 3 | | Decile 5 | | Decile 7 | | Decile 10 | | Decile 1 - 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Diff |
| **Expense ratio** | 37 | 19 | 95 | 9 | 123 | 11 | 157 | 17 | 261 | 238 | -224*** |
| **Δ(Expense ratio)** | -1 | 9 | -1 | 9 | -1 | 10 | -1 | 13 | 6 | 173 | -7*** |
| **Annual return** | 0.076 | 0.195 | 0.081 | 0.226 | 0.080 | 0.229 | 0.075 | 0.238 | 0.064 | 0.265 | 0.012*** |
| **Carhart alpha** | -0.004 | 0.069 | -0.008 | 0.087 | -0.010 | 0.089 | -0.013 | 0.096 | -0.022 | 0.116 | 0.018*** |
| **Beta_mkt** | 0.899 | 0.285 | 0.995 | 0.268 | 0.993 | 0.246 | 0.983 | 0.358 | 0.987 | 0.497 | -0.088*** |
| **Beta_smb** | 0.058 | 0.315 | 0.123 | 0.334 | 0.187 | 0.352 | 0.201 | 0.376 | 0.257 | 0.405 | -0.199*** |
| **Beta_hml** | 0.048 | 0.306 | -0.001 | 0.364 | 0.008 | 0.359 | -0.023 | 0.398 | -0.090 | 0.471 | 0.138*** |
| **Beta_umd** | -0.005 | 0.155 | 0.017 | 0.191 | 0.024 | 0.184 | 0.021 | 0.205 | 0.025 | 0.237 | -0.029*** |
| $R^2$ | 0.878 | 0.195 | 0.880 | 0.144 | 0.878 | 0.132 | 0.867 | 0.148 | 0.823 | 0.185 | 0.055*** |
| **Annual flow** | 1.019 | 4.872 | 1.215 | 5.688 | 0.935 | 4.548 | 0.946 | 4.564 | 0.833 | 4.550 | 0.186** |
| **ln(TNA)** | 5.147 | 2.628 | 4.292 | 2.582 | 3.723 | 2.443 | 3.041 | 2.430 | 1.919 | 1.982 | 3.23*** |
| **TNA** | 1958.091 | 6605.952 | 674.114 | 2390.214 | 321.450 | 978.862 | 185.910 | 652.200 | 36.535 | 124.755 | 1921.556*** |
| **Fund age** | 8.851 | 8.706 | 10.431 | 9.907 | 9.424 | 8.724 | 8.207 | 7.146 | 7.703 | 6.071 | 1.148*** |
| **Sdmret** | 0.044 | 0.022 | 0.050 | 0.024 | 0.051 | 0.023 | 0.053 | 0.025 | 0.059 | 0.030 | -0.015*** |
| **Turnover** | 0.405 | 0.512 | 0.815 | 0.793 | 0.936 | 1.472 | 1.180 | 2.619 | 1.738 | 4.861 | -1.333*** |
| **ln(MgmtComp TNA)** | 10.134 | 2.486 | 8.947 | 2.618 | 8.595 | 2.559 | 8.611 | 2.765 | 8.000 | 2.714 | 2.134*** |
| **Family1 dummy** | 0.888 | 0.316 | 0.860 | 0.347 | 0.883 | 0.321 | 0.884 | 0.320 | 0.889 | 0.315 | -0.001 |
| **Family10 dummy** | 0.861 | 0.346 | 0.780 | 0.414 | 0.776 | 0.417 | 0.787 | 0.410 | 0.792 | 0.406 | 0.069*** |
| **Family100 dummy** | 0.573 | 0.495 | 0.510 | 0.500 | 0.482 | 0.500 | 0.517 | 0.500 | 0.461 | 0.499 | 0.112*** |
| **Family250 dummy** | 0.243 | 0.429 | 0.272 | 0.445 | 0.240 | 0.427 | 0.240 | 0.427 | 0.173 | 0.379 | 0.070*** |
| **Institutional dummy** | 0.471 | 0.499 | 0.417 | 0.493 | 0.221 | 0.415 | 0.142 | 0.349 | 0.014 | 0.117 | 0.458*** |
| **Open dummy** | 0.744 | 0.437 | 0.741 | 0.438 | 0.737 | 0.441 | 0.732 | 0.443 | 0.680 | 0.467 | 0.064*** |
| **ETF dummy** | 0.128 | 0.334 | 0.013 | 0.112 | 0.000 | 0.009 | 0.001 | 0.024 | 0.001 | 0.022 | 0.127*** |

**Panel D. Pooled Correlation**

| | Expense ratio | Δ(Expense ratio) | Annual return | Carhart alpha | Beta_mkt | Beta_hml | Beta_smb | Beta_umd | $R^2$ | Annual flow | ln(TNA) | Fund age | Sdmret | Turnover |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Expense ratio** | | | | | | | | | | | | | | |
| **Δ(Expense ratio)** | 0.54*** | | | | | | | | | | | | | |
| **Annual return** | -0.05*** | -0.03*** | | | | | | | | | | | | |
| **Carhart alpha** | -0.08*** | -0.04*** | 0.38*** | | | | | | | | | | | |
| **Beta_mkt** | 0.03*** | -0.01*** | -0.01*** | -0.07*** | | | | | | | | | | |
| **Beta_smb** | 0.10*** | 0.01* | 0.08*** | -0.02*** | 0.17*** | | | | | | | | | |
| **Beta_hml** | -0.03*** | 0 | -0.03*** | -0.06*** | -0.16*** | 0.01*** | | | | | | | | |
| **Beta_umd** | 0.02*** | -0.01*** | -0.01*** | -0.08*** | 0.07*** | 0.10*** | -0.09*** | | | | | | | |
| **$R^2$** | -0.09*** | -0.02*** | 0 | -0.02*** | 0.37*** | 0.02*** | -0.10*** | -0.05*** | | | | | | |
| **Annual flow** | 0 | 0.01* | 0.08*** | 0.07*** | 0 | 0.01*** | 0.01*** | 0.02*** | -0.02*** | | | | | |
| **ln(TNA)** | -0.25*** | -0.03*** | 0.10*** | 0.05*** | -0.04*** | -0.05*** | 0.02*** | 0 | -0.01*** | -0.06*** | | | | |
| **Fund age** | -0.05*** | -0.01*** | 0.04*** | -0.01*** | -0.06*** | -0.07*** | -0.02*** | -0.03*** | -0.01*** | -0.16*** | 0.42*** | | | |
| **Sdmret** | 0.13*** | 0.02*** | -0.10*** | -0.05*** | 0.47*** | 0.32*** | -0.21*** | 0.05*** | 0.11*** | 0 | -0.09*** | -0.08*** | | |
| **Turnover** | 0.11*** | 0 | -0.03*** | -0.01*** | 0.02*** | 0.03*** | -0.04*** | 0.03*** | -0.10*** | 0.02*** | -0.09*** | -0.05*** | 0.13*** | |
| **ln(MgmtComp TNA)** | -0.09*** | -0.07*** | -0.01* | 0.03*** | 0.09*** | -0.10*** | 0 | -0.04*** | 0.17*** | -0.04*** | 0.31*** | 0.20*** | 0 | -0.02*** |

**Table 2. Base-Case Fund Expense Regressions**

The table reports results of Fama-MacBeth regressions in which yearly expense ratios are regressed on lagged fund characteristics (see Table A in the Data Appendix for a detailed description of the sample). The data covers the period of 1966 to 2014 and is a yearly panel. Variables are defined in Table B in the Data Appendix. All variables are lagged by one year. Expense ratio (the dependent variable in all regressions) is in basis points. We split the sample into pre-and post-1999 subperiods since information on management companies is only available after 1999. The specifications reported in this table represent the base-case specifications. Beta estimates are time series averages of cross-sectional regression betas obtained from annual cross-sectional regressions. We perform the regressions on the full sample of mutual funds and for the largest and smallest quintile of annually ranked *TNA* funds. Panel A reports the regression results. We standardize all the independent variables to mean 0 and standard deviation 1 using the full-sample mean of each variable's yearly cross-sectional mean and SD. In Panel B, in column (1) we report the time-series average of the cross-sectional mean, in column (2) the time-series standard deviation of the cross-sectional mean, and in column (3), the time-series average of the cross-sectional SD that are used to standardize the independent variables in panel A.

