Violations of the Law of One Fee in the Mutual Fund Industry

Michael Cooper, Michael Halling and Michael Lemmon*

March 28, 2013

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

JEL Classifications: G10, G11, G23.

* All authors are with the David Eccles School of Business, University of Utah. Halling is also at the Stockholm School of Economics and the Swedish House of Finance.
We thank 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 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 and VU University Amsterdam for their comments. An earlier version of this paper was titled "Fee Dispersion and Persistence in the Mutual Fund Industry".

Violations of the Law of One Fee in the Mutual Fund Industry

Abstract

In competitive markets, similar products should have similar prices. We apply this concept to mutual funds. We examine the residuals from regressions of fees (annual expenses and 12b-1 fees) on important fund characteristics, essentially allowing us to compare the fees of "identical" funds. We present striking new evidence of systematic differences in residual fees across *all* US equity funds. We find that the average spread in residual fees across funds over the sample is approximately 2.3%. The dispersion in fees has not decreased over time, despite the fact that significant numbers of new funds have entered and the aggregate amount of assets under management has increased substantially. An investor purchasing similar lower fee funds would have outperformed an investor purchasing higher fee funds by approximately 32% over our sample. We test a number of hypotheses to explain our results including a random fee, competition, service, captive investor, and strategic fee setting hypothesis, and are able to explain only a small portion of the spread in residual fees. Surprisingly, a main determinant of fees is the initial fee set by a fund, which varies little over time. Overall, our evidence is largely inconsistent with a competitive market for mutual funds.

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.[2] 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 papers, focusing on sub-categories of funds, also provide evidence of differential prices being charged for funds with similar characteristics.[3]

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.[4] 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 evidence of price dispersion in specific areas of the mutual fund market, there is little existing

---

[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 Hortacsu and Syverson (2004).

[3] See also Elton, Gruber, and Rentzler (1989) who find that public commodity funds exist that underperform the risk free rate and Christoffersen and Musto (2002) who find a wide dispersion in fees across similar money market funds.

[4] 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 fees 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 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 examine if the "law of one fee" (the idea that if the mutual fund market is more-or-less competitive, then similar mutual funds, as measured by important fund characteristics, should have roughly similar fees) holds. We examine the residuals from regressions of fees (annual expenses and 12b-1 fees) on important fund characteristics, essentially allowing us to compare the fees of "identical" funds. We present new evidence of systematic differences in residual fees across *all* US equity funds. Specifically, we find that the average spread in residual fees (between the 1st and 99th percentile) across all funds over the sample is 2.34%. More interestingly, the dispersion in residual fees has not decreased over time, despite the fact that significant numbers of new funds have entered and the aggregate amount of assets under management has increased substantially over time. Our results hold for both the largest total net asset (TNA) funds as well as the smaller TNA funds; the average spread in residual fees is 2.88% for the smallest quintile of TNA funds and is 1.18% for the largest quintile of funds. [5] In fact, for the largest quintile funds, representing 82% of the market value of our sample, the spread in residual fees has actually increased from 1990 to 2009, evidence that is potentially difficult to reconcile with a competitive market for mutual funds.

We examine the implications of our findings for investors. Based on raw (residual) fees, an investor purchasing the lowest fee funds would have earned compounded abnormal returns 67% (32%) higher than an investor purchasing the most expensive funds. As a basis for comparison, the compounded differences in fees (residual fees) over the period were 90% (64%). Thus, while the difference in abnormal returns between high fee and low fee funds is less than the cumulative difference in fees, it appears that investors bear significant costs from investing in high fee mutual funds that are not recouped through higher performance of these funds.

We explore various explanations for the large price dispersion across similar funds. We first note that controlling for product characteristics that investors are likely to care about when purchasing a fund, such as

[5] Our results are robust to multiple variations in the models used to estimate residual fees, variations in residual estimation techniques (including the use of stochastic frontier models), aggregation of share classes, and the use of before-fee returns in estimating residual fees.

search costs, service levels, fund size, retail versus institutional funds, fund age, fund flows, fund portfolio characteristics (i.e., lagged performance and style betas) explains about 44% of the dispersion in raw fees, leaving a sizable unexplained dispersion in fees.

We test various hypotheses to explain this dispersion. We first test a "random fee" hypothesis (Lach (2002) and others) which posits that mutual funds engage in frequent changes in their fees, resulting in fund consumers not being able to easily identify low fee funds, which in turn results in persistent price dispersion. We add a random fee change variable (based on the number of fee increases and decreases for a given fund) to our fee regressions and find that funds that change their fees more often charge higher fees, consistent with theory. We next examine the residuals from the regressions that include the random fee change variable and find a very small or even zero effect on residual fee spreads. Thus, despite the significance of the random fee change variable in fee regressions, the overall economic effect on the fee residuals is small, suggesting that the random fee hypothesis does not explain our results.

Given the small effect on residual fees from fee switching, we perform additional tests to better understand fee randomization in the mutual fund industry. We estimate transition probabilities among low and high fee funds and find evidence inconsistent with a random fee explanation. For both raw and residual fees, low fee funds tend to stay low and high fee funds tend to stay high. It is very rare that high fee funds become low or that low fee funds become high.[6] Given that there is scant evidence for fee switching over time, we examine the role of a fund's initial fee in explaining the cross-section of raw fees. As mentioned above, regression specifications that include standard determinants of fund fees obtain average adjusted R-squareds of approximately 44%. When we add a fund's initial fee to the regressions, the R-squareds of the regressions increase up to 70%. To shed further light on this issue we study the determinants of initial fees. We find that initial fees are higher for funds that enter with smaller size, smaller fund families, fund families that charge higher average fees, and for families that have a higher dispersion of fees within the fund family. We also find that factor returns (i.e., the market risk premium, SMB, HML, and UMD) are consistently negatively related to first fees. A potential interpretation is that in

[6] Liang (2000), among others, documents similar evidence concerning a lack of fee changes in the hedge fund industry.

periods when factors are doing poorly, actively managed funds can charge excess fees. Interactions between factor returns and betas are consistently positively related to first fees, implying that in situations when funds are founded in styles that have been successful in the past, higher fees are charged. Thus, first fees are strongly related to a fund's lifetime expense ratio.

We test four more hypotheses in an attempt to gain a better understanding of how funds set fees and how fees evolve over time. We test the competition hypothesis which predicts that funds that deal with more competing fund should have lower fees. For example, Wahal and Wang (2011) show that when existing funds face competition from new, similar funds, the existing funds lower their fees to better compete with the upstart funds. We regress fees on variables designed to capture the amount of competition that each fund is facing. We find that the number of competing funds is significantly negatively related to and the average fee of the competitors is significantly positively related to a fund's fee, supporting the competition hypothesis. Lastly, we test if the competition hypothesis can explain much of the spread in fee residuals. For the full sample and the sample of largest funds, there are only small drops in the residuals. For the smallest funds, there are larger drops, ranging from 15 to 77 basis points. However, even after controlling for competition, the small-fund residual fee spread is economically large. Thus, competition appears to play a role in the setting of mutual fund fees, especially so for smaller TNA funds, but does not drive away the large spreads in residual fees.

Next, we test the fund family service hypothesis. Hortacsu and Syverson (2004), Collins (2005) and others have suggested that variation in services, such as financial advice or complementary investment instruments, may explain fee variation. Assuming that large fund families offer better service, we find that funds that are part of a family with more than 100 funds charge, on average, an extra 6 to 27 basis points in fees, but controlling for large fund families (using fund family fixed effects in the fee regressions) does not alter our finding of large spreads in residual fees. Our results do not appear to be explained by differences in the services offered by funds.

Another hypothesis we test is the captive investor hypothesis. We examine if funds that are likely to inhibit easy investor exit (thus creating captive investors) are the funds with high residual fees. We define captive investors two ways. First, we define funds that are "easy-in, hard-out" funds. These are funds that spend more than other funds on advertising and have higher back-end loads. Second, using a subsample of funds with high flow autocorrelations, we examine the fees of funds that are likely to be held within pension funds, thus not allowing for easy investor exit. We find evidence consistent with the captive investor hypothesis: high fee funds have higher back-end loads and spend more on advertising than do lower fee funds. Also, high fee funds have higher positive autocorrelation of flows than do lower fee funds. Finally, we add flow autocorrelation and a dummy for "easy-in, hard-out" funds to the fee regressions and examine their effects on the residual fee spreads. Although these measures of captive investors result in significant positive regression coefficients, consistent with theory, they are not able to explain or substantially reduce the level of residual fee dispersion.

The last hypothesis we test is the strategic fee setting hypothesis (SFSH). 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 fees. To test the SFSH, we estimate each fund's flow-performance sensitivity and examine how it relates to fees. The SFSH suggests that funds whose investors are more performance sensitive should have lower fees. In regressions of fees on flow-performance sensitivity and other controls, we find a positive and significant coefficient on flow-performance sensitivity, inconsistent with the predictions from the SFSH. Finally, we examine if residual fee spreads decrease once we control for flow-performance sensitivity and find basically no change at all.

In a final step, we analyze the combined effect of the previously discussed hypotheses on mutual fund fees and spreads of residual fees. In a multiple regression of fees on the variables designed to capture our five hypotheses, all coefficients keep the signs that they showed when we controlled for each individually (i.e., fees increase as fees of competing funds, random fee changes, flow-performance sensitivity, and flow autocorrelation increases, and fees decrease as the number of competing funds increase) and, with the exception of the flow autocorrelation variable in the early part of the sample, all coefficients remain statistically significant. In order of importance, the fees of competing funds is most important, fund flow autocorrelation is next important, and random fee changes are third most important in determining fund fees. Finally, we estimate the joint effect of our hypotheses on the residual fee distribution. Controlling for all hypotheses results in residual fee distribution break points that are only slightly less than the base case.

Overall, our results raise two important questions. First, given that fees are important sources of underperformance, why do funds not manage their fees more actively?[7] Second, why do investors not learn to distinguish cheap from expensive funds? A potential explanation for these questions is that investors may have difficulty learning about the quality of funds, which allows different funds to charge different prices for delivering a similar product. This, however, does not necessarily mean that investors are unable or unwilling to learn. Carlin and Manso (2011) address this issue in a dynamic theoretical model and show that 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 enable investors to learn more quickly.[8] Overall, we conclude that the large dispersion in prices for similar funds is inconsistent with a competitive market for mutual funds.

The remainder of the paper is organized as follows. In Section I we describe the data used in our analysis and describe the characteristics of high and low fee funds. In Section II we present results that document price dispersion in the residual fee distribution of funds and perform tests to quantify the economic effects of fee dispersion for fund investors. In Section III we test various hypotheses to explain the apparent large mispricing of funds. Section IV 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,

---

[7] In related work, there are several papers that develop theoretical models of the mutual fund industry, including endogenous fee setting. Nanda, Narayanan and Warther (2000) 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.

[8] 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.

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 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 35% of all funds covered in the CRSP Mutual Fund Database (our sample consists of a total of 13,817 funds while the CRSP Mutual Fund Database universe has approximately 40,000 funds). As measured by total net assets, our sample covers approximately 32% of the cumulative net assets represented in the database. The sample period spans 1963 to 2008 and the data frequency is yearly, as we focus on fund fees.[9]

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 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 and flags for institutional funds 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 545, while it increases to 5562 in the post-1999 sample. Note that the mean fund size (*mtna*) also increases from 436 Million USD pre-1999 to 464 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. Average annual expense ratios (*exp_ratio*) and initial annual expense ratios of

[9] Quarterly data on fees and other fund characteristics is only available starting in 1999.

entering funds (*first_exp_ratio*) both increased, from 1.3% to 1.4% and 1.3% to 1.5%, respectively. It is also interesting to observe that average yearly changes of expense ratios (*Δ(exp_ratio)*) are on average zero (with a tiny standard deviation of 18 bps pre-1999 and 9 bps post-1999).

The average performance (*yalpha*) of our sample funds, as measured by annual four-factor alphas (Carhart (1997)), is slightly negative, consistent with Carhart (1997) and others who show that funds do not earn positive abnormal returns net of fees. 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 HML, SMB, 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-squareds (*r_squared*) of 84% and 87%, 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 of decile 10 exceed those of decile 1 by 2.1%, in both the pre-1999 and post-1999 periods. In the pre-1999 sample, average expense ratio changes are most negative (-6 bps) in decile 1 and most positive (15 bps) in decile 10. These mean changes become even smaller in the post-1999 sample: funds in the bottom expense ratio decile decrease their fees on average by 1 bps in the same year, while funds in the top decile increase their fees on average by 3 bps in the same year.

All of the fund performance variables decrease monotonically by expense ratio deciles. The spread in yearly four-factor alphas, for example, equals 2.7% (decile 1 alpha is -0.12% and decile 10 is -2.79%) pre-1999 and 2% (decile 1 alpha is 0.1% and decile 10 is -1.86%) post-1999, which in both cases basically equals the spread in expense ratios. Thus, these simple descriptive statistics suggest that funds with higher expense ratios on average underperform their cheaper competitors by approximately their expense ratios (consistent with Berk and Green (2004)).

We also find that average funds in decile 1 are much larger than average funds in decile 10 suggesting that economies of scale play a role for expense ratios. The average fund in decile 1 is approximately 1.5 Billion USD larger in both the pre-1999 and post-1999 periods than the average fund in expense ratio decile 10. We also find that funds which are part of a larger fund family on average have lower fees.[10] This result is potentially consistent with an economies-of-scope argument. Moreover, we also find that institutional funds and ETFs have lower fees, as one would expect.

Finally, Panel D of Table 1 shows time-series means of cross-sectional 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 correlated with expense ratios: more expensive funds tend to exhibit returns similar to small cap, value, and momentum styles of investing (as judged by their loadings on the SMB, HML, and UMD factors, respectively). Similarly, the average R-squared of the four-factor model decreases as we move from decile 1 to decile 10, suggesting that the managers of the higher fee funds may be following "unique" strategies, likely in an attempt to outperform. However, these managers also trade much more (the turnover (*turn_rat*) is much higher for the high fee funds relative to the low fee 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 also implement strategies that go beyond the standard risk factors.