**Panel A. Base Regression with Right-Hand-Side Variables Standardized**

| | Pre - 1999 | | | | | | Post - 1999 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full Sample | | Largest Funds | | Smallest Funds | | Full Sample | | Largest Funds | | Smallest Funds | |
| | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat |
| **(Intercept)** | 120.18 | 30.92 | 115.45 | 18.62 | 115.68 | 11.17 | 173.80 | 30.71 | 200.99 | 39.49 | 212.15 | 24.48 |
| **Annual return$_{t-1}$** | -7.23 | -4.51 | -2.68 | -2.24 | -16.25 | -3.94 | -14.44 | -3.90 | -7.62 | -1.97 | -40.05 | -3.03 |
| **Beta_mkt $_{t-1}$** | -0.59 | -0.35 | -6.21 | -1.12 | 2.52 | 0.40 | -4.32 | -1.77 | -1.51 | -0.29 | -11.85 | -1.40 |
| **Beta_smb $_{t-1}$** | 5.93 | 3.60 | 0.24 | 0.04 | 7.24 | 1.48 | 19.66 | 1.82 | 16.11 | 2.28 | 15.15 | 2.54 |
| **Beta_hml $_{t-1}$** | -0.80 | -0.60 | 6.02 | 2.61 | -4.22 | -1.21 | 1.70 | 0.81 | -3.69 | -2.43 | 12.55 | 1.95 |
| **Beta_umd $_{t-1}$** | 2.92 | 2.37 | 5.02 | 3.71 | 6.00 | 1.61 | 1.27 | 0.61 | -4.38 | -1.96 | 7.16 | 1.17 |
| **$R^2_{t-1}$** | -3.12 | -2.62 | -0.21 | -0.10 | -10.96 | -2.93 | -11.14 | -8.51 | -5.75 | -9.32 | -22.10 | -5.92 |
| **flow $_{t-1}$** | 0.34 | 0.29 | 4.46 | 1.35 | -0.46 | -0.09 | -0.90 | -2.56 | -2.42 | -3.23 | 3.25 | 2.11 |
| **ln(TNA) $_{t-1}$** | -30.80 | -25.72 | -18.43 | -23.11 | -47.18 | -5.82 | -23.74 | -40.72 | -25.21 | -22.96 | -22.26 | -3.63 |
| **Fund age $_{t-1}$** | 1.31 | 1.35 | -7.36 | -4.77 | 19.39 | 2.86 | 3.04 | 2.59 | -1.35 | -1.32 | 59.89 | 5.17 |
| **Sdmret $_{t-1}$** | 16.12 | 3.15 | 25.69 | 1.26 | 25.38 | 1.45 | 34.30 | 3.32 | 0.46 | 0.15 | 69.13 | 3.69 |
| **Turnover $_{t-1}$** | | | | | | | 1.70 | 3.03 | 11.09 | 5.84 | -1.63 | -1.02 |
| **ln(MgmtComp TNA) $_{t-1}$** | | | | | | | -3.79 | -7.41 | -6.43 | -15.63 | -5.21 | -3.67 |
| **Family100 dummy** | | | | | | | 13.41 | 7.44 | 19.03 | 7.46 | 2.79 | 0.68 |
| **Institutional dummy** | | | | | | | -53.62 | -20.70 | -38.23 | -10.94 | -61.90 | -15.04 |
| **Open dummy** | | | | | | | 10.57 | 2.61 | 4.59 | 1.98 | 10.38 | 1.29 |
| **ETF dummy** | | | | | | | -44.85 | -32.23 | -36.63 | -20.91 | -79.16 | -4.31 |
| **# of Obs.** | 30168 | | 6017 | | 6047 | | 104560 | | 20907 | | 20917 | |
| **Avg. R-Squared** | 24% | | 31% | | 20% | | 28% | | 35% | | 26% | |

**Panel B. Time Series Average (SD) of Cross-Sectional Mean and SD**

| | Pre - 1999 | | | | | | | | | Post - 1999 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | Largest Funds | | | Smallest Funds | | | Full Sample | | | Largest Funds | | | Smallest Funds | | |
| | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) |
| **Annual return$_{t-1}$** | 0.118 | 0.150 | 0.038 | 0.124 | 0.142 | 0.104 | 0.101 | 0.151 | 0.131 | 0.079 | 0.199 | 0.073 | 0.089 | 0.201 | 0.114 | 0.065 | 0.198 | 0.111 |
| **Beta_mkt $_{t-1}$** | 0.845 | 0.059 | 0.057 | 0.831 | 0.097 | 0.287 | 0.836 | 0.080 | 0.342 | 0.989 | 0.041 | 0.047 | 0.971 | 0.034 | 0.247 | 1.000 | 0.051 | 0.298 |
| **Beta_smb $_{t-1}$** | 0.228 | 0.089 | 0.116 | 0.108 | 0.067 | 0.286 | 0.312 | 0.152 | 0.534 | 0.167 | 0.031 | 0.018 | 0.121 | 0.033 | 0.326 | 0.166 | 0.034 | 0.365 |
| **Beta_hml $_{t-1}$** | -0.013 | 0.046 | 0.093 | -0.020 | 0.053 | 0.303 | 0.026 | 0.093 | 0.486 | -0.001 | 0.073 | 0.085 | 0.009 | 0.093 | 0.356 | -0.015 | 0.086 | 0.371 |
| **Beta_umd $_{t-1}$** | 0.074 | 0.065 | 0.106 | 0.064 | 0.055 | 0.193 | 0.064 | 0.106 | 0.384 | 0.017 | 0.050 | 0.060 | 0.019 | 0.048 | 0.163 | 0.014 | 0.057 | 0.190 |
| **$R^2_{t-1}$** | 0.775 | 0.040 | 0.038 | 0.810 | 0.084 | 0.234 | 0.714 | 0.069 | 0.244 | 0.871 | 0.035 | 0.021 | 0.878 | 0.027 | 0.150 | 0.870 | 0.043 | 0.138 |
| **flow $_{t-1}$** | 0.596 | 0.581 | 2.095 | 0.275 | 0.324 | 1.455 | 1.037 | 1.236 | 3.320 | 0.958 | 0.402 | 1.002 | 0.350 | 0.164 | 2.356 | 1.150 | 0.594 | 4.135 |
| **ln(TNA) $_{t-1}$** | 3.836 | 0.480 | 0.203 | 6.409 | 0.547 | 0.776 | 1.192 | 0.475 | 0.898 | 3.617 | 0.284 | 0.084 | 7.019 | 0.275 | 1.025 | -0.114 | 0.355 | 1.260 |
| **Fund age $_{t-1}$** | 9.630 | 3.187 | 3.269 | 13.056 | 4.182 | 6.094 | 7.093 | 3.344 | 5.024 | 8.965 | 1.876 | 0.467 | 14.518 | 1.428 | 10.871 | 5.154 | 1.850 | 4.235 |
| **Sdmret $_{t-1}$** | 0.046 | 0.009 | 0.004 | 0.041 | 0.008 | 0.017 | 0.050 | 0.011 | 0.022 | 0.052 | 0.015 | 0.009 | 0.050 | 0.014 | 0.017 | 0.053 | 0.016 | 0.018 |
| **Turnover $_{t-1}$** | | | | | | | | | | 1.022 | 0.193 | 1.229 | 0.661 | 0.115 | 0.683 | 1.378 | 0.293 | 3.574 |
| **ln(MgmtComp TNA) $_{t-1}$** | | | | | | | | | | 8.888 | 0.455 | 0.249 | 10.300 | 0.334 | 1.852 | 8.038 | 0.759 | 3.063 |

Table 3. **Residual Expense Spreads**

Using the residuals from the Table 2 fund expense regressions, this table presents the time-series average of the cross-sectional residual spreads, in basis points (bps), between percentiles of the residual expense distribution for our sample of mutual funds (see Table A in the Data Appendix for a detailed description of the sample). Panel A reports mean residuals for the full sample, Panel B reports residuals spreads for the bottom quintile of annually ranked TNA funds, and Panel C reports mean residual spreads for the top quintile of annually ranked TNA funds. The data covers the period of 1966 to 2014 and is a yearly panel. The variables are defined in Table B of the Data Appendix. In each panel, the first row reports residual spreads for the "base-case" regression models of Table 2. The other rows report robustness tests for models in which we vary the fund characteristics used to estimate residual expenses. Rows 2 to 5 report residual expense spreads varying fund performance measures. Rows 6 to 9 report results of specifications that use gross (i.e., before-expense) rather than net performance measures in the regressions to explain expense ratios. Row 10 reports the results for a specification that includes fund style fixed effects. Rows 11 to 12 report results that use performance measures derived from expanding rather than rolling windows (using beta estimates from expanding windows). Rows 13 to 15 report mean expense spreads for specifications that reduce the estimation noise in four-factor alphas and betas. In row 13 we set the estimated alpha and betas to 0 if the corresponding t-statistic is below 3 in absolute terms and in rows 14 and 15 we use full sample estimates of these asset pricing parameters (i.e., for each fund we estimate these parameters using all available data and then use the same parameters each year to explain expense ratios).