[10] This pattern, however, is non-monotonic across raw fee deciles. In later cross-sectional tests we find that large families actually tend to charge greater fees.

3. The Pricing of Mutual Funds

3.1 Residual Fee Estimation

Our goal is to compare prices (annual 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 fees (e.g., see Gil-Bazo and Ruiz-Verdu (2009) and Wahal and Wang (2011)).

We regress fund fees 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 fees. The residuals of these regressions can be interpreted as deviations of fund fees from expected fees 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. Later in the paper we perform robustness tests on the characteristics used to estimate the residuals, and show that our results are qualitatively similar.

3.2 Results

In Table 2 we present the results of the yearly cross-sectional regressions used to estimate the residuals. The reported coefficients are time series averages of cross-sectional regression betas 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.

For the full sample, the pre-1999 and post-1999 models explain approximately 44% of the variation in fees. The signs of the coefficients are consistent with the literature (note that it is not the goal of this paper to interpret these relationships): e.g., across the two periods we observe that better performing funds, less volatile funds, larger funds, older funds, lower turnover funds, institutional funds and ETFs, and funds with higher R-squareds from the Carhart four-factor model have lower fees. In the post-1999 period, we essentially see the same relationships, with the exception of some sign switching of the coefficients from the four-factor model.

Comparing the full sample coefficients to those obtained if we limit the analysis to the largest and smallest funds shows, with the exception of the coefficients on the four-factor model betas, minimal differences. In some cases, individual coefficients become more or less important but they don't change signs for important variables. Interestingly, the smallest TNA quintile of funds obtains the highest R-squareds, relative to the full sample and the largest funds, in both the pre and post-1999 periods.

Our main point of interest, the spread in residual fees for the full sample, is presented in Table 3 and in Figure 1. In the figure, each year we plot the residual fee spread between the 25th and 75th, 10th and 90th, and 1st and 99th percentile points of the distribution (note that the mean residual is, of course, zero) and the raw fee spreads. We do this for the full sample and for the largest and smallest quintile of annually-ranked TNA funds. Given that we have controlled for fund characteristics that investors care about in their selection of funds, the residual fee figures are striking. Essentially, these figures show that there exist huge dispersions in fees for basically identical funds across all years of the residual fee distribution. For the full sample, the fee dispersion (between the 1st and 99th 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%. Overall, as reported in Table 3, Panel A, the mean spread for the basic fee model for the full sample (see the row labeled "yearly return") is 2.34%. For the 25th to 75th and 10th to 90th percentile points of the excess fee distribution, the spreads are 44 and 89 basis points, respectively.[11] 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 fee spread, results apparently at odds with a competitively priced market. In fact for the largest funds, we actually see an increase in the residual spread; in pre-1990, the average spread is

[11] We examine the skewness and kurtosis of the fee residuals for the full sample, and for the bottom and top quintile of annually sorted TNA funds. Each year, we estimate the skewness and kurtosis for the residual fee distribution and then calculate simple averages across years. For the full sample, the average yearly skewness is 0.77 and the average yearly kurtosis is 7.78. For the largest funds, the skewness is 0.13 and the kurtosis is 3.46, and for the smallest funds, the skewness is 0.60 and the kurtosis is 6.64. Thus, it appears that there is some excess kurtosis (fat tails) and positive skewness for the full sample and smallest funds. In the case of largest funds, residuals are close to normally distributed (recall that the kurtosis of a normal distribution is 3 and the skewness is 0). Note that the assumption of normally distributed errors is not needed for the validity of the OLS method.

approximately 0.5% to 1%, and in the post-2000 period, it grows to an average of approximately 2% for the 1st to 99th percentile points, with similar patterns for the inner breakpoints of the distribution. We note that the largest quintile of funds represent 82% of the market value of our sample, suggesting market wide mispricing effects that are not confined solely to the 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 fees 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 3, we plot raw fees and estimate residual fees separately for both retail and institutional funds. The raw and residual spreads are indeed higher for retail funds, but we still see evidence of relatively large spreads in residual fees for institutional funds (ranging from about 1% to 1.2%) with no clear trend of decreasing fee spreads in more recent years. Thus, our results also apply to institutional funds.

Finally, we examine the implications of our findings for investors.[12] We implement a simple ex ante trading strategy that trades funds based on the residual fee distribution, illustrating the negative wealth effects of investing in similar, but higher fee funds.[13] For comparison purposes, we also report a similar strategy using raw fees. We compute the returns to a trading strategy that buys funds in the bottom decile of raw (residual) fees and sells funds in the top fee decile. We rebalance these portfolios every year and compute the cumulative Carhart four-factor model alphas over the sample period to equally-weighted portfolios.

The results are reported in Table 4 and Figure 4. Interestingly, in Panel B of Figure 4 and in Table 4, we observe that until the beginning of the 1980s, investors actually benefited from investing in higher residual fee funds, suggesting that managers of such funds were able to "earn their keep." However, over the entire sample,

[12] Panels A and B of Table 1 provide a sense of the ex post economic effects of investing in high fee funds versus low fee funds using raw fees. Investing in an equally–weighted portfolio of high fee funds would have resulted in a yearly average wealth loss of between 1.8% to 2.9%, depending on the period and the metric used to measure returns (e.g., raw or risk adjusted returns).

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

based on raw (residual) fees, an investor purchasing the lowest fee funds would have earned compounded abnormal returns 67% (32%) higher than an investor purchasing the most expensive funds. As a basis for comparison, the compounded differences in fees (residual fees) over the period were 90% (64%). Thus, while the difference in abnormal returns between high fee and low fee funds is less than the cumulative difference in fees, it appears that investors bear significant costs from investing in high fee mutual funds that are not recouped through higher performance of these funds.[14]

3.3 Robustness Tests: Fund Characteristics

The basic premise of our paper, that we can compare the fees of different mutual funds by examining the residuals from fund fee regressions, is obviously conditional on our choice of fund characteristics that serve as the independent variables in the regression. We are careful in Table 2 to include fund characteristics that should matter to the average investor. But we are the first to admit that the regressions may be misspecified; we may be including the wrong product characteristics or omitting other important ones. Thus, in this section, we examine the robustness of our results to variations in the mutual fund characteristics used to estimate fee residuals.

The first set of robustness tests examine different measures to control for fund performance. Our main results are based on the lagged yearly fund returns net of fees. Rows 2 to 5 of Table 3 show that our estimates of fee dispersion do not change if we also include a persistence dummy or if we measure performance in terms of abnormal returns (we look at four-factor alphas, the t-statistics of the four-factor alphas and Carhart alphas) rather than raw returns.

All the performance measures discussed so far are based on after-fee returns. The motivation to focus on after-fee rather than before-fee returns is that investors, in the end, care about after-fee rather than before-fee 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 link between after-fee performance and fees. If that is

[14] 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.

the case, then our specification using after-fee returns might miss the link between performance and fees. To address this concern, we calculate the same performance statistics as before but use before-fee returns. The mean spreads summarized in Table 3 (see the rows labeled "Before-Expense") show that this does not affect our results; the residual fee dispersion remains qualitatively similar whether we use before-expense or after-expense returns.

Finally, we analyze the level of fee dispersion for cases in which we vary the procedure used to estimate a fund's abnormal performance (four-factor alpha) 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 fee dispersion. To ameliorate this concern, we evaluate the following alternative estimation strategies: first, we replace our rolling-window estimates with expanding-window estimates (see the rows 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 the row labeled "Filtered Alphas/Betas"); 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 fee regressions (see the rows labeled "Full Sample"). All of these robustness tests do not affect our estimates of fee residuals in a noticeable way.

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 a small impact on the spreads of the full sample and the sample of largest funds. Only in the case of the smallest funds, we find a reduction of the inter-quartile (10^{th} to 90^{th} percentile) spread of 17 (36) basis points. The remaining spreads are, however, still very substantial at 48 (101) basis points.

3.4 Robustness Tests: Regression Specification

One potential criticism of our use of OLS residuals in estimating unexplained fees is that the residuals include a noise component. Thus, even if the mutual fund industry was perfectly competitive and funds with very similar characteristics charged close-to-identical fees, we would not expect that our empirical model could explain observed fees perfectly; i.e., without any error.

Thus, as a further robustness test, we estimate stochastic frontier models (Greene, (2002)). Early applications of these models included estimation of production and cost functions (e.g., Aigner, Lovell and Schmidt (1977)). More recently, they have been applied to issues in financial economics (e.g., Habib and Ljungqvist (2005) or Green, Hollifield and Schuerhoff (2007)). Stochastic Frontier Models are designed to decompose regression residuals into a symmetric noise component and into a directional mispricing (or, more generally, inefficiency) term. For identification, they require that the econometrician makes additional assumptions on the distribution (exponential, half-normal or truncated-normal) of the inefficiency term.

We estimate stochastic frontier models on the full sample of mutual funds using our main fee specification from Table 2. If we assume that the inefficiency term is exponentially distributed, we find that the mean excess fee is 30 basis points and the spread between the 25th and 75th, 10th and 90th, and 1st and 99th percentile points of the excess fee distribution are 33, 57, and 181 basis points, respectively. Comparing these numbers to the spreads of OLS regression residuals reported in row 1 of Table 3 (Panel A), we see that the noise component included in our main, full sample results most likely only accounts for a small portion, around 30% or less, of the OLS residual spreads.[15]

To conclude, the robustness tests show that the phenomenon of fee dispersion among US equity funds is strong and unaffected by different ways of measuring fund performance and residual fee dispersion. Overall, our finding of large pricing differences for essentially 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. In the next section, we test various hypotheses, motivated from the price dispersion and mutual fund literature, in an attempt to gain a better understanding of the pricing mechanisms at work in the mutual fund industry.

[15] We find very similar results when we assume that the inefficiency term follows a half-normal or truncated-normal distribution. For brevity, we do not report specific results from the stochastic frontier models. Detailed results are available from the authors upon request.

4. Explaining the Dispersion in Residual Fees

4.1 Different Share Classes

In our main results we treat each share class as an individual fund. If share classes proxy for different distributional channels[16] or different investor clienteles, then different share classes of the same fund could (and often times do) have different expense ratios. Thus, we evaluate whether our levels of fee 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.[17] 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. Once individual share classes are identified for a given fund, we aggregate the share classes into a common fund using equal-weighting or value-weighting (using the total net asset values as weights) of each share class. We then re-estimate our fee regressions on this new, aggregated sample.

Before discussing detailed fee dispersion results, it is interesting to look at some descriptive statistics of the resulting sample. First, the aggregated sample shows that before 1999 it was very uncommon to have multiple share classes.[18] Thus, we will focus on the post-1999 sample period in this section. Second, after aggregating multiple share classes into funds, we have on average an equal number of funds with and without multiple share classes each year. Third, the average size of funds without multiple share classes (around USD 1 billion) is slightly larger than the one for aggregated funds with multiple share classes (around USD 900 million using value-weighted aggregation).

Table 5 summarizes fee dispersion results. Row 1 of each panel reports the base case specification; i.e., the fee dispersion for a post-1999 sample without any aggregation of share classes. Comparing the values in Table 5

[16] Bergstresser, Chalmers and Tufano (2009) suggest a link between share classes and distribution channels.
[17] Alternatively, we identified different share classes of the same fund by parsing fund names. As the coding of share class information within the funds' names is, however, not systematic, the matching process using parsing is more error-prone than the one using MFLINKS tables. Thus, we focus on the results from the latter matching procedure in the paper.
[18] Actually, the number of share classes starts rising after 1995. For simplicity and consistency reasons, we focus on post-1999 results in this section. Results are qualitatively identical and quantitatively very similar if we look at post-1995 results.

to the ones reported in Row 1 in Table 3, emphasizes again that fee dispersion increased substantially during more recent years, especially for the sub-sample of largest funds.

Next, we analyze how fee dispersion varies across funds with (Row 3) and without (Row 2) multiple share classes. For this purpose, we split the sample according to this criterion, re-estimate the fee regressions and summarize residual fee spreads for the non-aggregated sample. We find that spreads are larger for funds with multiple share classes, except for the smallest funds. Differences in spreads are very pronounced in the case of largest funds: the interquartile (10^{th} to 90^{th} percentile) range increases from 28 (57) basis points for funds without multiple to 49 (94) basis points for fund with multiple share classes.

Finally, we analyze fee dispersion after aggregating across individual share classes. Rows 4 and 5 summarize the results using different weighting schemes. We find that after aggregating share classes, residual fee spreads decrease. For the full sample the interquartile (10^{th} to 90^{th} percentile) range decreases from 59 (108) basis points to 34 (70) basis points. The choice of weighting scheme for the aggregation does not have any substantial impact on the results. Interestingly, after aggregating across share classes results are very similar for largest and smallest funds.

Overall, as one would expect, we find that different share classes of otherwise identical funds contribute to fee dispersion, at least in recent years. Roughly speaking, spreads of residual fees decrease by 30 to 40 percent in the post-1999 period after aggregating across share classes. Importantly, however, the remaining fee spreads of 34 (73) basis points for the interquartile (10^{th} to 90^{th} percentile) range are still large and economically important. For example, the average expense ratio of a fund over the same sample period is 141 basis points and the average yearly return is 64 basis points.

In the remainder of this section, we will keep the analysis at the fund share level rather than aggregating across share classes. The main motivation for this is that we would like to broadly understand the drivers of fee dispersion including the dispersion across share classes. Most importantly, many of the variables that we will consider such as randomized fee changes, flow performance sensitivity or autocorrelations of flows might well vary across share classes of the same fund.

4.2 The Random Fee Hypothesis

If buyers and sellers are identical and in a world with perfect information (i.e., search is costless), the unique Nash equilibrium is the perfectly competitive price. If we relax the assumption of perfect information (i.e., if search becomes costly), then the equilibrium price would be the monopoly price (see Diamond (1971)). Price dispersion in equilibrium, thus, requires some heterogeneity: either sellers (e.g., differences in their production costs) and/or buyers (e.g., differences in search costs or frequency of purchase) differ (see Lach (2002)).

In this context, it is interesting that we find large fee dispersion in mutual funds even after controlling for many fund characteristics; either we are missing important dimensions of fund heterogeneity, or the price dispersion is driven by heterogeneity among fund investors. Our empirical results, however, highlight another important characteristic of fee dispersion, namely its persistence over time.

From a theoretical point of view, persistent price dispersion requires additional assumptions. Moving away from a static equilibrium concept challenges the previously mentioned explanations of price dispersion (i.e., the equilibrium price choice can't be a pure strategy equilibrium). For example, if stores always charge the same price for a product, (i.e., some always sell at a low price and some always sell at a high price), consumers can eventually learn prices in a multi-period world. Thus, if price dispersion persists over time, something must prevent consumers from identifying "cheap" stores. Varian (1980) argues that stores have to randomize their pricing in order to prevent investors from learning. This implies that empirically one expects stores/funds to change their prices/fees randomly over time.

Thus, we test a "random fee" hypothesis (Lach (2002) and others) which posits that mutual funds engage in frequent changes in their fees, resulting in fund consumers not being able to easily identify low fee funds, which in turn results in persistent price dispersion.[19] As a first empirical test, we add a new variable to the regressions of Table 2 to directly control for the random fee hypothesis and then re-estimate the residual fee spread. Specifically, we add a random fee changes variable (*rand_feechgs*). For each fund and each year, we determine the fraction of

[19] If investors are less than fully aware of the fees they pay, and given that fund fees 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 fees without garnering the attention of fund holders.

positive and negative fee 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 of the fractions of positive and negative changes as our variable, motivated by the idea that randomized pricing requires both increases and decreases of fees (and not just unidirectional changes).

Theoretically, we expect to find that funds which randomize their fees are able to charge higher fees on average because by randomizing they prevent investors from learning about fees. Panel A of Table 6 shows summary statistics of our proxy for random fee changes across raw expense ratio deciles. We do not observe a monotonic pattern in either the pre-1999 or the post-1999 period. Comparing extreme expense ratio deciles, we find more randomization of fees in the bottom decile pre-1999 but in the top decile post-1999.

If we include the proxy in our base case regression specifications, we find significantly positive coefficients pre-1999 (Panel B of Table 6) and post-1999 (Panel C of Table 6). Thus, after controlling for other fund characteristics, the influence of randomization on fees is consistent with theory. An important question, however, is whether controlling for randomization results in a material reduction in residual fee dispersion. Panel D of Table 6 reports mean spreads for the full sample, largest funds, and smallest funds. The results show a very small or even zero effect on residual fee spreads. The largest reduction is for the 1^{st} to 99^{th} percentile spread in residual fees of smallest funds and amounts to 9 basis points (out of a total spread of 288 basis points). Thus, while there are slight drops in the residual fee spreads, the random fee setting hypothesis does not come close to fully explaining the large differences in pricing across similar funds.

Given the small effect on residual fees from fee switching, we perform additional tests to better understand fee randomization in the mutual fund industry. A simple test of this hypothesis is to estimate transition probabilities between low and high fee funds. If mutual funds engage in random pricing, we should observe frequent movement of funds between cheap and expensive pricing. In Table 7, we estimate transition probabilities between low and high fee funds. In Panel A we examine raw fees and in Panel B we examine residual fees. We classify funds into quintiles of fees from year *t*-1 or year *t*-2, and estimate the percentage of funds that are in the same or different quintile in year *t*. For both raw and residual fees, low fee funds tend to stay low (70% - 87% transition probabilities) and high fee funds tend to stay high (70% - 85%).[20] Funds in the middle of the fee distribution tend to stay in the middle (36% - 69%). Also, it is very rare that high fee funds become low (0.7% - 2.4%) or that low fee funds become high (0.6% - 2%). These results are strongly inconsistent with a random fee explanation.

Note that entry of new funds might potentially bias these transition probabilities, as entering funds might observe the fee distribution of existing funds and chose their fee level accordingly. We want to make sure that entering funds are not causing or distorting the patterns that we observe in the data. Thus, we adjust the thresholds to construct the quintiles such that they only consider funds that existed in the prior year (i.e., "old" funds). Table 7, Panels C and D summarize these results. The results are qualitatively similar to the full sample. Thus, the results in Table 6 clearly document that on average funds do not migrate much between fee quintiles.

Given that we do not find evidence for fee switching over time, we examine the role of a fund's initial fee in explaining the cross-section of raw fees. We re-estimate the fee regressions from Table 2, adding a fund's initial fee to the models. In unreported results, the coefficient on the first fee is positive and highly statistically significant across different specifications and is economically large, especially compared to the other explanatory variables. Adding the first fee to the models increases the adjusted R-squareds from approximately 44% to approximately 57% (pre-1999) and 70% (post-1999).[21]

Thus, the first fee explains up to 30% of the variance in fees, a new finding that seems quite at odds with competitive pricing.[22] To better understand this result, we study the determinants of initial fees. In Table 8, we estimate cross-sectional regressions of a fund's total yearly fees from the year in which the fund was initiated on fund characteristics from that period. Each fund appears in the regression only during the year in which it was initiated. Fund family characteristics are potentially important drivers of an individual fund's initial fee. Thus, we

[20] The fact that we find this result for both raw fees and residual fees suggests (in addition to the extensive robustness tests performed in section 3) that our empirical strategy to control for product heterogeneity and to estimate residual fees is not driven by "noise" in the data.
[21] Detailed results of these regressions are available from the authors upon request.
[22] Including funds' initial fees in the regressions used to estimate residual fees results in a reduction in the residual fee spread. This, however, does not challenge our story, as initial fees *per se* do not represent a product characteristic that, presumably, investors would value. The initial fee results essentially reflect the fact that fees are very persistent.

include the mean and standard deviation of a fund's family return, along with other family characteristics, as explanatory variables and estimate these regressions for fund families with more than 10 funds in the family and for funds with more than 100 funds (see the columns labeled "Number of Funds in Family > 10"and "Number of Funds in Family > 100"). For each family definition, we also estimate separate models where we equal-weight or value-weight the fund characteristics within a family to arrive at an aggregate, across-fund characteristic values for each family.

The models can explain between 38 to 45% of the variation in first fees. Initial fees are statistically significantly higher for funds that enter with smaller size, smaller fund families, fund families that charge higher average fees, families that have a higher dispersion of fees within the fund family, families that have a higher average return, and for non-ETF and non-institutional funds.[23] We also find that factor returns (i.e., the market risk premium, SMB, HML, and UMD) are consistently negatively related to first fees. A potential interpretation is that in periods when factors are doing poorly, actively managed funds can charge excess fees. Interactions between factor returns and betas are consistently positively related to first fees, implying that in situations where funds are founded in styles that have been successful in the past, higher fees are charged.[24]

So far we have established that fees do not vary much, rejecting the random fee hypothesis, and that a fund's first fee is a strong indicator of the fund's lifetime expense ratio. We next test four additional hypotheses to see if we can gain more of an understanding of how fees are set and how fee evolution, what little does occur, is determined.

4.3 The Competition hypothesis

In this section we explore the notion of "competition among funds" and its effect on fund fees and fee dispersion in more detail. As a first step, we create variables designed to capture the amount of competition that each fund is facing. Specifically, we calculate the total number of competing funds for each existing fund

[23] Ramadorai and Streatfield (2011) perform a similar analysis for hedge fund fees. They also find that better performing fund families launch high fee funds. In contrast to our results for mutual funds, they document a positive relationship between fund family size and new hedge fund fees.
[24] Given that we don't observe fund performance before initiation, these betas are forward-looking; i.e., they are estimated using future returns.

(*compAll_funds*). For a given existing fund, we identify competing funds as funds that have similar betas to the existing fund. To estimate betas for an existing fund, 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. The second competition variable, the average fees of competing funds (*compAll_fees*) is based on the same procedure as described in the case of *compAll_funds* but instead of counting the number of competing funds we determine the average fees of these funds.

Theory predicts that funds that deal with more competing fund should have lower fees. In the case of the average fees of competitors, we interpret this variable as a proxy for the costs associated with following specific strategies. Thus, we expect to find a positive relation between a fund's fees and the fund's competitors' average fees.

Panel A of Table 6 shows summary statistics of our competition proxies across raw expense ratio deciles. In the case of *compAll_funds* we do not find any strong pattern. Pre-1999 it seems that funds with higher expense ratios face more competition than funds with lower expense ratios. Post-1999, the pattern is reversed, more consistent with the theoretical prediction. In the case of *compAll_fees* the summary statistics support the expected positive relation. Very expensive funds, on average, also have very expensive competitors.

Next, we add these variables to the regressions of Table 2 to directly control for competition when we estimate the residual fee spread. Panel B and C of Table 5 report the corresponding coefficient estimates. Across both panels, we find coefficient estimates that support our predictions. The number of competing funds is significantly negatively related to and the average fee of the competitors is significantly positively related to a fund's fee. Panel D of Table 6 reports the residual fee spreads accounting for the competition variables. For the full sample and the sample of largest funds, there are only small drops in the residual fees, ranging from 2 to 18 basis points. For the smallest funds, there are larger drops in the residual fee spreads, with the spread between the 25^{th} and 75^{th}, 10^{th} and 90^{th}, and 1^{st} and 99^{th} percentile points of the excess fee distribution dropping by 15, 38, and 77 basis points, respectively. However, even after controlling for competition, the small-fund residual fee spread is economically large, ranging from 50 to 211 basis points across the various excess fee distribution points. Thus, competition appears to play a role in the setting of mutual fund fees, especially so for smaller TNA funds, but does not drive away the large spreads in residual fees.

Given the relatively small influence of competition on fee dispersion, we examine fee changes next. Wahal and Wang (2011) show that when existing funds face competition from new, similar funds (as defined by the overlap in quarterly holdings), the existing funds lower their fees to better compete with the upstart funds, evidence consistent with a competitive market for mutual funds. To test for this effect in our sample, we define two additional competition variables (*compNew_funds* and *compNew_fees*). These new variables are calculated like the ones above but focus on *entering* rather than *all* funds. To estimate betas for a new fund, 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. Under the assumption that the matching funds are close substitutes and that there is little or no asymmetric information on the part of investors concerning that substitutability, the competition hypothesis suggests that the coefficient from a regression of fee changes on *compNew_funds* should be negative and that the coefficient on *compNew_fees* should be positive.

We regress fee changes on important fund characteristics and these two competition variables. The results are reported in Table 9. In the pre-1999 period for the full sample, the fee change model has an R-squared of 29.0% that decreases in the post-1999 period to 15.5%. Across both sample periods, the coefficients on both the number of entering competing funds and the average fees of entering competing funds are statistically insignificant, showing that incumbent funds do not lower their fees when faced with new competing funds. In the post-1999 case, we also look separately at results for the largest and smallest incumbent funds. In both cases, there are no significant influences of the number of new funds on the fees of incumbent funds. For the smallest funds, the coefficient on the average fee of new funds is positive and weakly significant, suggesting that smaller TNA funds lower their fees when faced with competition from similar lower fee funds, but the effect is economically small (e.g., as new funds' average fees go down by 1%, existing funds lower their fees by approximately 2 basis point).

4.4 The Service Hypothesis

We test a fund family service hypothesis. Hortacsu and Syverson (2004), Collins (2005) and others have suggested that variation in services, such as financial advice or complementary investment instruments, may explain fee variation.[25] As with the strategic fee setting, we note that our fee regressions from Table 2, where we estimate residual fees, already control for fund family characteristics that may proxy for service. For example, assuming that large fund families offer better service, we find in Table 2 that funds that are part of a family with more than 100 funds charge, on average, an extra 17 basis points in fees (this estimate increases to 27 basis points for largest funds and drops to 6 basis points for smallest funds), but obviously, controlling for large fund families does not result in a small spread in residual fees.

We also re-estimate the fee regressions of Table 2 controlling for fund family fixed effects; i.e., we add fund family specific dummies for families with more than 100 (250) funds. In unreported results, these specifications yield an increase in average R-squared in the post-1999 period for our main fee regressions of 44.1% to 50.8% for the full sample, 39.0% to 56.2% for the largest funds, and 56.2% to 63.9% for the smallest funds. Panel D of Table 6 summarizes mean fee spreads for these specifications (see the rows labeled "Family FE"). Despite the significant increase in explanatory power of the fee regressions, the decreases in the residual fee spread is small for both definitions of fund families.

Finally, we provide additional evidence on service and family size in Figure 2. We report plots of residual fees, using the base case fee regressions of Table 2 for funds that are part of a large fund family with greater than 100 funds ("funds within families") and for funds that are in families of less than 100 funds ("funds outside of families"). In the residual fee plots, for the funds outside of families, there is clearly a large spread (approximately 2%-2.5%). The more interesting finding is that for funds within large families, where presumably there is greater customer service, we still find large spreads in residual fees (approximately 2%). Assuming that the number of

[25] In an experimental setup, Choi, Laibson and Madrian (2010) reject the hypothesis that investors buy high-fee index funds because of non-portfolio services. Interestingly, they also report that their subjects did not minimize fees even when search costs were eliminated.

funds in a family is positively correlated with service, this clearly suggests that service does not explain our main finding of large spreads in residual fees for essentially identical funds.

4.5 The Captive Investor Hypothesis

We next test the captive investor hypothesis. We examine if funds that are likely to inhibit easy investor exit (thus creating captive investors) are the funds with high residual fees. The intuition behind this hypothesis is that for investors in certain funds, there may exist significant barriers to exit. The managers of such funds recognize that these investors are unable or unwilling to exit these funds, and thus charge high fees.

One potential mechanism is that investors get stuck with high-fee funds in situations in which they are very restricted in their investment choices, e.g., in the case of funds residing within pension plans. In order to proxy for funds that are most likely part of pension plans we look at each fund's flow autocorrelation (*flow_auto*), which is estimated using the entire time-series of monthly flows.[26] We also define a fund as a "pension-plan" fund if the fund's flow autocorrelation is in the top decile. The captive investor hypothesis suggests that funds that are associated with pension plans may charge higher fees.