**Panel A. Full Sample**

| | | **Mean Residual Spread (bps)** | | |
|---|---|---|---|---|
| | **Expense Models** | **25th to 75th Percentile** | **10th to 90th Percentile** | **1th to 99th Percentile** |
| 1 | Base-case | 62 | 124 | 247 |
| 2 | Annual return + persistence dummy | 62 | 124 | 247 |
| 3 | Alpha + persistence dummy | 62 | 125 | 249 |
| 4 | Tstat alpha + persistence dummy | 61 | 122 | 242 |
| 5 | Carhart alpha + persistence dummy | 62 | 123 | 245 |
| 6 | Before-expense annual return | 62 | 124 | 246 |
| 7 | Before-expense annual return+ before-expense persistence dummy | 62 | 124 | 246 |
| 8 | Before-expense alpha + before-expense persistence dummy | 61 | 122 | 243 |
| 9 | Before-expense Carhart alpha+ before-expense persistence dummy | 61 | 122 | 242 |
| 10 | Style fixed effects + annual return | 62 | 122 | 246 |
| 11 | Expanding window alpha | 61 | 123 | 244 |
| 12 | Expanding window Tstat alpha | 61 | 122 | 243 |
| 13 | Filtered alpha | 61 | 123 | 251 |
| 14 | Full Sample alpha | 62 | 123 | 244 |
| 15 | Full sample Tstat alpha | 62 | 122 | 243 |

**Panel B. Bottom Size Quintile of Funds**

| | | Mean Residual Spread (bps) | | |
|---|---|---|---|---|
| | **Expense Models** | **25th to 75th Percentile** | **10th to 90th Percentile** | **1th to 99th Percentile** |
| 1 | Base-case | 95 | 180 | 399 |
| 2 | Annual return + persistence dummy | 95 | 180 | 398 |
| 3 | Alpha + persistence dummy | 97 | 183 | 414 |
| 4 | Tstat alpha + persistence dummy | 93 | 175 | 383 |
| 5 | Carhart alpha + persistence dummy | 94 | 178 | 401 |
| 6 | Before-expense annual return | 94 | 178 | 403 |
| 7 | Before-expense annual return+ before-expense persistence dummy | 95 | 179 | 401 |
| 8 | Before-expense alpha + before-expense persistence dummy | 97 | 185 | 413 |
| 9 | Before-expense Carhart alpha+ before-expense persistence dummy | 94 | 182 | 403 |
| 10 | Style fixed effects + annual return | 90 | 170 | 388 |
| 11 | Expanding window alpha | 93 | 175 | 388 |
| 12 | Expanding window Tstat alpha | 92 | 175 | 382 |
| 13 | Filtered alpha | 88 | 164 | 402 |
| 14 | Full Sample alpha | 98 | 187 | 414 |
| 15 | Full sample Tstat alpha | 97 | 185 | 406 |

**Panel C. Top Size Quintile of Funds**

| | | Mean Residual Spread (bps) | | |
|---|---|---|---|---|
| | **Expense Models** | **25th to 75th Percentile** | **10th to 90th Percentile** | **1th to 99th Percentile** |
| 1 | Base-case | 42 | 93 | 177 |
| 2 | Annual return + persistence dummy | 42 | 93 | 177 |
| 3 | Alpha + persistence dummy | 42 | 93 | 177 |
| 4 | Tstat alpha + persistence dummy | 42 | 92 | 177 |
| 5 | Carhart alpha + persistence dummy | 42 | 93 | 177 |
| 6 | Before-expense annual return | 42 | 93 | 178 |
| 7 | Before-expense annual return+ before-expense persistence dummy | 42 | 93 | 177 |
| 8 | Before-expense alpha + before-expense persistence dummy | 42 | 92 | 177 |
| 9 | Before-expense Carhart alpha+ before-expense persistence dummy | 41 | 92 | 177 |
| 10 | Style fixed effects + annual return | 42 | 92 | 176 |
| 11 | Expanding window alpha | 42 | 94 | 177 |
| 12 | Expanding window Tstat alpha | 42 | 93 | 178 |
| 13 | Filtered alpha | 42 | 93 | 178 |
| 14 | Full Sample alpha | 42 | 92 | 176 |
| 15 | Full sample Tstat alpha | 42 | 92 | 176 |

## Table 4. Trading Strategy

The table summarizes a trading strategy that buys funds in the bottom decile of reported expense ratios (residual expense ratios), and sells funds in the top decile of reported expense ratios (residual expense ratios). We form the portfolio based on last year's expenses and rebalance each year. Residual expense ratios are estimated using the base-case expense regression models from Table 2. Funds are equally-weighed within portfolios. Using monthly returns from each year, we estimate the 4 factor alpha for each year and then convert it into an annual alpha by multiplying by 12. We then compound the annual alphas over time and report the cumulative alphas. The table also reports the compounded spread between average reported expense ratios (residual expense ratios) of funds in the top and the bottom decile. The sample consists of domestic equity mutual funds (see Table A in the Data Appendix for a detailed description of the sample). The data covers the period of 1966 to 2014 and is a yearly panel. Panel A reports the trading strategy based on full sample of funds. Panel B report the same strategy based on large funds (top size quintile).

**Panel A. All Funds**

| | Reported Expense Ratio | | | | | | Residual Expense Ratio | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **α** | **Expense Spread** | **Year** | **α** | **Expense Spread** | **Year** | **α** | **Expense Spread** | **Year** | **α** | **Expense Spread** |
| **1966** | 0.83% | 1.04% | **1991** | 56.36% | 67.82% | **1966** | 0.62% | 0.89% | **1991** | 30.76% | 58.57% |
| **1967** | 5.78% | 2.29% | **1992** | 61.21% | 72.51% | **1967** | 5.07% | 2.00% | **1992** | 32.04% | 63.05% |
| **1968** | 11.03% | 3.48% | **1993** | 49.59% | 76.84% | **1968** | -0.22% | 3.29% | **1993** | 29.21% | 66.59% |
| **1969** | 3.92% | 4.79% | **1994** | 57.98% | 80.85% | **1969** | -11.97% | 4.53% | **1994** | 34.16% | 69.83% |
| **1970** | 5.70% | 6.28% | **1995** | 69.71% | 84.88% | **1970** | -11.06% | 5.89% | **1995** | 40.00% | 73.20% |
| **1971** | 8.69% | 8.19% | **1996** | 74.29% | 88.83% | **1971** | -5.66% | 7.58% | **1996** | 42.08% | 76.46% |
| **1972** | 17.12% | 10.47% | **1997** | 92.42% | 92.86% | **1972** | 1.82% | 9.53% | **1997** | 41.50% | 79.73% |
| **1973** | 14.69% | 12.69% | **1998** | 97.98% | 97.26% | **1973** | -4.33% | 11.50% | **1998** | 49.45% | 83.80% |
| **1974** | 25.39% | 15.19% | **1999** | 93.65% | 101.97% | **1974** | 3.26% | 13.70% | **1999** | 58.06% | 88.03% |
| **1975** | 21.34% | 17.61% | **2000** | 94.98% | 106.44% | **1975** | 5.39% | 15.84% | **2000** | 62.18% | 91.92% |
| **1976** | 18.17% | 20.03% | **2001** | 97.73% | 110.59% | **1976** | 4.72% | 17.93% | **2001** | 65.22% | 95.09% |
| **1977** | 27.64% | 23.07% | **2002** | 105.35% | 115.26% | **1977** | 6.82% | 20.67% | **2002** | 68.65% | 98.70% |
| **1978** | 31.50% | 25.90% | **2003** | 109.76% | 120.51% | **1978** | 7.56% | 23.17% | **2003** | 69.98% | 102.79% |
| **1979** | 22.30% | 28.55% | **2004** | 112.83% | 126.21% | **1979** | 0.48% | 25.22% | **2004** | 73.31% | 107.26% |
| **1980** | 22.86% | 31.22% | **2005** | 112.92% | 131.32% | **1980** | 2.41% | 27.45% | **2005** | 74.61% | 111.00% |
| **1981** | 21.98% | 33.81% | **2006** | 121.63% | 136.54% | **1981** | 3.21% | 29.40% | **2006** | 71.14% | 114.82% |
| **1982** | 27.03% | 36.57% | **2007** | 123.71% | 142.05% | **1982** | 7.89% | 31.47% | **2007** | 66.44% | 119.89% |
| **1983** | 37.05% | 39.42% | **2008** | 132.99% | 147.27% | **1983** | 6.63% | 33.66% | **2008** | 72.09% | 123.76% |
| **1984** | 44.27% | 42.03% | **2009** | 133.19% | 152.38% | **1984** | 8.40% | 35.71% | **2009** | 74.70% | 127.47% |
| **1985** | 46.40% | 44.64% | **2010** | 138.82% | 157.81% | **1985** | 11.92% | 37.88% | **2010** | 78.16% | 131.42% |
| **1986** | 46.84% | 47.56% | **2011** | 146.65% | 163.24% | **1986** | 12.84% | 40.36% | **2011** | 81.55% | 135.32% |
| **1987** | 42.09% | 50.42% | **2012** | 152.07% | 168.56% | **1987** | 10.39% | 42.77% | **2012** | 86.02% | 139.06% |
| **1988** | 45.49% | 54.07% | **2013** | 153.14% | 173.98% | **1988** | 12.21% | 46.08% | **2013** | 81.00% | 142.83% |
| **1989** | 51.02% | 58.51% | **2014** | 161.91% | 179.45% | **1989** | 23.23% | 50.07% | **2014** | 84.22% | 146.72% |
| **1990** | 55.96% | 63.13% | | | | **1990** | 27.97% | 54.42% | | | |