Panel A of Table 6 reports summary statistics of both measures across raw expense ratio deciles. Across both sample periods, we find that high fee funds have flows that are much more autocorrelated than the flows of low fee funds. We also find that the share of "Pension Plans" within a fee decile increases substantially. Both results support the captive-investor hypotheses. Panel B and C report coefficient estimates for these variables if we include them in our base case fee regressions. Again, the hypothesis is strongly supported – especially post-1999. We find positive and statistically significant estimates across both sample periods. Note that post-1999, funds in the top decile of flow autocorrelations add, on average, another 13 basis points to their fees (even after controlling for the linear effect of flow autocorrelation on fees). Although flow autocorrelation seems to affect mutual fund fees significantly, it is not able to explain or substantially reduce the level of residual fee dispersion (see Panel D of Table 5).

[26] Empirical evidence on flow patterns of pension money is scarce. Sialm, Starks and Zhang (2012) study flow patterns of defined-contribution (DC) and non-DC money within the same funds and, surprisingly, find that DC-money is more volatile and more sensitive to performance.

Another potential "trapping" mechanism is the idea that investors may be lured into high-fee funds via low front-end loads and high marketing efforts. Once investors are shareholders in the high-fee funds, they are kept as shareholders by making exit costly, for example via high back-end loads. We deem these types of funds "easy-in, hard-out" funds. Specifically, we define a fund to be *"Easy-In Hard-Out"* when its back-end load is in the top decile and its 12b-1 fee is in the top quartile of all funds within a given year.

The captive investor hypothesis suggests that *"Easy-In Hard-Out"* funds are predominantly expensive funds. This prediction is strongly supported by the data. In univariate tests, there is a strong positive relation between raw expense ratios and the fraction of *"Easy-In Hard-Out"* funds within an expense ratio decile. For example, no *"Easy-In Hard-Out"* funds are found in the lowest 5 deciles of raw expense ratios (Panel A of Table 6). Similarly, in our fee regressions we find a significantly positive coefficient for a dummy indicating an *"Easy-In Hard-Out"* fund (see Panel C of Table 6); on average, these funds charge a premium of 21 basis points. Finally, in Panel D of Table 6 we estimate the residual fee spread controlling for "*Easy-In Hard-Out"* funds. The effect of *"Easy-In Hard-Out"* funds on the residual fee spreads is minimal for the full sample and for the smallest and largest funds.

Overall, the results in this section show that captive investor funds charge on average higher fees and thus help to explain which funds reside in the higher points of the residual fee distribution. The captivity story, however, does not substantially reduce the fee dispersion that we document.

4.6 The Strategic Fee Setting Hypothesis

Finally, we test the strategic fee setting hypothesis (SFSH). 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 fees. We note that our fee regressions from Table 2, where we estimate residual fees, already control for lagged fund returns, thus to some extent controlling for a SFSH.

In order to directly test the SFSH, we estimate each fund's flow-performance sensitivity (*flow_perf*) by regressing monthly flows on lagged monthly net-of-fee returns using an expanding window (with a minimum of 12 monthly observations). Because monthly MTNA data is sparse in early years, we only calculate this proxy for our latter sample period. The idea is that funds whose investors are more performance-sensitive, i.e., funds for which we find a more positive coefficient in these simple time-series regressions, have lower fees.

Panel A of Table 6 shows simple summary statistics of our flow-performance proxy across raw expense ratio deciles. Looking across deciles, we do not find a monotonic pattern. Also, comparing the most extreme fee deciles, we observe that the most expensive funds show higher flow-performance sensitivity estimates than the cheapest funds. Similarly, Panel C of Table 6 reports a positive and significant coefficient of flow-performance sensitivity in our standard fee regressions. These results are inconsistent with the predictions from the SFSH. Finally, in Panel D of Table 6 we examine if residual fee dispersion decreases once we control for flow-performance sensitivity and find basically no change at all.

Given that the strategic fee setting hypothesis has received some attention in the literature but does not seem to affect mutual fund fees in our setup, we provide additional evidence on this issue in Table 9, where we regress fee changes on lagged flows and lagged returns. The coefficients on lagged returns are negative and statistically significant (except for the pre-1999 period and smallest funds post-1999), consistent with the SFSH, however, the economic effects are small. For example, a 10% drop in returns for a fund results in an average increase in fees of approximately 1.3 basis points (based on the full sample post-1999 estimate). The economic effect from decreasing flows is even smaller and statistically insignificant.

In Table 10, we further examine flows and changes in fees for funds segmented by good and bad prior performance. We perform this analysis for first fees, average fees, and residual fees. The SFSH posits that flows should be low or close to zero for already-high fee funds that have performed poorly, under the assumption that those funds are primarily held by performance insensitive investors. We find negative mean and median flows for high-fee poor-performing funds, inconsistent with the strategic fee setting hypothesis that suggests little or no outflow for high-fee poor-performing funds. The SFSH also posits that fees should increase for poor performing funds as performance sensitive investors flee these funds, leaving behind primarily fee-insensitive investors. We find some increase in the means of poor performing high fee funds, but little increase in mean fees for poor performing low fee funds. Also, for median fees, the change in fees for poor performing funds, across high and low fee funds, is approximately zero, a result that is inconsistent with the SFSH.[27]

4.7 Putting It All Together

In a final step, we analyze the combined effect of the previously discussed hypotheses on mutual fund fees and spreads of residual fees. Specifically, we control for fee randomization, fund competition and investor captivity (*"Pension Plan"* mechanism) pre-1999. Post-1999 we also control for flow-performance sensitivity and fund family fixed effects (using the threshold of 250 funds per management company to define families). We exclude the *"Easy-In Hard-Out"* variable from this analysis because it results in a substantial reduction of observations.

The last two columns of Panel B of Table 6 show the coefficient estimates for the pre-1999 sample period. All variables keep the sign that they showed when we controlled for each one individually and, except for the flow autocorrelation variable, all coefficients remain statistically significant. The R-squared of this model is 52.5 % and represents a sizeable increase from the base case R-squared of 44.3%. In the post-1999 sample period (Panel C), we observe a very similar picture. One important difference is that the proxies for the captive investor hypothesis are now highly statistically significant even controlling for all other hypotheses.. In the post-1999 case the R-squared increases from 44.1% to 53.5%.

In Panel D of Table 6, we estimate the joint effect of our hypotheses on the residual fee distribution. Controlling for all hypotheses results in residual fee distribution break points that are only slightly less than the base case levels for all funds and for the largest funds. The only exception is for the smallest funds, where we observe a greater reduction in residual fees. This reduction, however, seems to be mostly driven by the variables proxying for fund competition.

[27] In related work on fund flows, Barber, Odean and Zheng (2005) find no link between fund flows and expense ratios.

Given these results, it seems difficult to rank hypothesis by their power to explain fee dispersion among mutual funds. Overall, none of the evaluated hypotheses is able to substantially reduce the residual fee spreads for all funds. The only exception is the fund competition hypothesis in the case of the smallest funds. If we look beyond fee dispersion and consider the statistical significance of the hypothesis variables in the fee regressions as our metric, then we observe a clearer ranking. In general, average fees of competitors play an important role. Post-1999, the autocorrelation of flows as a proxy for funds related to “Pension Plans” also shows a very strong relation to individual funds’ fees. Randomization of fees and flow-performance sensitivity of investors seem to play a smaller role in determining fund fees.

5. Conclusion

In this paper we examine how mutual funds price their services (management and 12b-1 fees). Surprisingly, after we control for a variety of fund characteristics we find that the unexplained portion of fund fees exhibits considerable dispersion and that this dispersion has not declined over time, despite significant entry and growth in assets under management.

Similar to others, we first show that fees are an important determinant of fund underperformance; investors earn low returns on high fee funds, which indicates that investors are not rewarded through superior performance when purchasing “expensive” funds. We explore a number of hypotheses to explain the dispersion in fees and find that none adequately explain the data. Most importantly, there is little evidence that funds change their fees over time. In fact the most important determinant of a fund’s fee is the initial fee that it charges when it enters the market. There is little evidence that funds reduce their fees following entry by similar funds or that they raise their fees following large outflows as predicted by the strategic fee setting hypothesis. We also do not find evidence that higher fees are associated with proxies for higher service levels provided to investors.

Overall, our findings are largely inconsistent with a competitive market for mutual funds. However, our findings leave an important question unanswered – namely, why investors are not able to distinguish cheap from expensive funds. We hypothesize that this is the case because performance of funds is noisy and not persistent on average. Thus, although fees are observable and persistent, after-fee performance – which is presumably the decision criterion of the average investor – is not, which makes it difficult for investors to distinguish good from bad investments. One possible explanation is that high fee funds “market” themselves to investors.

6. 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.

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*, forthcoming.

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.

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.

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.

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. *The Quarterly Journal of Economics*, 403-456.

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 funds 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

"On the Size of the Active Management Industry" (with Rob Stambaugh), 2012, *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, 2012, Defined Contribution Pension Plans: Sticky or Discerning Money?, Working Paper.

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.

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
Total yearly expense ratio (*exp_ratio*)	Ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees.	CRSP Mutual Fund Database
Change in yearly expense ratios (Δ*(exp_ratio)*)	Yearly change in total expense ratio.	Calculated
First expense ratio (*first_exp_ratio*)	The total yearly expense ratio in the year when the fund was initiated.	Calculated
Average expense ratio. of funds within a fund family (*avgFamFee*)	The value-weighted mean of expense ratios for all funds within a fund family	Calculated
Standard deviation of expense ratios of funds within a fund family (*sdFamFee*)	The value-weighted standard deviations of expense ratios for funds within a fund family.	Calculated
Yearly after expenses raw return (*yret*)	Yearly returns are calculated by combining monthly returns within a calendar year. 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.	CRSP Mutual Fund Database and Calculated
Standard deviation of monthly returns (*sd_mret*)	The standard deviation of monthly returns calculated from 3 years of monthly fund returns.	Calculated
Yearly after expenses raw return if positive (*yret_pos*)	A fund's return if it is positive and zero otherwise.	Calculated
Yearly after expenses raw return if negative (*yret_neg*)	A fund's return if it is negative and zero otherwise.	Calculated
Yearly four-factor alpha (*yalpha*)	For each December and each fund, we estimate the monthly four-factor alpha using 3 years of monthly after-expense, excess fund returns. The yearly four-factor alpha is the estimated monthly alpha (i.e., the constant in the time-series regression) multiplied by 12.	Calculated
T-statistic of monthly four-factor alpha *(TStat-Alpha)*	The t-statistic associated with *yalpha.*	Calculated
Yearly Carhart alpha (*ycarh_alpha*)	For each month a fund's Carhart-alpha is 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. Yearly alphas are calculated by combining the monthly alpha estimates within a calendar year.	Calculated

Variable Name	Variable Definition	Source
Average performance of funds within a fund family (*avgFamPerf*)	The value-weighted average Carhart alpha of funds that belong to a fund family.	Calculated
Standard deviation of performances of funds within a fund family (*sdFamPerf*)	The value-weighted standard deviation of Carhart alphas of funds that belong to a fund family.	Calculated
Fund style measured in betas with respect to the four-factor model (*beta_mkt, beta_hml, beta_smb, beta_umd*)	For each December and each fund, we estimate the monthly four-factor model betas using 3 years of monthly fund returns.	Calculated
Explanatory power of the four-factor asset pricing model (*r_squared*)	For each December and each fund, we estimate the four-factor model using 3 years of monthly fund returns. Then we collect the R^2 of these models.	Calculated
Fund size measured as total net assets in million USD (*mtna*)	Total net asset as of December-end.	CRSP Mutual Fund Database
Fund size measure as the share of all funds in our sample (*mtna_share*)	Each year we add up the MTNAs of all funds in our sample to calculate the Total MTNA. The share of an individual fund is this fund's MTNA divided by the Total MTNA.	Calculated
Log of fund size measured as total net assets in million USD (*ln_mtna*)	Log of total net assets as of December-end.	Calculated
Yearly fund flow winsorized at the 1% level (*w_yflow*)	We determine the yearly flow in the following way (we winsorize it because it suffers from some extreme outliers): $F_t = \left(MTNA_t - MTNA_{t-12}\left(1 + yret\right)\right) / MTNA_{t-12}$	Calculated
Fund age (*fund_age*)	Age of fund calculated as difference between current year and year of fund initiation.	Calculated
Turnover ratio (*turn_rat*)	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
Log size of management company (*ln_mgmt_mtna*)	Each December we sum up all MTNAs across funds belonging to the same management company.	Calculated
Number of funds with the same management company (*nr_funds*)	Each December we count all funds belonging to the same management company.	Calculated

Variable Name	Variable Definition	Source
Different definitions of funds being part of a fund family (*part_family1, part_family10, part_family100, part_family250*)	We define a fund family as a management company with more than 1 (10) [100] {250} funds associated with it. The standard case in our analysis is *part_family100*.	Calculated.
Flags identifying whether a fund is institutional (*inst_flag*), open to new investment (*open_flag*) or an ETF (*etf_flag*)	Three flags indicating whether a fund is an institutional fund, whether it is open to new investment and whether it is an ETF.	CRSP Mutual Fund Database
Number of competing funds (*compAll_funds*)	For a given existing fund, we identify competing funds in year *t* as funds for which each four-factor model beta in year *t* is in the same quartile as the existing fund's corresponding betas in year *t*. The quartile thresholds for the betas are determined using the entire sample.	Calculated
Average fees of competing funds (*compAll_fees*)	We use the same procedure as described in the case of *compAll_funds* but instead of counting the number of competing funds in any given year we determine the average fees of these competing funds.	Calculated
Number of entering competing funds (*compNew_funds*)	For a given existing fund, we identify an entering, competing fund using the matching procedure described for *compAll_funds*. For the entering fund we use its four-factor model betas estimated over the next 3 years.	Calculated
Average fees of entering competing funds (*compNew_fees*)	We use the same procedure as described in the case of *comp_funds* but instead of counting the number of entering competing funds we determine the average first fees of these funds.	Calculated
Random fee changes (*rand_feechgs*)	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. Then we use the minimum value of the frequency of positive and negative changes as our variable.	Calculated
Flow-performance sensitivity (*flow_perf*)	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
12b-1 fees	Ratio of the total assets attributed to marketing and distribution costs. Available since 1992.	CRSP Mutual Fund Database
Front load	Front loads for investments represent maximum sales charges. They often change with the level of investment. Thus, the database reports front load schedules. The front load value is the equal weighted average of all front loads charged by a fund across different investment levels.	CRSP Mutual Fund Database
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 Mutual Fund Database

Variable Name	Variable Definition	Source
Flow autocorrelation (*flow_auto*)	For each fund, we calculate monthly flows (see definition of yearly flows, *w_yflow*, for details) and then estimate the autocorrelation of these monthly flows.	Calculated
Easy-In Hard-Out fund	We define funds to be "easy-in hard-out" funds when their rear loads are in the top decile and their 12b-1 fees are in the top quartile of all funds within a given year.[28]	Calculated
"Pension Plan" fund	We define a mutual fund to be a "Pension Plan" fund if its monthly autocorrelation is in the top decile of all funds. This classification does not vary over time.	Calculated

[28] An obvious, alternative definition also considers front loads. If a fund is "easy-in" it should have low front loads. The load data is, however, not very complete and imposing the restriction that we have data on both a fund's front and rear loads dramatically reduces the sample size.

Table 1. Summary Statistics

The table reports summary statistics (means and between standard deviations, i.e., means of yearly standard deviations) and correlation tables of our sample of domestic equity mutual funds (see Table A in the Appendix for a detailed description of the sample). The data covers the period of 1963 to 2008 and is a yearly panel. Variables are defined in Table B in the 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 fund families) and, thus, we split the sample into a pre-1999 and a post-1999 subset. Panel B and C summarize the sample by expense ratio deciles. The last column in each table reports the difference between decile 1 and decile 10. Stars indicate significance at the 1% (***), 5% (**) and 10% (*) level.

Panel A. Full Sample

	Pre-1999		**Post-1999**	
	Mean	**SD**	**Mean**	**SD**
Number of funds per year	545	586	5562	1318
exp_ratio	0.0129	0.0061	0.0141	0.0065
Δ(exp_ratio)	0.0000	0.0018	0.0000	0.0009
yret	0.1546	0.1149	0.0064	0.1324
ycarh_alpha	0.0329	0.4022	-0.0133	0.0431
beta_mkt	0.9243	0.2156	0.9766	0.2612
beta_hml	-0.0591	0.3834	-0.0274	0.369
beta_smb	0.1619	0.3859	0.0665	0.2579
beta_umd	0.0557	0.2518	0.0241	0.1783
r_squared	0.8396	0.1495	0.8683	0.13
w_yflow	0.3191	1.8946	0.5046	1.6483
ln_mtna	4.0982	2.0987	3.3519	2.6044
mtna	436.4834	669.054	463.5951	1790.59
fund_age	9.2409	4.592	6.5168	5.8506
sd_mret	0.0444	0.0135	0.0466	0.0196
turn_rat			0.9054	0.911
ln_mgmt_mtna			9.7297	2.323
part_family1			0.9809	0.1257
part_family10			0.9116	0.2674
part_family100			0.6009	0.4521
part_family250			0.2664	0.3993
inst_flag			0.2734	0.4587
open_flag			0.975	0.1088
etf_flag			0.0136	0.1257

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.
exp_ratio	0.0052	0.0018	0.0089	0.001	0.0111	0.0014	0.0141	0.0022	0.0257	0.0059	-0.021***
Δ(exp_ratio)	-0.0006	0.0052	-0.0002	0.0018	-0.0001	0.0021	-0.0003	0.0025	0.0015	0.0057	-0.002***
yret	0.1581	0.112	0.1613	0.1152	0.1518	0.1241	0.1503	0.1332	0.1287	0.1479	0.029***
ycarh_alpha	-0.0021	0.0423	-0.0041	0.0547	-0.0055	0.0592	-0.0119	0.0629	-0.0251	0.0711	0.023***
beta_mkt	0.9327	0.2071	0.929	0.1699	0.9274	0.211	0.918	0.2143	0.9274	0.2723	0.005
beta_hml	-0.026	0.3245	-0.0461	0.3033	-0.05	0.3711	-0.0419	0.3583	-0.108	0.4576	0.082***
beta_smb	-0.0029	0.2884	0.0733	0.2886	0.1579	0.3586	0.2008	0.3685	0.3341	0.511	-0.337***
beta_umd	0.0116	0.1893	0.0395	0.1942	0.0473	0.23	0.0746	0.2324	0.0807	0.3337	-0.069***
r_squared	0.8896	0.1613	0.8698	0.1257	0.8446	0.1448	0.8224	0.1594	0.7632	0.1968	0.126***
w_yflow	0.1908	1.7286	0.2367	1.6338	0.2603	1.409	0.3424	1.3676	0.4338	2.0533	-0.243***
ln_mtna	5.7637	2.2359	4.9996	1.926	4.2314	1.9302	3.6769	1.8869	2.2615	1.7367	3.502***
mtna	1581	4294	581	1870	294	1088	215	671	48	105	1533.5***
mtna_share	0.723%	0.553%	0.237%	0.474%	0.119%	0.314%	0.067%	0.122%	0.025%	0.103%	0.70%***
fund_age	13.2252	9.1036	12.2635	8.9289	10.1815	7.4482	7.5967	5.9195	6.329	4.8624	6.896***
sd_mret	0.0405	0.0171	0.0415	0.0122	0.0436	0.0166	0.0449	0.0154	0.0511	0.0164	-0.011***

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.**
exp_ratio	0.0042	0.0021	0.0098	0.0009	0.0127	0.0009	0.0164	0.0016	0.0253	0.0049	-0.021***
Δ(exp_ratio)	-0.0001	0.001	-0.0001	0.001	-0.0001	0.0011	-0.0001	0.0014	0.0003	0.0024	-0.0004***
Yret	0.0121	0.1522	0.0115	0.1789	0.0117	0.1892	0.0048	0.2019	-0.0061	0.2049	0.018***
ycarh_alpha	-0.0049	0.0446	-0.0104	0.0564	-0.0118	0.0639	-0.0139	0.0651	-0.0233	0.0828	0.018***
beta_mkt	0.8789	0.2617	0.9735	0.2085	0.9836	0.2402	0.9886	0.2679	1.0389	0.3234	-0.160***
beta_hml	0.0351	0.2856	-0.0002	0.339	-0.0008	0.3601	-0.044	0.3902	-0.1738	0.4545	0.209***
beta_smb	0.0075	0.191	0.0272	0.2404	0.0751	0.2586	0.0875	0.2763	0.1755	0.3102	-0.168***
beta_umd	-0.0073	0.1459	0.0202	0.1701	0.0299	0.1787	0.0323	0.191	0.0426	0.2236	-0.050***
r_squared	0.8929	0.146	0.8803	0.1078	0.8683	0.1113	0.863	0.1303	0.8264	0.1503	0.066***
w_yflow	0.563	2.1902	0.6233	2.5717	0.5171	1.9354	0.5043	1.9244	0.3448	1.5014	0.218***
ln_mtna	4.5465	2.9541	4.156	2.6665	3.4314	2.524	3.0345	2.3985	2.0143	1.9524	2.532***
Mtna	1523	4353	652	1977	273	656	223	641	44	98	1479***
mtna_share	0.060%	0.175%	0.025%	0.075%	0.010%	0.025%	0.009%	0.025%	0.002%	0.004%	0.06%***
fund_age	6.0691	6.5409	8.5349	8.9145	7.3196	7.6957	5.691	5.465	5.2391	4.2274	0.830***
sd_mret	0.0404	0.0174	0.0453	0.0178	0.0465	0.0217	0.0475	0.0206	0.0537	0.0241	-0.013***
turn_rat	0.4624	0.4833	0.7992	0.6617	0.9202	0.9211	1.023	1.181	1.3328	1.2522	-0.870***
ln_mgmt_mtna	10.7632	2.0674	9.8911	2.2031	9.4268	2.3247	9.6709	2.5008	8.6126	2.4426	2.151***
part_family	0.9974	0.0647	0.9833	0.116	0.9783	0.1421	0.9758	0.1606	0.9729	0.1429	0.025***
part_family10	0.9618	0.1956	0.9064	0.2757	0.8671	0.3149	0.9068	0.3032	0.8952	0.2818	0.067***
part_family100	0.6482	0.4376	0.5753	0.4716	0.5583	0.4781	0.6309	0.4653	0.5155	0.4651	0.133***
part_family250	0.2775	0.4345	0.2842	0.4307	0.2618	0.4232	0.2823	0.4275	0.1506	0.3545	0.127***
inst_flag	0.612	0.4777	0.4868	0.495	0.2413	0.4423	0.1325	0.3772	0.0183	0.1644	0.594***
open_flag	0.9748	0.1236	0.9792	0.1245	0.9682	0.1494	0.9834	0.1109	0.9657	0.1654	0.009***
etf_flag	0.0799	0.2143	0.0024	0.0606	0.0002	0.0219	0	0	0.0009	0.0566	0.079***

Panel D. Average (time-series) Cross-Sectional Correlations

	Δ(exp_ratio)	yret	ycarh alpha	beta mkt	beta hml	beta smb	beta umd	r_squared	w_yflow	ln mtna	fund age	sd mret	turn rat	ln mgmt mtna
exp_ratio	0.21	-0.07	-0.07	0.01	-0.02	0.22	0.06	-0.23	0.07	-0.49	-0.18	0.19	0.25	-0.18
Δ(exp_ratio)	1.00	-0.05	-0.05	0.00	-0.02	-0.03	-0.02	0.01	-0.06	-0.02	0.02	0.01	0.00	-0.03
yret		1.00	0.60	0.01	0.08	0.07	0.07	0.02	0.19	0.07	-0.03	0.02	0.02	-0.01
ycarh_alpha			1.00	-0.08	-0.06	0.01	-0.06	-0.01	0.13	0.05	-0.04	-0.02	-0.03	-0.02
beta_mkt				1.00	-0.10	0.07	0.05	0.36	-0.01	0.08	0.00	0.52	0.07	-0.01
beta_hml					1.00	-0.09	-0.14	-0.10	0.00	-0.04	0.02	-0.42	-0.09	0.00
beta_smb						1.00	0.20	-0.14	0.10	-0.17	-0.13	0.50	0.21	-0.07
beta_umd							1.00	0.00	0.05	0.01	-0.02	0.21	0.24	-0.02
r_squared								1.00	-0.03	0.25	0.05	-0.17	-0.15	0.07
w_yflow									1.00	-0.05	-0.15	0.05	0.07	0.02
ln_mtna										1.00	0.33	-0.08	-0.14	0.18
fund_age											1.00	-0.06	-0.12	0.03
sd_mret												1.00	0.22	-0.05
turn_rat													1.00	-0.04
ln_mgmt_mtna														1.00

Table 2. Base Case Fund Fee Regressions

The table reports results of Fama-MacBeth regressions, in which we use the yearly expense ratio as dependent variables (see Table A in the Appendix for a detailed description of the sample). The data covers the period of 1963 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix. All variables are lagged by one year. Some information is only available after 1999 (e.g., information on fund families) and, thus, we split the sample into a pre-1999 and a post-1999 subset. The specifications reported in this table represent the base case specifications. We look at the full sample of mutual funds, the largest, and smallest (funds in the top or bottom quintile of *mtna* in a given year) funds.

	Pre 1999						Post 1999					
	Full Sample		Largest Funds		Smallest Funds		Full Sample		Largest Funds		Smallest Funds	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Yret $_{t-1}$	-0.0077	-4.61	-0.0045	-2.19	-0.0129	-1.62	-0.0064	-4.88	-0.0052	-3.61	-0.0112	-6.47
beta_mkt $_{t-1}$	0.0016	1.72	-0.0067	-2.51	0.0032	0.85	-0.0005	-0.72	0.0009	0.87	-0.0005	-0.49
beta_hml $_{t-1}$	0.0007	1.37	0.0036	4.21	-0.0026	-1.22	0.0007	2.50	0.0001	0.16	0.0004	0.56
beta_smb $_{t-1}$	0.0019	3.35	-0.0010	-1.13	0.0014	0.56	-0.0004	-1.73	0.0003	0.79	-0.0009	-1.81
beta_umd $_{t-1}$	0.0009	1.62	0.0025	2.71	0.0027	1.27	0.0001	0.16	0.0010	2.60	-0.0026	-1.34
r_squared $_{t-1}$	-0.0049	-5.26	-0.0060	-1.60	-0.0115	-3.00	-0.0030	-3.83	-0.0034	-4.19	-0.0047	-3.67
flow $_{t-1}$	0.0001	0.18	0.0000	0.04	-0.0014	-1.06	-0.0001	-2.63	-0.0002	-1.55	0.0000	-0.77
ln_mtna $_{t-1}$	-0.0016	-18.64	-0.0006	-8.98	-0.0031	-7.01	-0.0007	-29.24	-0.0008	-11.89	-0.0003	-3.59
fund_age $_{t-1}$	-0.0000	-5.08	-0.0001	-0.90	0.0000	0.11	-0.0001	-9.72	-0.0001	-8.29	0.0003	5.29
sd_mret $_{t-1}$	0.0245	1.34	0.1332	2.46	0.0537	0.56	0.1001	7.04	0.0181	0.70	0.1318	5.51
turn_rat $_{t-1}$							0.0002	3.85	0.0003	3.68	0.0001	1.01
ln_mgmt_mtna $_{t-1}$							-0.0004	-11.06	-0.0008	-11.15	-0.0006	-7.41
part_family100							0.0017	8.81	0.0027	10.93	0.0006	2.51
inst_flag							-0.0063	-44.74	-0.0048	-25.53	-0.0071	-19.75
open_flag							-0.0001	-0.26	0.0004	1.02	-0.0025	-1.87
etf_flag							-0.0032	-4.29	-0.0028	-3.68		
Constant	0.0203	21.59	0.0184	4.33	0.0291	8.26	0.0210	19.16	0.0257	20.30	0.0238	16.87
# of years	34		34		34		10		10		10	
# of obs.	12108		3018		1670		33323		8592		3994	
Avg. R-Squared	44.3%		49.3%		54.7%		44.1%		39.0%		56.2%	

Table 3. Residual Fee Spreads Including Robustness Tests

The table summarizes (time-series) mean spreads between percentiles of the residual fee distribution for our sample of mutual funds (see Table A in the Appendix for a detailed description of the sample). The residual fee is defined as the regression residual of the corresponding (full sample/largest funds/smallest funds) fund fee regression model as specified in Table 2. The first row of each panel contains the residual fee spreads from these specific models. The other rows represent robustness tests and provide residual fee spreads for models in which we vary the fund characteristics used to estimate fee residuals. The data covers the period of 1963 to 2008 and is a yearly panel. The variables are defined in Table B of the Appendix. Rows 2 to 5 report residual fee spreads if we vary fund performance measures. Rows 6 to 9 report results of specifications that use gross (i.e., before-fee) 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 (in this case, we also use beta estimates from expanding windows). Rows 13 to 15 report mean fee spreads for specifications in which we 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 we use the same parameters each year to explain expense ratios).