| Panel B. Large Funds (Top Size Quintile) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Reported Expense Ratio | | | | | | Residual Expense Ratio | | | | |
| **Year** | **α** | **Expense Spread** | **Year** | **α** | **Expense Spread** | **Year** | **α** | **Expense Spread** | **Year** | **α** | **Expense Spread** |
| **1966** | 2.17% | 0.48% | **1991** | 43.52% | 24.56% | **1966** | 1.68% | 0.30% | **1991** | 0.86% | 18.95% |
| **1967** | 10.68% | 0.92% | **1992** | 50.54% | 26.64% | **1967** | 1.71% | 0.64% | **1992** | 6.00% | 20.68% |
| **1968** | 13.90% | 1.40% | **1993** | 49.19% | 28.61% | **1968** | 3.92% | 0.93% | **1993** | 5.57% | 22.38% |
| **1969** | 21.03% | 1.99% | **1994** | 52.70% | 30.46% | **1969** | 5.77% | 1.23% | **1994** | 9.79% | 23.93% |
| **1970** | 37.21% | 2.70% | **1995** | 62.25% | 32.50% | **1970** | 12.08% | 1.57% | **1995** | 11.67% | 25.64% |
| **1971** | 44.28% | 3.47% | **1996** | 66.36% | 34.66% | **1971** | 15.21% | 2.03% | **1996** | 12.12% | 27.39% |
| **1972** | 61.03% | 4.40% | **1997** | 84.13% | 36.94% | **1972** | 17.77% | 2.68% | **1997** | 13.30% | 29.26% |
| **1973** | 60.27% | 5.37% | **1998** | 93.32% | 39.15% | **1973** | 22.36% | 3.31% | **1998** | 16.88% | 31.07% |
| **1974** | 63.47% | 6.24% | **1999** | 93.39% | 41.48% | **1974** | 27.05% | 3.88% | **1999** | 20.32% | 33.04% |
| **1975** | 61.55% | 7.08% | **2000** | 93.30% | 43.86% | **1975** | 23.81% | 4.52% | **2000** | 19.78% | 35.13% |
| **1976** | 68.20% | 7.80% | **2001** | 97.86% | 46.28% | **1976** | 29.07% | 5.10% | **2001** | 23.62% | 36.89% |
| **1977** | 64.90% | 8.42% | **2002** | 115.33% | 48.92% | **1977** | 28.53% | 5.58% | **2002** | 29.73% | 38.79% |
| **1978** | 62.50% | 9.09% | **2003** | 123.34% | 51.79% | **1978** | 27.77% | 6.01% | **2003** | 31.81% | 40.85% |
| **1979** | 47.77% | 9.77% | **2004** | 126.75% | 54.77% | **1979** | 22.12% | 6.48% | **2004** | 35.17% | 42.99% |
| **1980** | 40.59% | 10.44% | **2005** | 122.61% | 57.68% | **1980** | 19.65% | 6.98% | **2005** | 33.11% | 45.13% |
| **1981** | 26.41% | 11.23% | **2006** | 132.27% | 60.67% | **1981** | 7.26% | 7.55% | **2006** | 34.11% | 47.29% |
| **1982** | 35.55% | 12.04% | **2007** | 135.73% | 63.60% | **1982** | 9.36% | 8.23% | **2007** | 34.86% | 49.42% |
| **1983** | 34.42% | 12.85% | **2008** | 147.70% | 66.43% | **1983** | 4.27% | 8.86% | **2008** | 40.63% | 51.53% |
| **1984** | 31.21% | 13.87% | **2009** | 144.11% | 69.25% | **1984** | 2.74% | 9.70% | **2009** | 41.01% | 53.63% |
| **1985** | 40.39% | 14.97% | **2010** | 147.37% | 72.10% | **1985** | 4.93% | 10.68% | **2010** | 43.00% | 55.80% |
| **1986** | 34.35% | 16.09% | **2011** | 164.92% | 74.79% | **1986** | 5.51% | 11.62% | **2011** | 49.55% | 57.84% |
| **1987** | 29.63% | 17.29% | **2012** | 166.81% | 77.38% | **1987** | 5.13% | 12.70% | **2012** | 49.61% | 59.84% |
| **1988** | 30.38% | 18.93% | **2013** | 176.36% | 79.98% | **1988** | 5.87% | 14.14% | **2013** | 46.80% | 61.78% |
| **1989** | 38.00% | 20.69% | **2014** | 190.14% | 82.55% | **1989** | 7.90% | 15.64% | **2014** | 51.76% | 63.73% |
| **1990** | 44.93% | 22.67% | | | | **1990** | 0.84% | 17.31% | | | |

**Table 5. Share Class Aggregation and Expense Dispersion**

This table presents the time-series average of the cross-sectional residual spreads, in basis points (bps), between percentiles of the residual expense distribution for our sample of mutual funds (see Table A in the Data Appendix for a detailed description of the sample) for share class aggregation. Panel A reports mean residuals for the full sample, Panel B reports residuals spreads for the bottom quintile of annually ranked TNA funds, and Panel C reports mean residual spreads for the top quintile of annually ranked TNA funds. The sample period covers 1980 to 2014. Row 1 in each panel reports the results from the base-case specification in which we do not aggregate across share classes. Rows 2-4 report results for samples in which we aggregate share classes using three different aggregation schemes: equal-weighting (specification 2), value-weighting (specification 3) and selection of the largest share class (specification 4).