Panel A. Full Sample

		Mean Spread (bps) 25th to 75th Percentile	Mean Spread (bps) 10th to 90th Percentile	Mean Spread (bps) 1st to 99th Percentile
1	Yearly return ($Yret_{t-1}$)	44	89	234
2	Yearly return ($Yret_{t-1}$) + persistence dummy	44	88	234
3	Four-factor alpha ($Yalpha_{t-1}$) + persistence dummy	44	88	231
4	T-statistic of four-factor Alpha ($TStat\text{-}Alpha_{t-1}$) + persistence dummy	43	87	234
5	Carhart alpha ($Ycarh\_alpha_{t-1}$) + persistence dummy	44	88	234
6	Before-expense yearly return	44	88	230
7	Before-expense yearly return + before-expense persistence dummy	44	88	230
8	Before-expense four-factor alpha + before-expense persistence dummy	44	88	228
9	Before-expense Carhart performance + before-expense persistence dummy	44	87	230
10	Style fixed effects +yearly return ($Yret_{t-1}$)	42	87	215
11	Expanding window + four-factor alpha	43	86	239
12	Expanding window + t-statistic of four-factor Alpha	44	86	241
13	Filtered alphas/betas + four-factor alpha	43	88	236
14	Full Sample + four-factor alpha	43	86	227
15	Full sample + t-statistic of alpha	44	87	233

Panel B. Bottom Size Quintile of Funds

		Mean Spread (bps) 25^{th} to 75^{th} Percentile	Mean Spread (bps) 10^{th} to 90^{th} Percentile	Mean Spread (bps) 1^{st} to 99^{th} Percentile
1	Yearly return ($Yret_{t-1}$)	65	137	288
2	Yearly return ($Yret_{t-1}$) + persistence dummy	65	136	284
3	Four-factor alpha ($Yalpha_{t-1}$) + persistence dummy	62	131	279
4	T-statistic of four-factor Alpha ($TStat\text{-}Alpha_{t-1}$) + persistence dummy	65	135	280
5	Carhart alpha ($Ycarh\_alpha_{t-1}$) + persistence dummy	65	134	282
6	Before-expense yearly return	65	133	282
7	Before-expense yearly return + before-expense persistence dummy	65	130	279
8	Before-expense four-factor alpha + before-expense persistence dummy	66	129	275
9	Before-expense Carhart performance + before-expense persistence dummy	65	129	279
10	Style fixed effects +yearly return ($Yret_{t-1}$)	48	101	220
11	Expanding window + four-factor alpha	64	126	284
12	Expanding window + t-statistic of four-factor Alpha	64	130	288
13	Filtered alphas/betas + four-factor alpha	66	136	302
14	Full Sample + four-factor alpha	63	125	279
15	Full sample + t-statistic of alpha	65	131	287

Panel C. Top Size Quintile of Funds

		Mean Spread (bps) 25^{th} to 75^{th} Percentile	Mean Spread (bps) 10^{th} to 90^{th} Percentile	Mean Spread (bps) 1^{st} to 99^{th} Percentile
1	Yearly return ($Yret_{t-1}$)	28	60	118
2	Yearly return ($Yret_{t-1}$) + persistence dummy	28	60	117
3	Four-factor alpha ($Yalpha_{t-1}$) + persistence dummy	28	60	118
4	T-statistic of four-factor Alpha ($TStat\text{-}Alpha_{t-1}$) + persistence dummy	28	60	117
5	Carhart alpha ($Ycarh\_alpha_{t-1}$) + persistence dummy	28	60	117
6	Before-expense yearly return	29	61	117
7	Before-expense yearly return + before-expense persistence dummy	28	60	116
8	Before-expense four-factor alpha + before-expense persistence dummy	28	60	117
9	Before-expense Carhart performance + before-expense persistence dummy	28	60	116
10	Style fixed effects +yearly return ($Yret_{t-1}$)	27	57	111
11	Expanding window + four-factor alpha	27	57	117
12	Expanding window + t-statistic of four-factor Alpha	27	57	116
13	Filtered alphas/betas + four-factor alpha	29	61	121
14	Full Sample + four-factor alpha	28	59	122
15	Full sample + t-statistic of alpha	29	59	122

Table 4. Trading Strategy

The table summarizes the cumulative (i.e., compounded) Carhart alphas of a strategy that buys funds in the bottom decile according to reported expense ratios (residual expense ratios), and shorts funds in the top deciles according to reported expense ratios (residual expense ratios). Funds are equally-weighed within portfolios. The table also reports the compounded spread between the average reported expense ratio (residual expense ratio) of funds in the top and the bottom decile. The residual fee is defined as the regression residual of Spec. 1 (pre-1999) and Spec. 4 (post-1999) as specified in Panel A of Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Appendix for a detailed description of the sample). The data covers the period of 1963 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix.

		Reported Expense Ratio						Residual Expense Ratio			
Year	**α**	**Fee Spread**	**Year**	**α**	**Fee Spread**	**Year**	**α**	**Fee Spread**	**Year**	**α**	**Fee Spread**
1963	0.2%	1.5%	**1986**	30.0%	43.9%				**1986**	2.1%	28.1%
1964	3.7%	2.6%	**1987**	31.5%	46.1%				**1987**	5.9%	29.8%
1965	-0.6%	3.8%	**1988**	31.9%	48.6%				**1988**	8.2%	31.5%
1966	1.1%	5.1%	**1989**	32.3%	51.0%	**1966**	1.0%	0.9%	**1989**	8.6%	33.3%
1967	0.1%	6.7%	**1990**	32.8%	53.3%	**1967**	-10.7%	2.2%	**1990**	9.5%	35.2%
1968	-3.3%	7.8%	**1991**	34.0%	55.5%	**1968**	-8.9%	2.9%	**1991**	8.2%	37.0%
1969	6.6%	9.7%	**1992**	35.4%	57.7%	**1969**	-6.6%	3.9%	**1992**	5.9%	38.9%
1970	7.2%	11.5%	**1993**	41.5%	59.8%	**1970**	-5.6%	5.2%	**1993**	9.1%	40.5%
1971	9.4%	14.0%	**1994**	46.1%	61.8%	**1971**	-10.7%	6.9%	**1994**	11.7%	42.2%
1972	2.3%	15.6%	**1995**	48.6%	63.9%	**1972**	-9.9%	7.9%	**1995**	14.9%	43.8%
1973	1.5%	17.8%	**1996**	54.2%	65.8%	**1973**	-4.6%	9.6%	**1996**	16.3%	45.5%
1974	0.9%	19.9%	**1997**	52.4%	67.8%	**1974**	-4.4%	11.0%	**1997**	19.3%	47.1%
1975	0.5%	22.1%	**1998**	48.1%	69.7%	**1975**	-2.4%	12.6%	**1998**	20.0%	48.7%
1976	5.1%	24.4%	**1999**	46.7%	71.6%	**1976**	-1.8%	14.3%	**1999**	21.5%	50.0%
1977	9.9%	26.5%	**2000**	52.4%	73.6%	**1977**	-1.7%	15.6%	**2000**	23.6%	51.5%
1978	10.1%	28.5%	**2001**	56.3%	75.7%	**1978**	-4.2%	17.0%	**2001**	27.1%	53.0%
1979	11.1%	30.4%	**2002**	58.5%	78.0%	**1979**	-5.7%	18.4%	**2002**	28.2%	54.5%
1980	14.3%	32.5%	**2003**	61.9%	80.2%	**1980**	-2.6%	20.0%	**2003**	30.1%	56.2%
1981	28.2%	34.6%	**2004**	60.9%	82.3%	**1981**	1.7%	21.4%	**2004**	31.5%	57.8%
1982	31.3%	36.6%	**2005**	63.5%	84.4%	**1982**	0.6%	22.8%	**2005**	32.9%	59.3%
1983	33.2%	38.5%	**2006**	64.5%	86.4%	**1983**	2.3%	24.1%	**2006**	33.5%	60.8%
1984	31.1%	40.2%	**2007**	67.1%	88.5%	**1984**	4.2%	25.3%	**2007**	32.2%	62.3%
1985	29.1%	42.1%	**2008**	67.1%	90.5%	**1985**	3.4%	26.8%	**2008**	32.2%	63.8%

Table 5. Share Classes and Fee Dispersion (post-1999)

The table summarizes (time-series) mean spreads between percentiles of the residual fee distribution for our sample of mutual funds (see Table A in the Appendix for a detailed description of the sample). The residual fee is defined as the regression residual of the corresponding (full sample/largest funds/smallest funds) fund fee regression model as specified in Table 2. In this table we focus on the issue of different share classes. Specifications 2 and 3 summarize results for the sub-samples of funds with and without multiple share classes. Specifications 4 and 5 report results for funds with multiple share classes but after aggregating across share classes. The data covers the period of 1999 to 2008 and is a yearly panel.

Panel A. Full Sample

		Mean Spread (bps) 25th to 75th Percentile	Mean Spread (bps) 10th to 90th Percentile	Mean Spread (bps) 1st to 99th Percentile
1	Base Case	59	108	202
2	Funds without multiple share classes	43	84	256
3	Funds with multiple share classes (no aggregation)	58	103	189
4	Funds with multiple share classes (equal-weighted aggregation)	34	70	154
5	Funds with multiple share classes (size-weighted aggregation)	34	73	153

Panel B. Bottom Size Quintile of Funds

		Mean Spread (bps) 25th to 75th Percentile	Mean Spread (bps) 10th to 90th Percentile	Mean Spread (bps) 1st to 99th Percentile
1	Base Case	59	110	228
2	Funds without multiple share classes	60	123	312
3	Funds with multiple share classes (no aggregation)	51	100	193
4	Funds with multiple share classes (equal-weighted aggregation)	36	72	163
5	Funds with multiple share classes (size-weighted aggregation)	39	85	182

Panel C. Top Size Quintile of Funds

		Mean Spread (bps) 25th to 75th Percentile	Mean Spread (bps) 10th to 90th Percentile	Mean Spread (bps) 1st to 99th Percentile
1	Base Case	47	96	176
2	Funds without multiple share classes	28	57	111
3	Funds with multiple share classes (no aggregation)	49	94	172
4	Funds with multiple share classes (equal-weighted aggregation)	35	71	129
5	Funds with multiple share classes (size-weighted aggregation)	32	68	131

Table 6. Testing Explanations of Residual Fee Spreads

The table shows results related to variables that capture different hypotheses that we evaluate in order to explain the dispersion in mutual fund fees. Panel A reports means and standard deviations of our proxies by raw expense ratio deciles. The last column reports the difference between decile 1 and decile 10. Stars indicate significance at the 1% (***), 5% (**) and 10% (*) level. Panel B and C report coefficients of these variables if they are added individually or all together to the base case specifications described in Table 2. For brevity we focus on the results for the full sample of funds. Panel D, reports mean residual fee spreads for groups of funds after including these proxies individually or jointly in the fee regressions. Variables are defined in Table B in the Appendix.

Panel A. Summary Statistics of Proxies by Raw 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	**rand_feechgs**	0.158	0.126	0.175	0.142	0.161	0.134	0.138	0.126	0.100	0.097	0.058***
	compALL_funds	9.104	10.996	8.99	10.65	10.53	13.57	10.22	13.41	11.69	14.87	-2.58***
	compALL_fees	0.011	0.003	0.012	0.002	0.013	0.003	0.014	0.003	0.017	0.003	-0.006***
	flow_auto	0.019	0.275	0.027	0.257	0.061	0.287	0.124	0.341	0.182	0.362	-0.163***
	"*Pension Plan*"	0.019	0.162	0.013	0.154	0.029	0.203	0.078	0.301	0.087	0.327	-0.068***
Post-1999	**rand_feechgs**	0.068	0.089	0.128	0.129	0.128	0.128	0.113	0.121	0.119	0.116	-0.051***
	compALL_funds	63.12	49.46	54.16	40.75	53.49	42.59	54.51	41.46	56.16	40.72	6.96***
	compALL_fees	0.012	0.002	0.014	0.002	0.014	0.002	0.014	0.002	0.016	0.003	-0.004***
	flow_perf	0.140	3.347	0.004	1.905	0.165	2.209	0.080	2.087	0.187	1.920	-0.046***
	flow_auto	0.183	0.310	0.163	0.298	0.231	0.316	0.341	0.349	0.364	0.369	-0.181***
	"*Pension Plan*"	0.048	0.226	0.041	0.207	0.077	0.268	0.161	0.338	0.184	0.375	-0.136***
	"Easy-In Hard-Out"	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.053	0.033	0.175	-0.033***

Panel B. Coefficients in Fee Regressions (Pre-1999)

Controlling for…	Randomization		Competition		Captivity		All	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
rand_feechgs	0.0016	2.97					0.0016	2.85
compALL_funds			-0.0001	-3.11			-0.0001	-3.24
compALL_fees			0.5126	10.63			0.4970	11.99
flow_auto					0.0016	2.79	0.0007	1.05
"Pension Plan"					0.0003	2.14	0.0002	2.22
Family Fixed Effects	No		No		No		No	
Other Controls	Like Table 2		Like Table 2		Like Table 2		Like Table 2	
# of years	34		34		34		34	
# of obs.	12108		10416		12108		10416	
Avg. R-Squared	44.7%		51.3%		45.1%		52.5	

Panel C. Coefficients in Fee Regressions (Post-1999)

Controlling for…	Randomization		Competition		Flow-Perf. Sens.		Captivity 1		Captivity 2		All	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
rand_feechgs	0.0038	8.84									0.0031	9.59
compALL_funds			-0.0000	-2.21							-0.0000	-4.50
compALL_fees			0.5259	24.24							0.4650	22.24
flow_perf					0.0002	2.25					0.0001	1.76
flow_auto							0.0035	17.78			0.0031	15.24
"Pension Plan"							0.0012	11.12			0.0013	12.87
"Easy-In Hard-Out"									0.0021	3.64		
Family Fixed Effects	No		No		No		No		No		Yes	
Other Controls	Like Table 2		Like Table 2		Like Table 2		Like Table 2		Like Table 2		Like Table 2	
# of years	10		10		10		10		10		10	
# of obs.	33323		33257		33315		33323		15745		33249	
Avg. R-Squared	44.7%		46.9%		44.2%		48.8%		36.0%		53.5%	

Panel D. Average Fee 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
Full Period	**Base Case**	44	89	235	65	137	288	28	60	118
	Randomization	43	88	235	65	137	279	28	59	113
	Competition	42	84	228	50	99	211	26	52	100
	Captivity: Pension Plans	42	87	233	64	135	277	26	58	115
	Controlling for All	40	84	229	50	102	212	24	51	98
Post-1999	**Base Case**	59	108	202	59	110	228	47	96	176
	Perf-Flow Sensit.	59	107	202	59	110	229	47	96	175
	Family FE (100)	55	99	187	51	101	211	40	77	157
	Family FE (250)	58	105	198	57	107	223	46	90	169
	Captivity: "Easy-In Hard-Out"	47	96	198	41	87	177	47	87	183

Table 7. Transition Probabilities between Fee Quintiles

The table summarizes 1-year and 2-year transition probabilities between fee quintiles for our sample of mutual funds (see Table A in the Appendix for a detailed description of the sample). In Panel A and C we look at expense ratios. In Panel B and D, the residual fee is defined as the regression residual of Spec. 1 (pre-1999) and Spec. 4 (post-1999) as specified in Panel A of Table 2. In Panels A and B, we determine the quintile thresholds using all funds within one year. In Panels C and D, we determine the quintile thresholds using only "old" funds (i.e., funds that were in the sample in the previous year) within one year. The data covers the period of 1963 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix.