**Panel A. Full Sample**

| | Mean Residual Spread (bps) | | |
|---|---|---|---|
| | **25$^{th}$ to 75$^{th}$ Percentile** | **10$^{th}$ to 90$^{th}$ Percentile** | **1$^{th}$ to 9$^{th}$ Percentile** |
| No Aggregation | 63 | 125 | 243 |
| Aggregated Share Classes (EW) | 63 | 126 | 268 |
| Aggregated Share Classes (VW) | 58 | 122 | 265 |
| Aggregated Share Classes (Largest) | 55 | 117 | 266 |

**Panel B. Bottom Quintile of Funds**

| | Mean Residual Spread (bps) | | |
|---|---|---|---|
| | **25$^{th}$ to 75$^{th}$ Percentile** | **10$^{th}$ to 90$^{th}$ Percentile** | **1$^{th}$ to 9$^{th}$ Percentile** |
| No Aggregation | 91 | 184 | 386 |
| Aggregated Share Classes (EW) | 110 | 222 | 492 |
| Aggregated Share Classes (VW) | 107 | 221 | 490 |
| Aggregated Share Classes (Largest) | 107 | 218 | 498 |

**Panel C. Top Quintile of Funds**

| | Mean Residual Spread (bps) | | |
|---|---|---|---|
| | **25$^{th}$ to 75$^{th}$ Percentile** | **10$^{th}$ to 90$^{th}$ Percentile** | **1$^{th}$ to 9$^{th}$ Percentile** |
| No Aggregation | 50 | 101 | 184 |
| Aggregated Share Classes (EW) | 45 | 89 | 164 |
| Aggregated Share Classes (VW) | 40 | 79 | 157 |
| Aggregated Share Classes (Largest) | 37 | 77 | 158 |

## Table 6. Differences in Reported Expense Ratios and Residual Expense Ratios for Holdings-matched Fund Pairs

The table reports mean absolute differences in expense (residual) ratios and spreads of absolute differences in expense (residual) ratios for matched fund pairs. The matching is based on holdings' overlap measured in terms of "uniqueness." For each possible fund pair, we estimate, yearly, the sum, across all holdings, of absolute differences in weights. For each fund, its uniqueness value is defined as the value of this sum for the fund pair that results in the maximal holdings overlap. The uniqueness measure is bounded between zero (perfect overlap) and two (no overlap). We refer to this sample of matched fund pairs as the "full pairs sample." We rank uniqueness into quintiles, where quintile 1 contains the most similar fund pairs and quintile 5 contains the least similar funds pairs. We also define "very similar funds" as the bottom decile of the uniqueness measure. In Panel A we present mean absolute differences and interquartile ranges (IQR) for fund characteristics of the matched pairs. In Panel B we present mean absolute differences, interquartile ranges and inter-percentile spreads for reported expense ratios and residual expense ratios, in basis points. The residual expense ratios are from the base-case expense regression of Table 2. All variables are contemporaneous to the matching of fund pairs.

### Panel A. Differences in Fund Characteristics for Matched Pairs

| | | Avg. # of fund pairs/year | Uniqueness (Matching Criterion) | | Annual return | | $R^2$ | | Beta_mkt | | Beta_smb | | Beta_hml | | Beta_umd | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Mean | IQR | Mean | IQR | Mean | IQR | Mean | IQR | Mean | IQR | Mean | IQR | Mean | IQR |
| **Full pairs sample** | | 1145.4 | 1.05 | 0.58 | 0.07 | 0.07 | 0.08 | 0.08 | 0.16 | 0.18 | 0.23 | 0.25 | 0.2 | 0.23 | 0.12 | 0.13 |
| **Very similar funds** | | 114.94 | 0.15 | 0.12 | 0.03 | 0.03 | 0.03 | 0.02 | 0.15 | 0.15 | 0.08 | 0.08 | 0.09 | 0.09 | 0.05 | 0.05 |
| **Uniqueness Quintiles** | **1** | 229.41 | 0.32 | 0.42 | 0.03 | 0.03 | 0.03 | 0.03 | 0.13 | 0.15 | 0.09 | 0.1 | 0.1 | 0.11 | 0.06 | 0.07 |
| | **2** | 229.12 | 0.9 | 0.34 | 0.05 | 0.05 | 0.05 | 0.05 | 0.13 | 0.14 | 0.14 | 0.14 | 0.16 | 0.17 | 0.1 | 0.1 |
| | **3** | 229 | 1.18 | 0.2 | 0.06 | 0.06 | 0.06 | 0.06 | 0.16 | 0.16 | 0.18 | 0.19 | 0.2 | 0.21 | 0.12 | 0.12 |
| | **4** | 229.12 | 1.36 | 0.18 | 0.08 | 0.08 | 0.09 | 0.09 | 0.18 | 0.18 | 0.27 | 0.29 | 0.25 | 0.26 | 0.14 | 0.15 |
| | **5** | 228.71 | 1.49 | 0.25 | 0.11 | 0.12 | 0.13 | 0.14 | 0.22 | 0.23 | 0.45 | 0.52 | 0.31 | 0.33 | 0.18 | 0.18 |

**Panel B. Differences in Expenses for Matched Pairs**

| | | Reported Expense Ratio | | | | Residual Expense Ratio | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Spreads** | | Mean | IQR | $10^{th}$ to $90^{th}$ | $1^{st}$ to $99^{th}$ | Mean | IQR | $10^{th}$ to $90^{th}$ | $1^{st}$ to $99^{th}$ |
| **Full pairs sample** | | 49 | 54 | 103 | 219 | 46 | 47 | 94 | 206 |
| **Very similar funds** | | 41 | 48 | 94 | 174 | 38 | 41 | 84 | 167 |
| **Uniqueness Quintiles** | **1** | 42 | 49 | 101 | 176 | 40 | 41 | 83 | 172 |
| | **2** | 43 | 51 | 98 | 192 | 40 | 43 | 84 | 176 |
| | **3** | 47 | 52 | 98 | 204 | 45 | 48 | 93 | 190 |
| | **4** | 51 | 55 | 104 | 240 | 50 | 52 | 104 | 214 |
| | **5** | 63 | 57 | 111 | 321 | 56 | 53 | 105 | 274 |

**Table 7. Testing Explanations of Residual Expense Spreads**

The table reports results for tests of various hypotheses formulated to explain the dispersion in mutual fund expenses. Panel A reports means and standard deviations of the variables used to test the hypotheses, sorted by reported expense ratio deciles. The last column in Panel A reports the difference between decile 1 and decile 10 characteristics. Stars indicate significance at the 1% (***), 5% (**) and 10% (*) level. Panel B (pre-1999) and C (post-1999) report coefficients of on these variables when they are added individually or jointly to the base-case expense regressions from Table 2. We standardize all the independent variables to mean 0 and standard deviation 1 using the full-sample mean of each variable's yearly cross-sectional mean and SD. Panel D reports mean residual expense spreads for the full sample and for the bottom and top quintile of annually ranked TNA funds after including the hypothesis variables individually or jointly in the expense regressions. In Panel D we report the spreads for 3 periods: Pre-1999, Post-1999, and Full Period. Variables are defined in Table B in the Data Appendix. All variables are measured at the share class level, except for fund average uniqueness (i.e., our measure of fund competition) that is estimated at the fund level.

**Panel A. Summary Statistics of Proxies by Reported Expense Ratio Deciles**

| | | Decile 1 | | Decile 3 | | Decile 5 | | Decile 7 | | Decile 10 | | Decile 1-10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Diff. |
| Pre-1999 | **Fund average uniqueness** | 1.858 | 0.087 | 1.883 | 0.066 | 1.903 | 0.061 | 1.919 | 0.059 | 1.933 | 0.057 | 0.074*** |
| | **Random fee changes** | 0.074 | 0.125 | 0.172 | 0.155 | 0.198 | 0.157 | 0.181 | 0.155 | 0.130 | 0.149 | 0.057*** |
| | **Flow autocorrelation** | 0.220 | 0.340 | 0.223 | 0.321 | 0.243 | 0.332 | 0.288 | 0.356 | 0.321 | 0.375 | 0.101*** |
| | **Pension plan dummy** | 0.074 | 0.262 | 0.058 | 0.233 | 0.067 | 0.250 | 0.118 | 0.323 | 0.116 | 0.320 | 0.042*** |
| Post-1999 | **Fund average uniqueness** | 1.839 | 0.119 | 1.855 | 0.093 | 1.879 | 0.084 | 1.896 | 0.081 | 1.904 | 0.080 | 0.065*** |
| | **Random fee changes** | 0.085 | 0.115 | 0.142 | 0.140 | 0.143 | 0.137 | 0.133 | 0.138 | 0.156 | 0.142 | 0.071*** |
| | **Flow autocorrelation** | 0.241 | 0.302 | 0.244 | 0.287 | 0.284 | 0.311 | 0.321 | 0.349 | 0.345 | 0.378 | 0.104*** |
| | **Pension plan dummy** | 0.080 | 0.272 | 0.061 | 0.240 | 0.096 | 0.294 | 0.146 | 0.353 | 0.188 | 0.391 | 0.108*** |
| | **Flow-perf sensitivity** | -0.088 | 14.620 | 0.080 | 1.592 | 0.147 | 1.548 | 0.076 | 1.693 | 0.189 | 1.910 | 0.277*** |