Panel A. Expense Ratios (All Funds)

	Low Fees (t-12)	2 (t-12)	3 (t-12)	4 (t-12)	High Fees (t-12)
Low Fees	87.0%	11.0%	0.7%	0.7%	0.6%
2	8.4%	72.7%	16.5%	1.7%	0.7%
3	1.1%	11.3%	68.7%	17.4%	1.5%
4	0.5%	1.6%	11.8%	69.8%	16.3%
High Fees	0.7%	0.5%	1.6%	12.4%	84.7%
	Low Fees (t-24)	**2 (t-24)**	**3 (t-24)**	**4 (t-24)**	**High Fees (t-24)**
Low Fees	80.9%	16.1%	1.4%	0.8%	0.7%
2	10.7%	61.4%	24.1%	2.7%	1.0%
3	1.9%	14.1%	57.3%	24.0%	2.7%
4	0.7%	2.5%	14.0%	59.5%	23.3%
High Fees	0.8%	0.7%	1.8%	15.6%	81.0%

Panel B. Residual Fees (All Funds)

	Low Fees (t-12)	2 (t-12)	3 (t-12)	4 (t-12)	High Fees (t-12)
Low Fees	70.1%	19.4%	5.9%	2.5%	2.0%
2	20.6%	46.1%	22.5%	7.7%	3.0%
3	6.6%	21.8%	43.2%	21.9%	6.5%
4	3.4%	7.9%	21.3%	48.8%	18.5%
High Fees	2.4%	4.1%	6.1%	17.7%	69.7%
	Low Fees (t-24)	**2 (t-24)**	**3 (t-24)**	**4 (t-24)**	**High Fees (t-24)**
Low Fees	62.2%	22.5%	7.5%	4.5%	3.2%
2	23.9%	38.5%	23.8%	9.1%	4.6%
3	9.1%	22.9%	36.7%	23.2%	8.1%
4	4.7%	11.0%	21.5%	41.5%	21.4%
High Fees	3.2%	4.7%	8.7%	20.9%	62.5%

Panel C. Expense Ratios (Old Funds Only)

	Low Fees (t-12)	2 (t-12)	3 (t-12)	4 (t-12)	High Fees (t-12)
Low Fees	86.8%	11.3%	0.7%	0.4%	0.8%
2	8.3%	71.6%	17.5%	2.1%	0.5%
3	1.0%	11.1%	67.5%	18.4%	1.9%
4	0.5%	1.3%	12.5%	69.9%	15.8%
High Fees	0.7%	0.4%	1.5%	10.4%	87.0%
	Low Fees (t-24)	**2 (t-24)**	**3 (t-24)**	**4 (t-24)**	**High Fees (t-24)**
Low Fees	80.3%	16.5%	1.5%	0.7%	0.9%
2	10.8%	60.1%	25.0%	3.0%	1.1%
3	2.0%	13.3%	56.9%	25.2%	2.7%
4	0.6%	2.4%	13.9%	59.9%	23.2%
High Fees	0.7%	0.5%	1.7%	12.9%	84.1%

Panel D. Residual Fees (Old Funds Only)

	Low Fees (t-12)	2 (t-12)	3 (t-12)	4 (t-12)	High Fees (t-12)
Low Fees	70.1%	19.2%	6.2%	2.3%	2.1%
2	21.5%	44.9%	22.7%	7.7%	3.1%
3	7.5%	22.0%	41.7%	22.2%	6.7%
4	3.8%	7.5%	20.9%	47.8%	20.1%
High Fees	2.7%	4.1%	5.9%	17.9%	69.5%
	Low Fees (t-24)	**2 (t-24)**	**3 (t-24)**	**4 (t-24)**	**High Fees (t-24)**
Low Fees	63.0%	21.4%	8.1%	4.2%	3.4%
2	25.0%	37.9%	22.6%	9.7%	4.9%
3	10.1%	22.3%	36.2%	23.0%	8.4%
4	4.8%	11.1%	21.0%	40.4%	22.8%
High Fees	3.5%	4.9%	8.6%	20.4%	62.6%

Table 8. Determinants of First Fees

The table summarizes results from cross-sectional regressions (one observation per fund) that use the first reported expense ratio of a fund as their dependent variable. Our sample consists of domestic equity mutual funds (see Table A in the Appendix for a detailed description of the sample). The data covers the period of 1963 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix.

	Number of Funds in Family > 10				Number of Funds in Family > 100			
	Value-Weighted Family Char.		Equal-Weighted Family Char.		Value-Weighted Family Char.		Equal-Weighted Family Char.	
Variables	**Coeff.**	**t-value**	**Coeff.**	**t-value**	**Coeff.**	**t-value**	**Coeff.**	**t-value**
ln_mtna_t	-0.0004	-12.51	-0.0003	-11.04	-0.0003	-8.23	-0.0003	-6.94
$ln\_mgmt\_mtna_t$	-0.0002	-5.72	-0.0003	-6.74	-0.0004	-5.52	-0.0005	-5.01
$avgFamFee_t$	0.3531	14.56	0.4922	18.33	0.1314	3.49	0.3016	6.28
$sdFamFee_t$	0.1425	2.57	0.0871	1.42	0.3259	3.93	0.3256	3.07
$avgFamPerf_t$	0.0031	1.75	0.0048	2.32	0.0092	2.9	0.013	3.43
$sdFamPerf_t$	0.0075	3.31	0.0026	1.24	-0.0008	-0.22	0.0011	0.34
$beta\_mkt_{t+3}$	0.0024	9.32	0.0026	10.28	0.0035	10.75	0.0038	11.69
$yret_{mkt,t}$	-0.0136	-5.13	-0.0111	-4.19	-0.0196	-3.88	-0.0102	-2.01
$beta\_mkt_{t+3}$ x $yret_{mkt,t}$	0.0033	2.1	0.0026	1.68	-0.0003	-0.18	-0.0005	-0.29
$beta\_smb_{t+3}$	0.0008	3.38	0.0009	3.97	0.0005	1.45	0.0006	1.75
$yret_{smb,t}$	-0.0072	-4.69	-0.0057	-3.72	-0.0119	-4.37	-0.0081	-2.95
$beta\_smb_{t+3}$ x $yret_{smb,t}$	0.0074	3.91	0.0062	3.33	0.0095	3.56	0.0087	3.27
$beta\_hml_{t+3}$	-0.001	-6.04	-0.001	-6.01	-0.0011	-4.86	-0.0011	-5.26
$yret_{hml,t}$	-0.0051	-2.96	-0.0045	-2.6	-0.0119	-3.41	-0.0047	-1.28
$beta\_hml_{t+3}$ x $yret_{hml,t}$	0.0044	4.29	0.0036	3.63	0.0031	2.33	0.0034	2.59
$beta\_umd_{t+3}$	-0.0003	-0.97	-0.0004	-1.64	-0.0003	-0.92	-0.0004	-1.14
$yret_{umd,t}$	-0.0029	-2.54	-0.0029	-2.55	-0.0038	-2.29	-0.0029	-1.72
$beta\_umd_{t+3}$ x $yret_{umd,t}$	0.0043	2.86	0.0049	3.28	0.0052	2.52	0.0048	2.36
inst_flag	-0.0054	-33.89	-0.0052	-33.14	-0.005	-26.27	-0.0049	-25.87
etf_flag	-0.0015	-3.29	-0.0003	-0.7	-0.0037	-5	-0.0016	-2.21
Constant	0.0140	18.24	0.0115	14.46	0.0190	12.30	0.0136	7.89
Year FE	Yes		Yes		Yes		Yes	
# of funds.	4935		4948		3288		3297	
R-Squared	42.8%		45.4%		38.7%		39.7%	

Table 9. Determinants of Fee Changes

The table reports results of Fama-MacBeth regressions using the yearly changes in expense ratios as dependent variables (see Table A in the Appendix for a detailed description of the sample). The data covers the period of 1963 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix. Δ indicates that we calculate simple changes of our base variables. Variables with subscripts *t-1* are lagged by one year. Some information is only available after 1999 (e.g., information on fund families) and, thus, we split the sample into a pre-1999 and a post-1999 subset. In the pre-1999 case we only report results for our full sample because sample sizes become very small if we focus on largest and smallest funds.

	Pre 1999		Post 1999					
	Full Sample		Full Sample		Largest Funds		Smallest Funds	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
$Yret_{t-1}$	-0.0028	-0.85	-0.0013	-5.43	-0.0012	-5.65	-0.0007	-1.27
Δbeta_mkt	0.0025	0.30	0.0000	-0.02	0.0001	0.69	0.0016	1.60
Δbeta_hml	-0.0013	-0.60	-0.0005	-1.06	-0.0002	-0.76	-0.0023	-1.03
Δbeta_smb	-0.0034	-2.27	0.0010	1.85	0.0003	1.41	0.0033	1.03
Δbeta_umd	0.0014	0.28	0.0011	1.53	-0.0005	-1.16	0.0014	0.43
Δr_squared	-0.0028	-0.44	0.0001	0.13	-0.0002	-0.91	0.0013	0.78
CompNew_Funds	0.0014	1.25	0.0000	0.24	0.0000	-0.88	0.0000	0.77
CompNew_Fees	-0.1088	-1.60	0.0025	1.00	0.0001	0.05	0.0192	1.76
$flow_{t-1}$	0.0007	1.03	0.0000	-1.17	0.0000	-2.07	0.0000	0.61
Δln_mtna	-0.0006	-0.83	-0.0002	-1.34	-0.0001	-2.92	0.0000	-0.09
fund_age	-0.0001	-1.00	0.0000	3.45	0.0000	2.21	0.0000	-0.63
Δsd_mret	0.0771	0.97	0.0056	0.92	0.0003	0.06	0.0233	0.55
Δturn_rat			0.0002	1.22	0.0000	0.57	0.0000	-0.18
Δln_mgmt_mtna			0.0000	-0.50	-0.0001	-2.79	-0.0003	-2.57
part_family100			0.0000	-0.93	0.0000	-0.52	0.0000	0.08
inst_flag			0.0001	1.60	0.0001	1.00	0.0001	0.30
open_flag			0.0002	3.44	0.0001	0.85	0.0007	1.40
etf_flag			0.0000	0.31	0.0000	0.99	0.0000	0.00
Constant	0.0026	1.60	-0.0002	-2.51	-0.0001	-0.72	-0.0007	-2.10
# of years	18		10		10		10	
# of obs.	4506		21124		5499		2522	
Avg. R-Squared	29.0%		15.5%		22.2%		15.6%	

Table 10. Performance-Flow Sensitivity

The table shows the means, standard deviations and medians of flows and expense ratio changes of groups of funds. All statistics are calculated from pooled data. We group funds by performance: low (high) performance funds are funds in the bottom (top) decile of past year's returns. We also split funds by different measures of fees into "cheap" (below median) and "expensive" (above median) funds. Performance deciles and expense medians are calculated separately for each year.

			First Expense Ratio		**Expense Ratio**		**Residual Fee**	
			Below Median	**Above Median**	**Below Median**	**Above Median**	**Below Median**	**Above Median**
Yearly Return$_{t-1}$	Low	Mean Flows	3.6%	-1.3%	4.7%	-2.1%	7.5%	-7.3%
		SD of Flows	113.1%	115.6%	128.4%	106.0%	130.1%	94.7%
		Median Flows	-11.1%	-15.4%	-11.2%	-15.3%	-11.1%	-16.8%
		Mean Fee Changes	3 bps	3 bps	-1 bps	5 bps	0 bps	7 bps
		SD of Fee Changes	20 bps	28 bps	13 bps	30 bps	17 bps	32 bps
		Median Fee Changes	0 bps	0 bps	0 bps	0 bps	0 bps	1 bps
		Funds	1434	2692	1507	2619	2153	1973
	High	Mean	79.4%	65.3%	72.4%	69.6%	86.2%	56.9%
		SD	258.5%	188.9%	235.1%	203.7%	272.4%	154.6%
		Median	14.0%	15.4%	15.3%	14.3%	15.9%	14.2%
		Mean Fee Changes	-2 bps	-6 bps	-3 bps	-5 bps	-5 bps	-4 bps
		SD of Fee Changes	11 bps	23 bps	11 bps	24 bps	16 bps	22 bps
		Median Fee Changes	0 bps	-2 bps	-1 bps	-2 bps	-1 bps	-1 bps
		Funds	1638	2449	1991	2096	1960	2127

Figure 1. Fund Fee Dispersion

The figure shows the fee 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 (connected, dark line). In rows 2 and 3 we include a line (connected, dark line) that 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 fee is defined as the regression residual of the fee models specified in Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Appendix for a detailed description of the sample). The data covers the period of 1963 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix.