**Panel B. Coefficients in Expense Regressions (Pre-1999)**

| Controlling for… | Competition | | Randomization | | Captivity | |
|---|---|---|---|---|---|---|
| | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat |
| **Fund average uniqueness** | 3.59 | 3.08 | | | | |
| **Random fee changes** | | | 7.06 | 7.11 | | |
| **Flow autocorrelation** | | | | | 2.11 | 2.60 |
| **Pension plan dummy** | | | | | 5.29 | 1.23 |
| **Family Fixed Effects** | No | | No | | No | |
| **Other Controls** | Like Table 2 | | Like Table 2 | | Like Table 2 | |
| **# of years** | 18 | | 34 | | 34 | |
| **# of obs.** | 14629 | | 29836 | | 27698 | |
| **Avg. R-Squared** | 30.89% | | 25.35% | | 29.33% | |

**Panel C. Coefficients in Expense Regressions (Post-1999)**

| Controlling for… | Competition | | Randomization | | Captivity | | Flow-Perf. Sens. | |
|---|---|---|---|---|---|---|---|---|
| | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat | Coeff. | t-stat |
| **Fund average uniqueness** | -1.65 | -0.80 | | | | | | |
| **Random fee changes** | | | 7.71 | 10.36 | | | | |
| **Flow autocorrelation** | | | | | 11.73 | 50.99 | | |
| **Pension plan dummy** | | | | | 12.03 | 10.46 | | |
| **Flow-perf sensitivity** | | | | | | | 7.19 | 2.44 |
| **Family Fixed Effects** | No | | No | | No | | No | |
| **Other Controls** | Like Table 2 | | Like Table 2 | | Like Table 2 | | Like Table 2 | |
| **# of years** | 15 | | 15 | | 15 | | 15 | |
| **# of obs.** | 36422 | | 104559 | | 104559 | | 104548 | |
| **Avg. R-Squared** | 29.18% | | 28.93% | | 30.80% | | 27.99% | |

**Panel D. Average Expense Spreads in Basis Points**

| | Full Sample | | | Smallest Funds | | | Largest Funds | | |
|---|---|---|---|---|---|---|---|---|---|
| | 25th to 75th | 10th to 90th | 1st to 99th | 25th to 75th | 10th to 90th | 1st to 99th | 25th to 75th | 10th to 90th | 1st to 99th |
| **Base Case** | 62 | 124 | 247 | 95 | 180 | 399 | 42 | 93 | 177 |
| **Fund average uniqueness** | 54 | 113 | 260 | 114 | 232 | 580 | 33 | 68 | 144 |
| **Random fee changes** | 62 | 122 | 245 | 95 | 180 | 397 | 42 | 92 | 174 |
| **Flow autocorrelation + pension plan dummy** | 59 | 118 | 240 | 93 | 176 | 391 | 41 | 88 | 174 |
| **Flow-Perf Sensitivity (only post-1999)** | 63 | 123 | 232 | 90 | 170 | 369 | 44 | 95 | 180 |

## Table 8. US Household Participation, Average Fee Levels and Fee Dispersion

This table investigates the time-series relation between US household participation in the mutual fund industry and average fees or measures of fee dispersion, respectively. Panel A reports summary statistics of the variables in levels and percentage changes. Panel B presents the regression results in which all variables are included as percentage growth rates (i.e., relative changes). US Household participation is the percentage of US household owning mutual funds. The data is obtained from the Investment Company Institute (ICI) Perspective Report (2014) and is available starting in 1980. VW (EW) average fees are TNA-weighted (equally-weighted) averages of reported expense ratios. 90-10 reported (residual) expense spread is the $90^{th}$ percentile of reported (residual) expenses minus the $10^{th}$ percentile of reported (residual) expense. The percentiles of reported fees are derived from the empirical fee distribution of each yearly cross-section. Residual fees are derived from the regressions reported in Table 2.

### Panel A. Descriptive Statistics

| | Full Sample | | | | Largest Funds | | | |
|---|---|---|---|---|---|---|---|---|
| | Levels | | %-Changes | | Levels | | %-Changes | |
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| US Household participation | 32.51% | 13.39% | 7.17% | 12.27% | | | | |
| VW Average Fees | 0.79% | 0.12% | -0.05% | 7.19% | 0.74% | 0.12% | 1.05% | 7.38% |
| EW Average Fees | 1.26% | 0.23% | 0.98% | 9.88% | 0.94% | 0.17% | 1.01% | 6.27% |
| 90-10 Reported Expense Spread | 1.47% | 0.32% | 1.72% | 11.14% | 1.06% | 0.33% | 3.59% | 13.52% |
| 90-10 Residual Expense Spread | 1.24% | 0.32% | 2.39% | 16.96% | 0.84% | 0.24% | 3.67% | 12.84% |

**Panel B. Time-Series Regressions**

| | Full Sample | | | | Largest Funds | | | |
|---|---|---|---|---|---|---|---|---|
| | VW Average Fees (growth) | EW Average Fees (growth) | 90-10 Reported Expense Spread (growth) | 90-10 Residual Expense Spread (growth) | VW Average Fees (growth) | EW Average Fees (growth) | 90-10 Reported Expense Spread (growth) | 90-10 Residual Expense Spread (growth) |
| Growth in US Household Participation | 0.19 | 0.15 | 0.34 | 0.27 | 0.18 | 0.20 | 0.46 | 0.42 |
| | [1.86] | [1.06] | [2.23] | [1.09] | [1.69] | [2.38] | [2.56] | [2.42] |
| Constant | -0.01 | 0.00 | -0.00 | 0.00 | -0.01 | -0.01 | 0.00 | 0.00 |
| | [-0.96] | [0.03] | [-0.29] | [0.10] | [-0.86] | [-0.44] | [0.12] | [0.10] |
| Adj. R-squared | 7.4% | 0.4% | 11.4% | 0.6% | 5.6% | 13.1% | 15.2% | 13.6% |
| # of Years | 32 | 32 | 32 | 32 | 32 | 32 | 32 | 32 |

**Figure 1. Fund Expense Dispersion**

These figures show the dispersion of expense ratios (left column) and residual expense ratios (right column) across funds and over time. The graphs show the ranges between the 25th and 75th (darkest grey), 10th and 90th (medium dark grey) and 1st and 99th percentile (light grey) points of the distributions. Graphs in the top row also plot the aggregate TNA of all funds in the graph in Billions of USD (red line). In rows 2 and 3, the red line represents the fraction of aggregate TNA represented by funds in the bottom size quintile (row 2) and the top size quintile (row 3) of our sample. The residual expenses are defined as the regression residuals of the expense models specified in Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Data Appendix for a detailed description of the sample). The data covers the period of 1966 to 2014 and is a yearly panel.

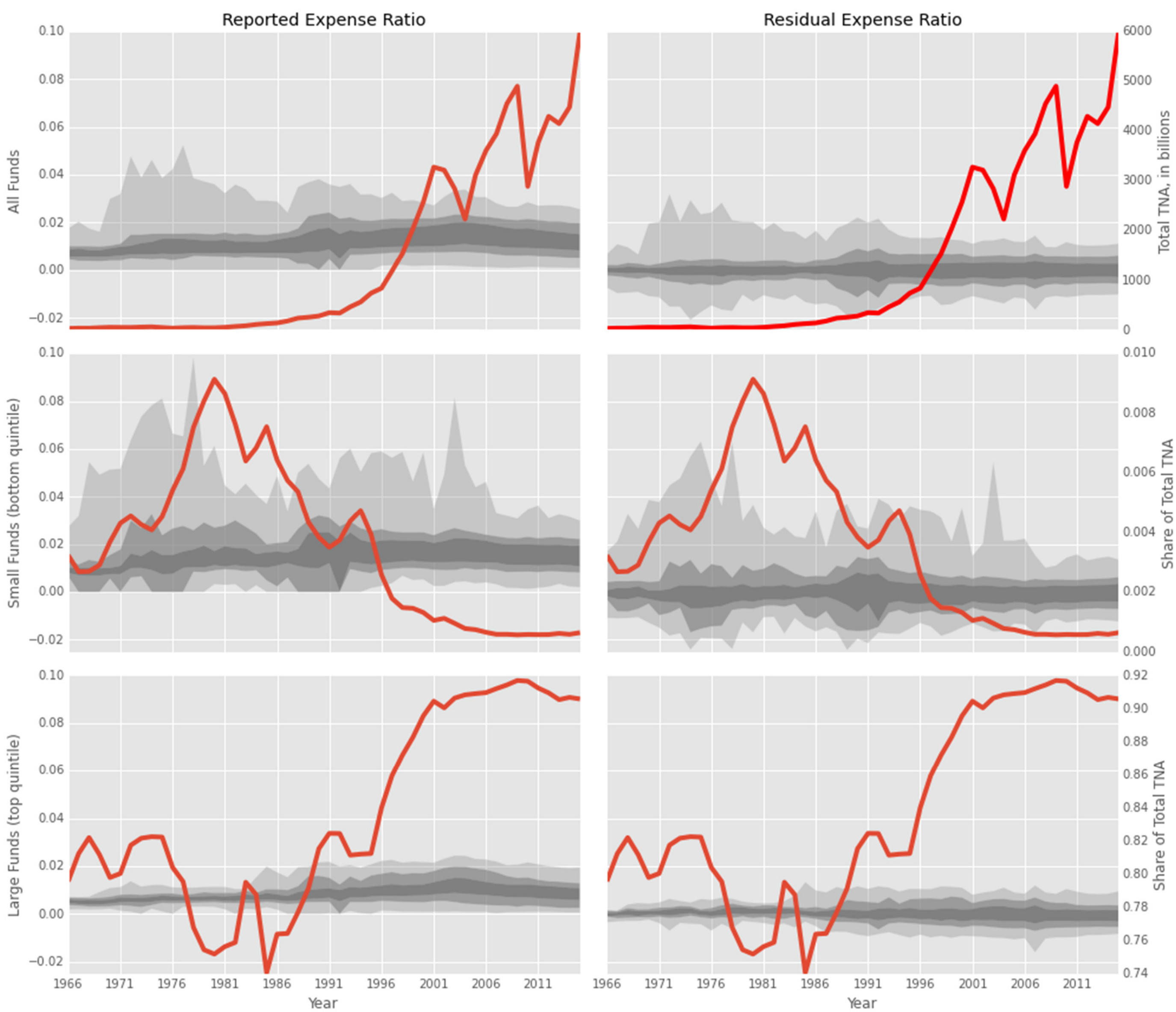

**Figure 2. Fund Expense Dispersion of Institutional and Retail Funds**

These figures show the dispersion of reported expense ratios (left column) and residual expense ratios (right column) across funds that are institutional funds (top row) and funds that are retail funds (bottom row). The graphs show the ranges between the 25th and 75th (darkest grey), 10th and 90th (medium dark grey) and 1st and 99th percentile (light grey) points of the distributions. The residual expenses are defined as the regression residuals of the expense models specified in Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Data Appendix for a detailed description of the sample). The data in this analysis covers the period of 1999 to 2014 and is a yearly panel.

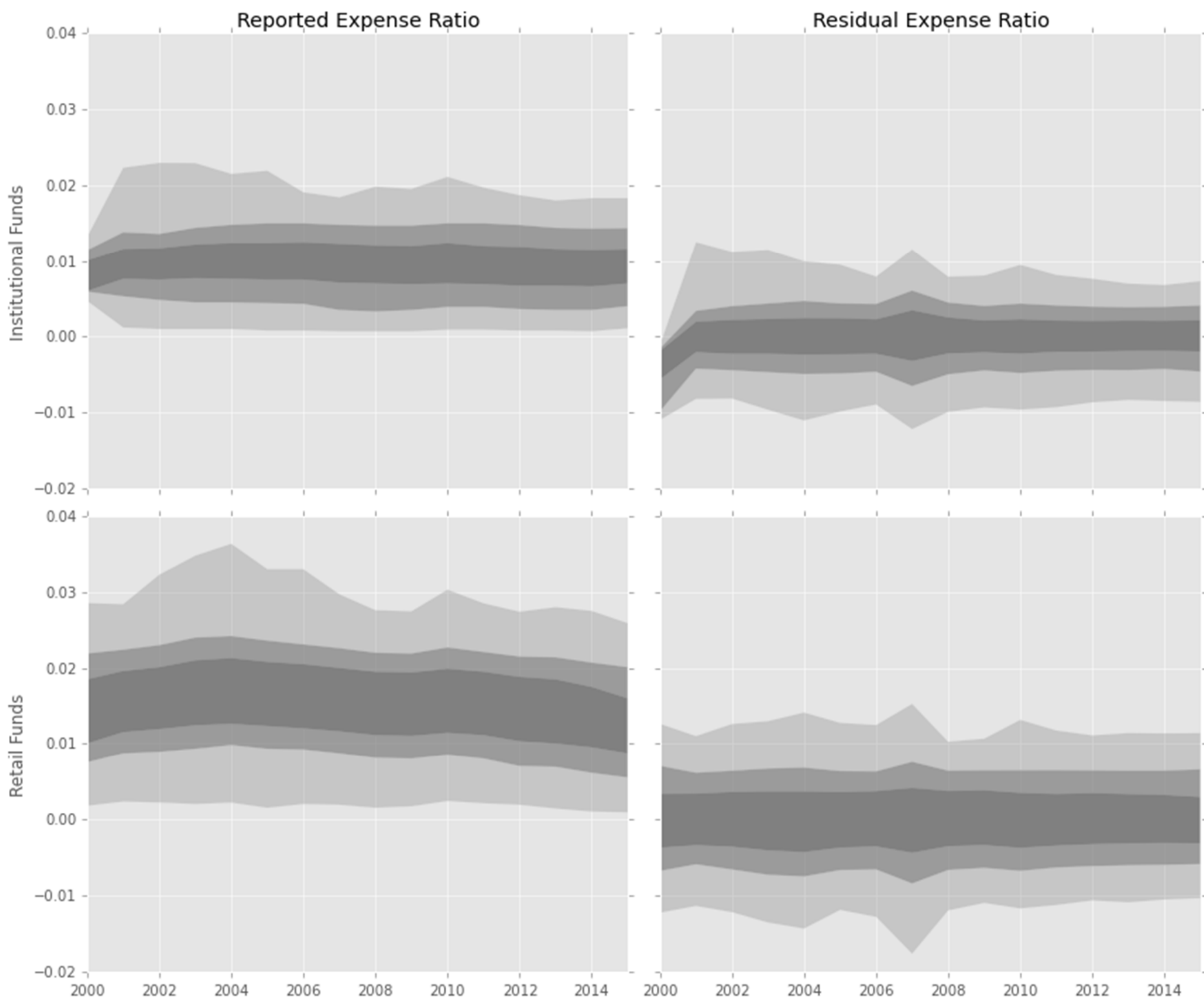

**Figure 3. Evaluation of Trading Strategy**

These figures show the cumulative Carhart alpha (the solid line) of a strategy that buys funds in the bottom decile of reported expense ratios (residual expense ratios) and shorts funds in the top decile of reported expense ratios (residual expense ratios). The figures also reports the cumulative spread between average reported expense ratios (residual expense ratios) of funds in the top and the bottom decile (the dashed line). The residual expenses are defined as the regression residuals of the expense models specified in Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Data Appendix for a detailed description of the sample). The data covers the period of 1966 to 2014 and is a yearly panel.