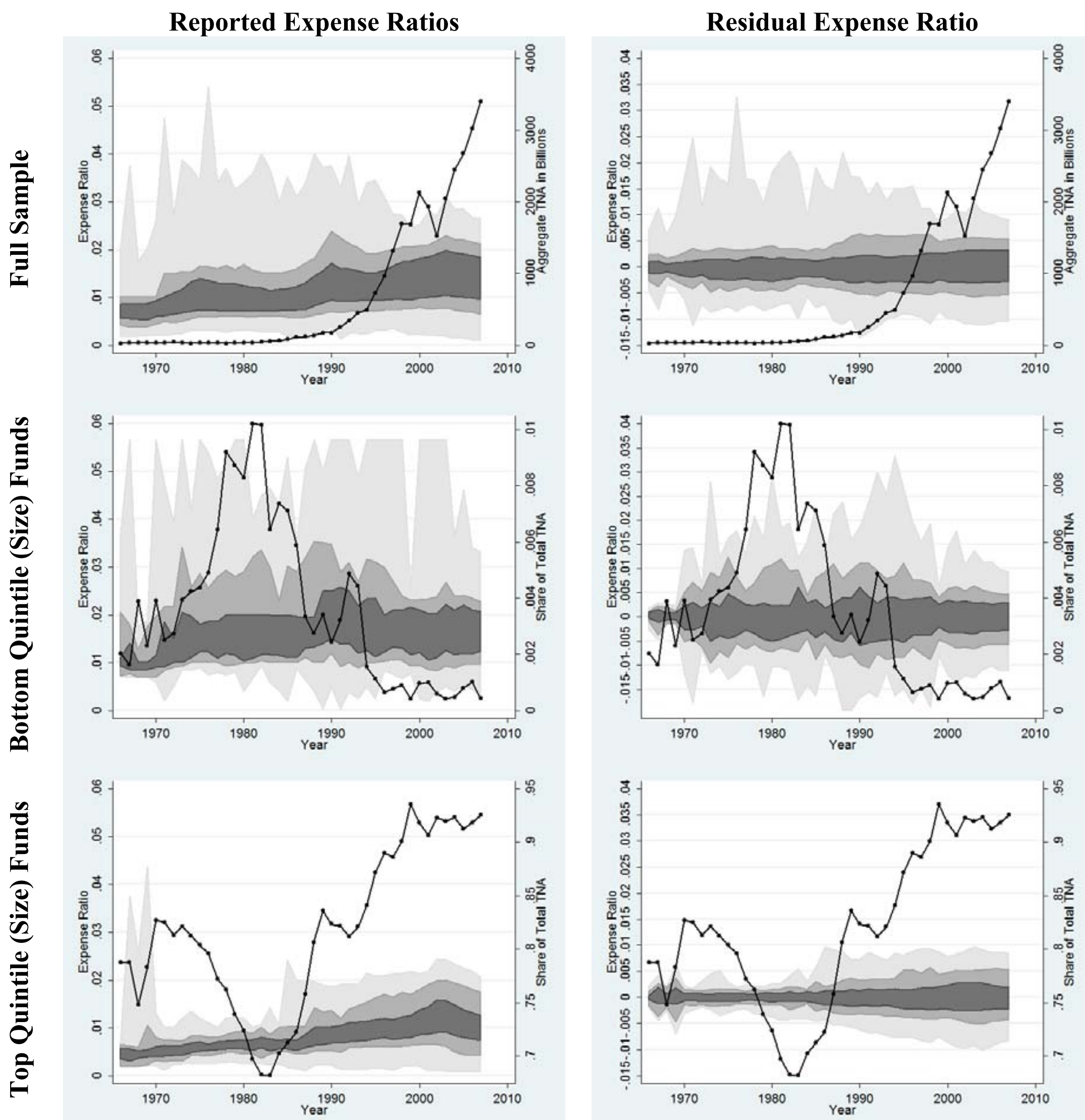


Figure 2. Fund Fee Dispersion Within and Outside of Fund Families

The figure shows the fee dispersion of expense ratios (left column) and residual expense ratios (right column) across funds that are part of a fund family (top row) and funds that are not (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.. In addition, all graphs include the mean expense ratios or the mean residual expense ratios (black dots). For these plots management companies with more than 100 funds are defined as fund families. The residual fee is defined as the regression residual of the full sample fee model in Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Appendix for a detailed description of the sample). The data in this analysis covers the period of 1999 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix.

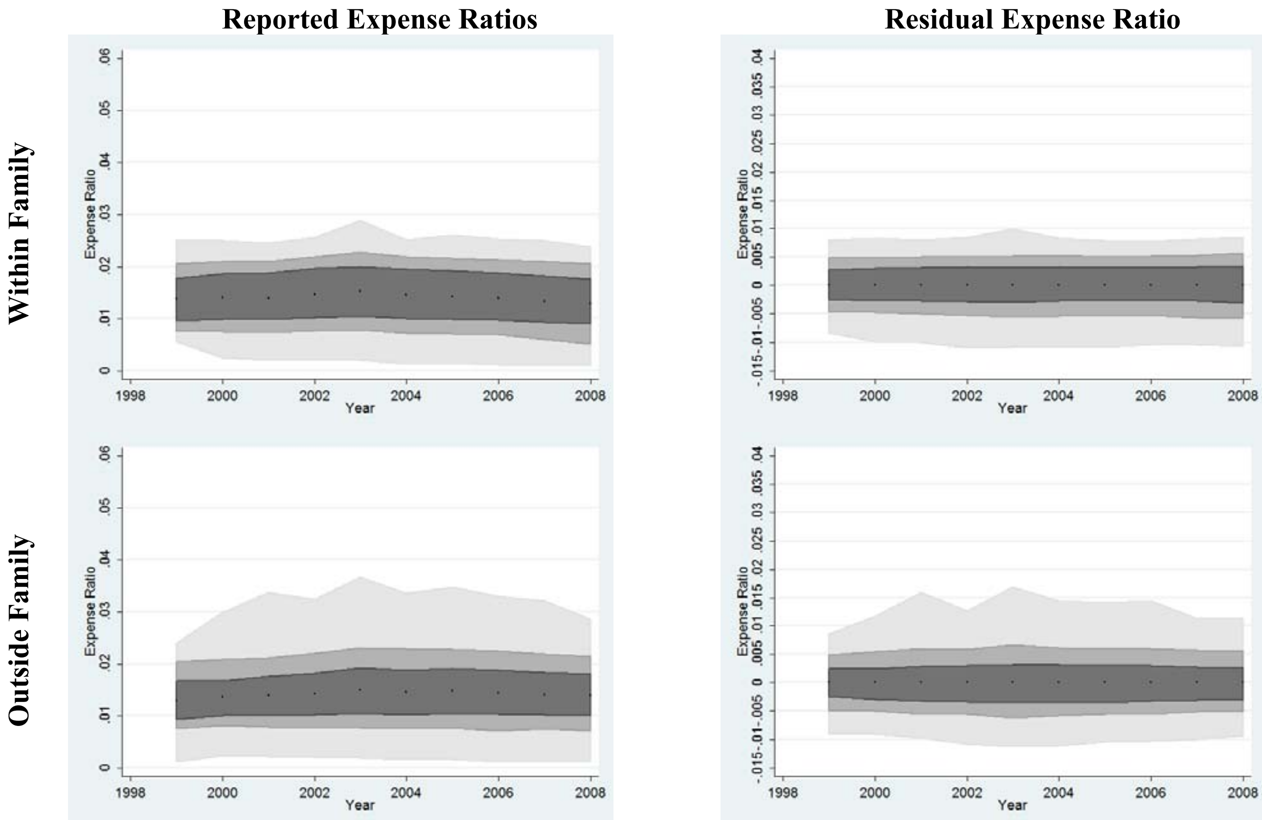


Figure 3. Fund Fee Dispersion of Institutional and Retail Funds

The figure shows the fee dispersion of 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 an1st and 99th percentile (light grey) points of the distributions.. In addition, all graphs include the mean expense ratios or the mean residual expense ratios (black dots). The residual fee is defined as the regression residual of the full sample fee model in Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Appendix for a detailed description of the sample). The data in this analysis covers the period of 1999 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix.

Reported Expense Ratios | **Residual Expense Ratio**

Institutional Funds

Retail Funds

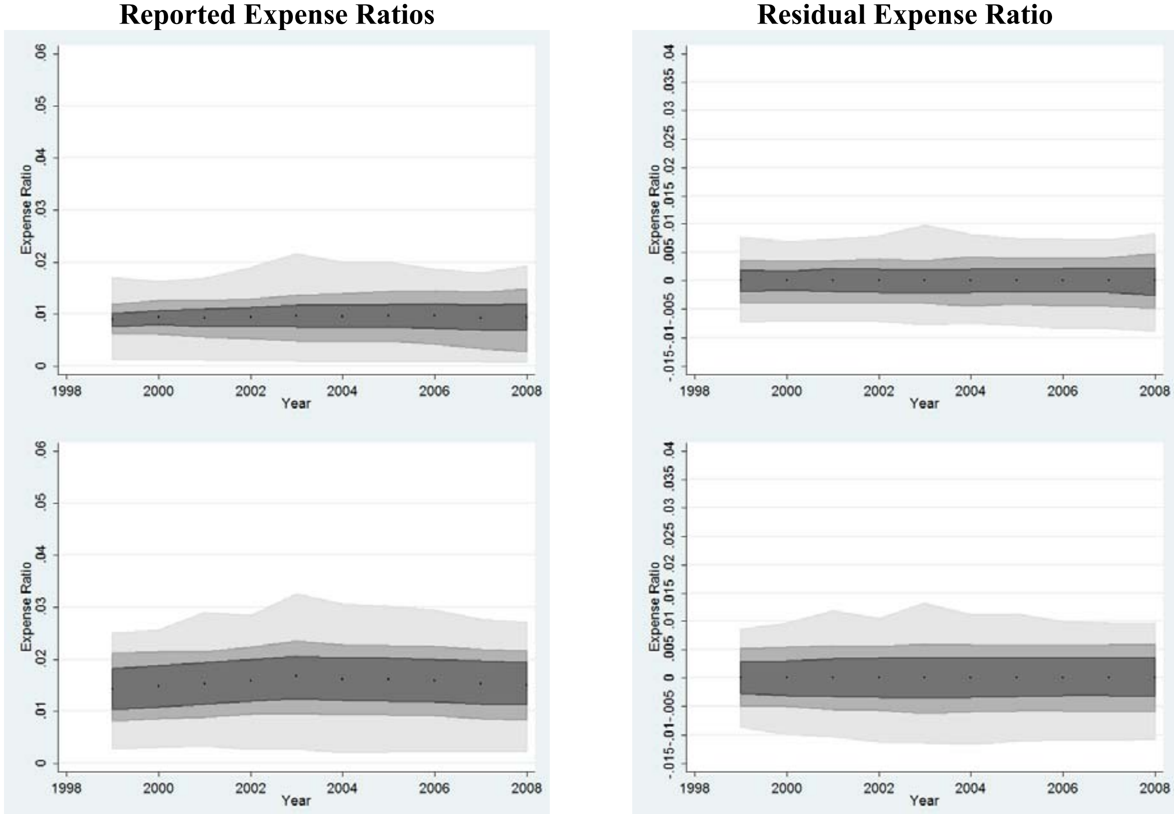
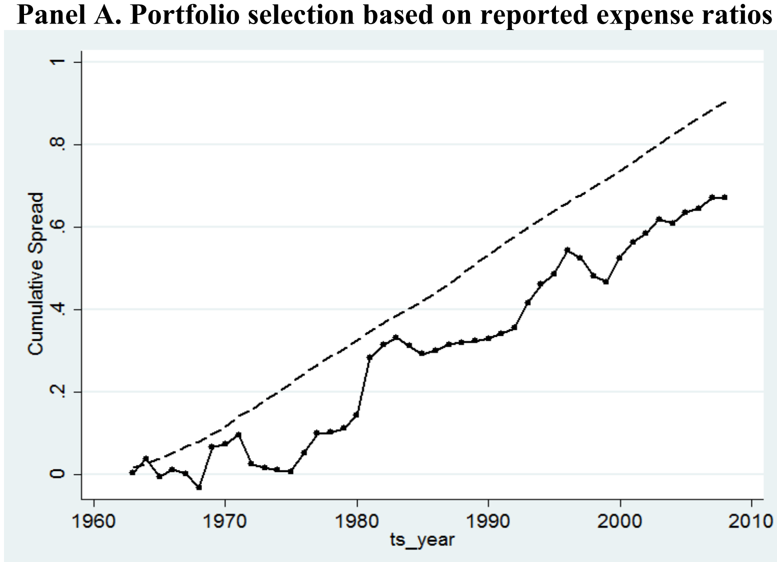


Figure 4. Evaluation of Trading Strategy

The figure summarizes the cumulative Carhart alpha (the solid line with markers) of a strategy that buys funds, which are in the bottom decile according to reported expense ratios (residual expense ratios), and shorts funds, which are in the top deciles according to reported expense ratios (residual expense ratios). The table also reports the cumulative spread between the average reported expense ratio (residual expense ratio) of funds in the top and the bottom decile (the dashed line). The residual fee is defined as the regression residual of Spec. 1 (pre-1999) and Spec. 4 (post-1999) as specified in Panel A of Table 2. Our sample consists of domestic equity mutual funds (see Table A in the Appendix for a detailed description of the sample). The data covers the period of 1963 to 2008 and is a yearly panel. Variables are defined in Table B in the Appendix.

Panel A. Portfolio selection based on reported expense ratios



Panel B. Portfolio selection based on residual fees