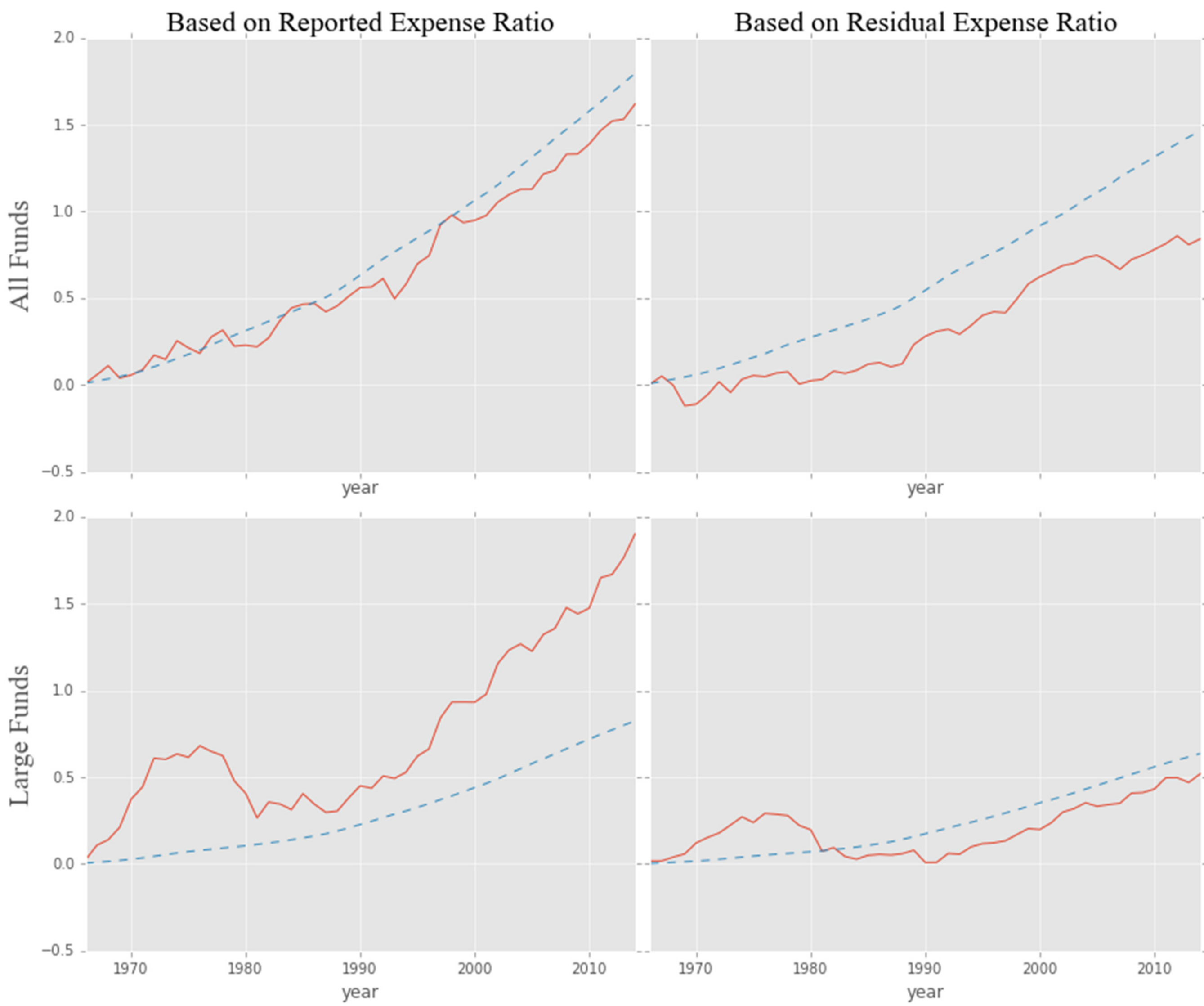

**Figure 4. Fund Expense Dispersion at the Share Class and Fund Level**

These figure show residual expense ratios across funds and over time for aggregated and non-aggregated share classes. In the 1st (2nd) column, the sample consists of observations at the share class (fund; if a fund has multiple share classes we select the largest share class) level. The graphs reported in the 1st row are based on all observations, while the graphs in the 2nd row only consider the top-20% share classes/funds in terms of fund TNA at the beginning of each year. The graphs show the ranges between the 25th and 75th (darkest grey), 10th and 90th (medium dark grey) and 1st and 99th percentile (light grey) points of the distributions. The residual expense is defined as the regression residual of the expense models specified in Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Data Appendix for a detailed description of the sample). The data covers the period of 1980 to 2014 and is a yearly panel.

**Figure 5. Fund Expense Dispersion for Holdings-matched Fund Pairs**

These figures show the interquartile spread (dark grey), 10th to 90th percentile spread (medium grey) and 1st to 99th percentile spread (light grey) for the absolute differences in reported expense ratios (1st column) and residual expenses (2nd column) for holdings-matched fund pairs. The matching is based on holdings' overlap measured in terms of "uniqueness." For each possible fund pair, we estimate, yearly, the sum, across all holdings, of absolute differences in weights. For each fund, its uniqueness value is defined as the value of this sum for the fund pair that results in the maximal holdings overlap. The uniqueness measure is bounded between zero (perfect overlap) and two (no overlap). The first row shows reported expense ratio spreads for the full sample of pairs, the second row shows the most similar pairs (i.e., quintile 1 of uniqueness) and the third row shows least similar pairs (i.e., quintile 5 of uniqueness). The solid red lines show the sample's mean uniqueness measure each year. The residual expense is defined as the regression residual of the expense models specified in Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Data Appendix for a detailed description of the sample). The data covers the period of 1980 to 2014 and is a yearly panel.

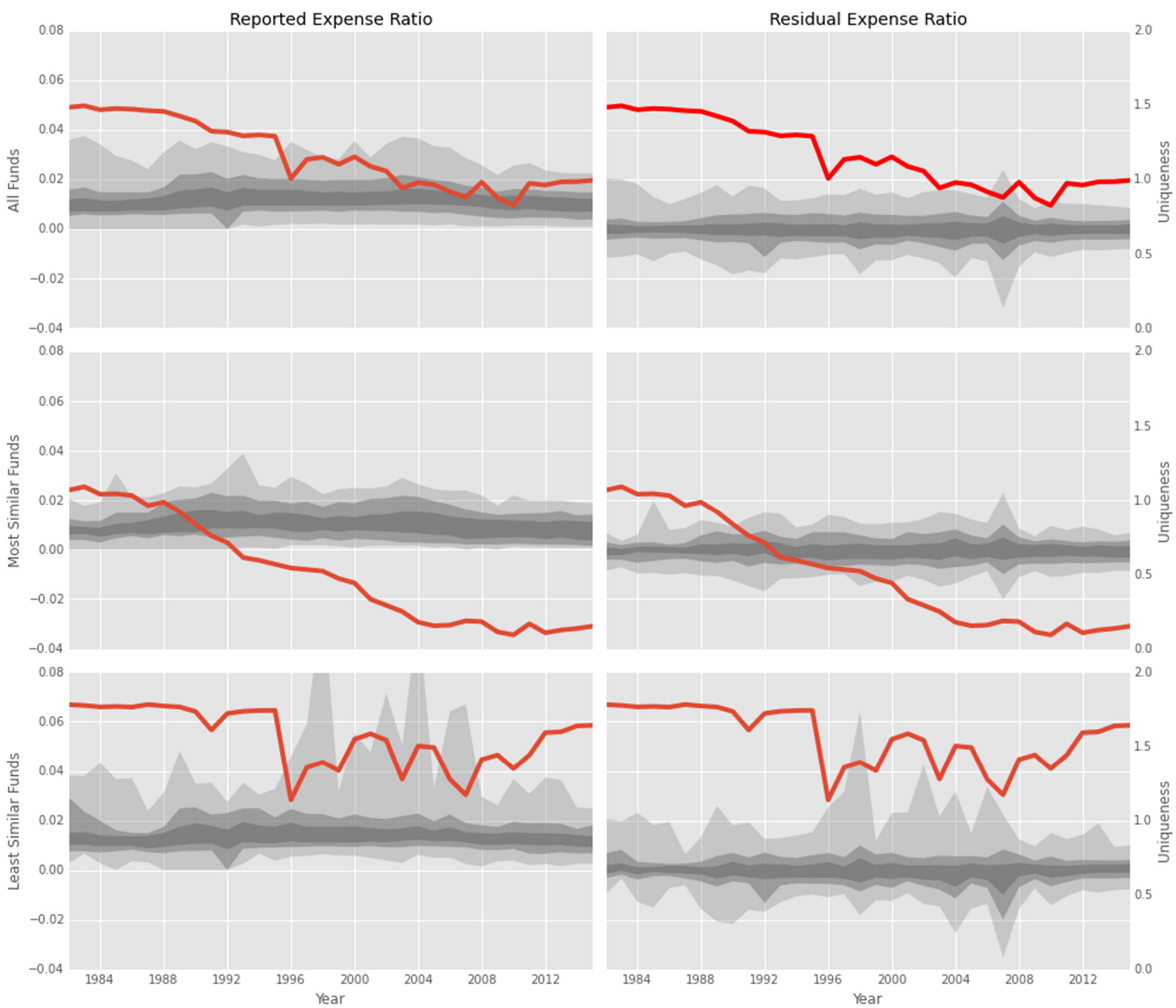

**Figure 6. Yearly Time-Series of Average Fees, Spreads in Residual Fees and US Household Participation in the Mutual Fund Industry**

This figure plots 3 time-series: (1) the residual fee spread (the solid line), calculated as the 90th percentile minus the 10th percentile of the residual fee distribution extracted from the regressions reported in Table 2, (2) the TNA-weighted average reported expense ratio (dashed line), and (3) the percentage of U.S household ownership of mutual funds (dotted line). The graphs share their axes. Series (1) and (2) correspond to the left y-axis while series (3) is depicted on the right y-axis. The US household data is obtained from the ICI Research Perspective Report (2014). The data spans the period from 1980 to 2014.